Indonesian Journal of Electrical Engineering and Computer Science
Vol. 31, No. 1, July 2023, pp. 359~368
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v31.i1.pp359-368

Age and gender classification with bone images using deep learning algorithms

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Article Info

Article history:

Received Oct 7, 2022
Revised Mar 8, 2023
Accepted Mar 12, 2023

Keywords:

Bone age assessment
Chronological age
Classification
Convolutional network
Deep learning

ABSTRACT

In paediatrics, bone age is a crucial indicator of how a child's skeleton is developing. They have had great success ever since the creation of deep learning (DL)-based bone age prediction tools. Deep features learning, however, has a significant computing overhead problem. Deep convolution layers are used in this technique to learn representative features in the small yet useful regions that are extracted for feature learning. This work suggests using an extreme learning machine algorithm as the fundamental architecture in the final bone age assessment study to realise the rapid computation speed and feature interaction. The viability and efficacy of the suggested strategy have been verified by experiments using data that is openly accessible. The suggested model is explicitly trained using a cutting-edge end-to-end learning architecture employing bone scans to extract the most discriminative patches from the original high-resolution image. The bone picture is the foundation of the procedure. Our main objective is to categorize individuals by age using convolution neural network (CNN) classification models, such as the Xception and Mobile Net models. As a result, we have achieved results that are 90% and 94% accurate in classifying people by age using CNN models.

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1. INTRODUCTION

A person's skeletal and biological maturity can be determined by their bone age. Unlike chronological age, which is established by a person's birth date, this age is different. Paediatricians used to compare a child's bone age to their chronological age to diagnose conditions that make kids to shape their stature. These measures are helpful to evaluate how well these diseases' treatments are working. Formula have also been developed for calculating a child's final adult height from figures for the child's bone age in healthy, normal children. The estimation of bone age is used to determine chronological age for the kids whose birth records are not available. A major issue in our region of the world is the lack of birth records. The hand and wrist bones' ossification pattern is frequently predictable and age-specific. By comparing the maturity of the hand and wrist bones, the standard age associated with normal ageing has been determined.

The bone age study can assess how quickly or slowly a child's skeleton is developing, which can assist doctors in identifying diseases that either slow down or accelerate up physical development. Typically, doctors or paediatric endocrinologists will request this test. Identifying the age of death, birth date, year of death, and gender of unidentified human remains in the context of a criminal investigation might help detectives make the right identification out of a possible match.

An ultrasonography of the hand bones is being tested, but still not useful to demonstrate how much the hand bones have grown and evolved using a plain wrist radiography. In forensics and anthropology, determining the age is critical for the identification of unknown individuals or skeletal remains. The quality and quantity of the mortal remains, as well as the period between autopsy and death, environmental circumstances, and the structure of the corporeal remains or skeleton parts, are all important considerations in postmortem examination. It may also be affected by other case-specific considerations such as expenses, time, and equipment requirements. There are numerous techniques for estimating age when those important aspects are considered. Teeth can be used as a biological indicator of ageing. Teeth have a highly mineralized structure that protects them from postmortem decomposition and allows them to endure fires, alkalis, and acids. Even bone can deteriorate over time, but teeth can be kept for a long time and hence can be used for identification in disasters.

Since the advent of social media and platforms, automatic age and gender classification has become increasingly crucial for a variety of applications. Even Although there have been significant performance advances recently for the closely related issue of facial recognition, the performance of existing techniques on actual photographs still trails well behind those results. In order to extract the attributes, the network needs first be trained on a lot of photos. Experimental validation on the industry benchmark Radiological Society of North America (RSNA) bone age, images of groups, and benchmarks shows that the use of attention processes enhances the robustness and accuracy of convolution neural networks (CNNs). For age or gender estimation jobs, the majority have used classification schemes like and others. To do this, proposed a simple convolutional net design that may be used even with a little training data. We compare the most recent methods to state-of-the-art techniques using the RSNA bone age standard for age and gender estimate. The ability to accurately determine age and gender of a person from media has a big advantage.

However, the poor performance of CNN's members was brought on by the great diversity of facial photos found in the wild, such as those gathered from the internet. When individuals acknowledge that their performance has declined, they become unhappy.

The fundamental aspect of the research is to find a new feed forward technique with attention mechanism to enhance the robustness of existing CNN. For the unrestricted face images with high resolution analysis, in order to locate the different patches of low resolution, by the recent success of attention mechanisms. Therefore, in addition to improving resolution, our strategy enables the network to give greater weight to the portions of the image that are least obscured or deformed, making the model more resistant to noise and distractions. We carefully compare the effectiveness of our attention pipeline to the most recent, cutting-edge CNNs that have been trained for facial recognition utilising age and gender recognition criteria. Applying standard CNNs to the RSNA images and images of group (IoG) datasets to determine the age and gender recognition results in improved performance compared to standard CNNs. Because RSNA and IoG are composed of unrestricted facial photos that were captured in the field, they serve as examples of how our model is able to recognise soft biometric features from facial images (age and gender).

2. LITERATURE REVIEW

A skeleton's bones age is examined using forensic anthropology. Ultrasonography and radiography are methods used in forensic anthropology. Thus, the Tanner Whitehouse method and the greulich-pyle method make up the radiograph method. The use of ultrasound is a Atlas and scoring technique are two examples of each category. But a thorough explanation of the forensic anthropology method is provided [1]. The study's primary goal is to estimate and determine the age and gender of the middle eastern population. This approach is implemented using a random forest classification algorithm, which considers 126 wrist radiographs from age groups between 6 and 78, totaling 76 male samples and 50 female samples. The current work achieves accuracy of 97% [2].

Numerous factors, such as gender, diet, metabolic, genetic, and social factors, as well as acute and chronic diseases, particularly hormone change, might influence bone age. The many standardised techniques created throughout the years can also be used to characterise several differences. Therefore, to effectively employ this knowledge for all of its key medical and non-medical fields of application, it is necessary to be aware of the full characterization of the main methods and procedures that are available, specifically of all of its advantages and disadvantages [3]. A variety of forensic techniques were used to assess the deceased's skeletal characteristics, cause of death, and life stature. Conclusion: From a forensic perspective, early sex determination by bone analysis is crucial. By measuring the skull, sex can be determined based on measurements and characteristics. Male long bones often tend to be longer and more massive than female long bones, with more pronounced muscle attachments, having sex evaluation by long bones simpler. Using various odontometric procedures, teeth are particularly helpful in identifying gender [4].

Bone age estimation using non-radiation means such as ultrasonography has been theorised, these techniques are not as accurate as radiographic techniques for seeing the hand and wrist bones. Although the computerized tomography (CT) visualisation of the clavicle has been thoroughly researched, a considerable radiation dose is needed. Although more research is needed, magnetic resonance imaging (MRI)-based techniques are being developed. A different method of estimating bone age that also provides a skeletal age estimate is dental age [5].

Separate gender models were constructed considering the observed disparity in growth rates between the sexes. Image data for some age categories, such as infancy and very early childhood, are much sparser and show a significant departure from other age ranges in terms of morphology. Different region of interest definitions was used to train a variety of deep learning architectures. This research was preliminary, and we intend to investigate different angles not included in the current study in the future [6].

The procedure of estimating the skeletal age of a patient by utilising the age assessment method is tough. In the medical field today, computerised approaches are used in place of hand-held procedures to the extent that this produces superior evaluation to address these limitations. The research is to minimize issues with algorithms and high diagnostic accuracy when dividing up current systems [7]. An innovative Tanner-Whitehouse bone age assessment method is proposed by this work. In this method, small yet valuable regions are identified, and layers of convolution are employed to characteristics. In order to realise the faster computation, this work recommends adopting an algorithm [8].

The following are the key findings and accomplishments: i) The grayscale image is pre-processed by ImageNet's EfficientNet into a three-channel image. ii) Combining the size and cutting of an X-ray picture of the hand bone and decreasing the image area without the hand bone [9]. The goal is to model a system that supports for decision making a paediatric bone age assessment using wrist radiographs that will speed radiologists' workflow [10]. Our approach entails networks, where every node and edge stand for a region-of-interest (ROI) and its correlation [11]. Describes an approach to extract latent spatial characteristics from multimodal magnetic resonance (MR) images, which may enhance the early multiple sclerosis (MS) disease identification [12].

This paper proposes a novel, comprehensive, deep automated skeletal bone age assessment model based on region-based convolutional neural networks (R-CNN) [13]. The procedure, known as BoneXpert, uses radiographs of the hand to mechanically recreate the borders of 15 bones. It then determines the "intrinsic" bone ages for each of 13 bones (radius, ulna, and 11 short bones [14].

We offer a technique for estimating age of a bone from radiographs based on deep learning. It offers a quick, deterministic technique for determining bone age [15]. The new trends in this field of study have been examined and debated [16]. This study's objective was to assess how storage phosphor plate (SPP) system images acquired at various compression settings and image resolutions affected the fractal dimension of alveolar bone [17]. A remodelling of a bone funder external loads was simulated [18]. Modern deep learning techniques, such as data augmentation, an optimal learning rate finder, and fine-tuning, were employed to train the model [19], [20]. The X-ray hand bone image is then automatically evaluated using a convolution neural network that has been trained to recognise its features [21].

Identification of skeletal remains relies heavily on age determination from bones. We describe an unique age estimation technique that was created by applying algorithm to bone images from postmortem computed tomography (PMCT) [22]. The purpose of this study was to compare the Greulich-Pyle approach against an automated building automation (BA) assessment to determine how accurate and effective it was [23]. To create an automatic and manual bone age assessment method based on Greulich and Pyle, and to compare it with the deep learning strategy developed based on a training set of developmentally normal paediatric hand radiographs (GP) [24]. We use six pre-built, CNNs with weights that have been trained on ImageNet. With the use of a transfer learning technique, technique to extract features from preprocessed hand photos [25]. CNN architectures like VGG16, DeseNet121, MobileNet, NASNet, Xception, and EfficientNet are used in the suggested work [26].

3. METHOD

The vast number of examples and image data made available through the internet was not properly utilised by the machine learning techniques used by these systems to enhance categorization performance. In this study, we attempt to close the gap between age and gender estimation methods and automatic facial recognition technologies. To do this, we use the efficient model established by existing facial recognition systems: Recent research has shown that deep convolutional neural networks may significantly improve facial recognition algorithms (CNN). A deep learning model takes care of this for the programmer instead of the programmer having to explicitly fix the problem when a machine learning model predicts incorrectly.

3.1. Data collection

The datasets are gathered from Kaggle. The dataset is made up of two files, training and testing, which together contain over 23,000 photos. In the data, there are 70% of photos are used for training t and 30% of images are used for testing. This dataset is 9.28 GB in size. The test folder has 2,000 photos (162 MB). The training folder has 10,611 pictures (9.12 GB). Jpeg files are used for the photos.

Several of the stages taken to create the estimating model include:

- Import all required layers.
- Create the required functions for the following blocks: Conv-BatchNorm block, SeparableConv-BatchNorm block.
- Create a function for each of the three flow directions: entry, middle, and exit.
- Using these functions, construct the entire model.

3.2. Data preprocessing

Pre-processing is a stage when the collected data could have null values, missing values, or undesirable data that could produce inaccurate findings. Therefore, pre-processing is a crucial stage where irrelevant data can be removed to obtain better results. Preprocess the data in order to delete pointless image. Divide data sets into training and testing groups. Here, pre-processing is carried out based on the scanning image's size, correct shape, and zoom level. Three folders include the transfer of the accessible photos (training, validation, testing).

3.3. Generating sample images

A selection of the sample photographs is shown following the dataset splitting. Figures 1 and 2 are gallery of grayscale pictures of the dataset. The Figure 1 illustrates the sample for the training the model. As shown in Figure 2 displays the sample images for testing the model. The sample images for training and testing the model is shown in Figures 1 and 2.

Figure 1. Selection of training photos

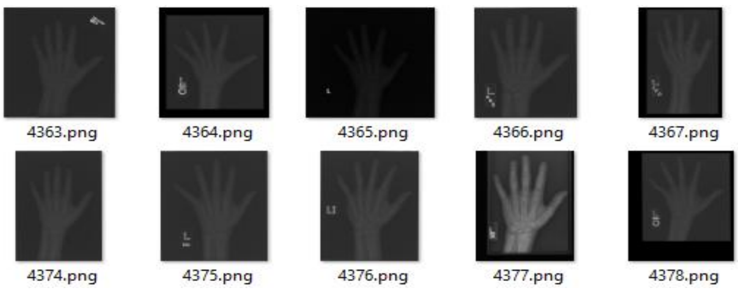

Figure 2. Selection of testing images

3.4. Xception model

A 71-layer convolutional neural network is known by the moniker of Xception. A pretrained version of the network, which was created using training data from over a million photos, is present in the ImageNet database. State-of-the-art accuracy on SVHN and CIFAR10/100 (with or without data augmentation) is produced by this connectivity pattern. On the massive RSNA dataset, Xception achieves a reasonable level of accuracy while utilising just around half as many parameters and Flops. Figure 3 provides the layered approach of the Xception model with the growth rate.

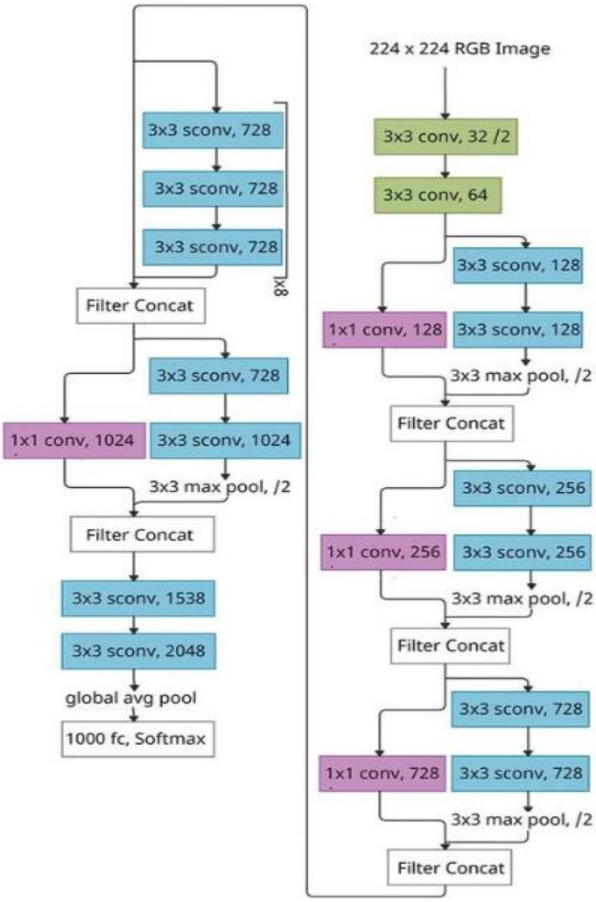

Figure 3. Layered Xception model with growth rate

3.5. Model with Mobile Net

Depth-wise separable convolutions are used by Mobile Net. When compared to a network with standard convolutions of the same depth in the nets, the number of parameters is significantly decreased. Deep neural networks that are lightweight are the outcome. When it comes to training our relatively small and incredibly speedy classifiers, Mobile net provides us with a terrific starting point.

Older studies from the 1990s also used to estimate age of a person in addition to more recent techniques like the pipeline used in, which presented a combination of biologically inspired features (BIF) and then used canonical correlation analysis (CCA) and partial least square (PLS) based methods. The use of BIF for face image representation paved the way for further works and demonstrated how closely the automatic method had gotten to imitating human performance. Before CNNs, the majority of techniques relied on a two-stage pipeline that entailed extracting features like local binary patterns (LBP) and then classifying the data with a support vector machine (SVM) or multi-layer perceptron (MLP).

Age and gender can also be determined using more complex CNN models, but most of them need prior knowledge in the area. Deep model cascades were also considered in the database. The pre-trained network is capable of classifying photos into 1,000 different object categories, including a variety of animals, a keyboard, a mouse, and a pencil. CNNs for facial image processing have been used to ascertain gender, authenticate faces, and estimate facial traits in addition to age assessment. For instance, on the difficult labeled faces in the raw dataset, the strategy suggested in achieves a stunning 89.2% face verification accuracy. Unfortunately, this outstanding performance has not yet been shown for facial analysis applications such as gender recognition.

3.5.1. Feed forward focus to identify people's ages and gender

The proposed model is made up of three basic modules, as shown in Figure 4: i) CNN path that assesses the patches with higher resolution in accordance with their priority predicted by the attention grid; ii) a patch CNN that chooses attention grid that is best to perform the glimpses; and iii) MLP, which combines the data from both CNNs and completes the classification.

An image with reduced resolution is given to CNN, which forecasts a k-kattention grid. The CNN then receives the patches, and the attention grid weights its output. An MLP classifier is then given the combined feature maps from the streams. Figure 4 illustrates the feed forward mechanism architecture to determine the age and gender. The interest CNN receives all the training images. This CNN has been trained specifically to forecast an attention spike:

$$H(k * k)\varepsilon J \geq 0, Y \quad (1)$$

- k - an arbitrary number.
- Hk,-j represent the (nor-malized) importance of each patch.

Then, a high-resolution version of the input image is divided in l×lpatches and fed to CNN's patch.

A tactic CNN receives high-quality face patches. Any model, including the attention CNN, might be employed However, we utilise the early convolutional layers of the attention CNN for this purpose to lower the processing needs of this design. The resultant value is:

$$Q(x2 * m) \in T \quad (2)$$

where x2 is the last convolutional layer's dis output dimension and patch count.

The spatial dimension of Pto one is then decreased using global average pooling (GAP), allowing images to be fed in their standard resolution. The significance of each grid patch is then considered by weighting these feature maps using G. We also take into account two methods for integrating the feature maps of the two CNNs: i) Learning a projection of the patch CNN feature maps to the attention CNN feature map space, and ii) concatenating them after Z normalisation. In this part that follows, we demonstrate how the normed concatenation methodology slightly outperformed the project-and-add method in terms of results.

Figure 5 illustrates the samples of RSNA bone age dataset's fourth fold for age and gender. The resultant classifier is typically composed of the dc6, dc7, and dc8 layers of the CNN literature, is then fed the generated feature maps. This network's input was a grayscale image of fixed size (224 * 224), demonstrating the matrix's form (224,224,3). Using kernels of size (3 * 3) and a stride size of 1 pixel, they were able to cover the entire image. To maintain the image's spatial resolution, spatial padding was applied.

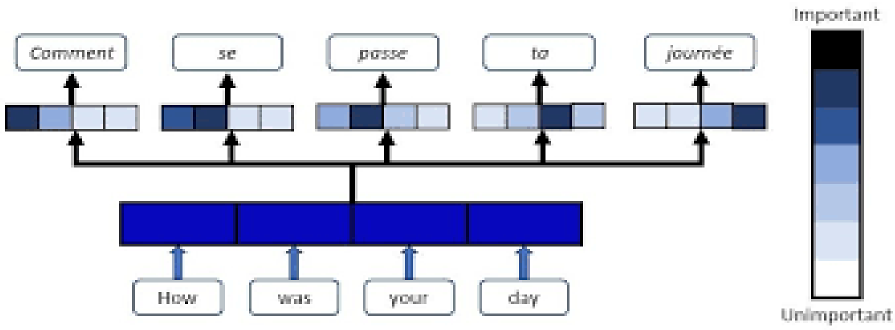

Figure 4. Feed forward mechanism

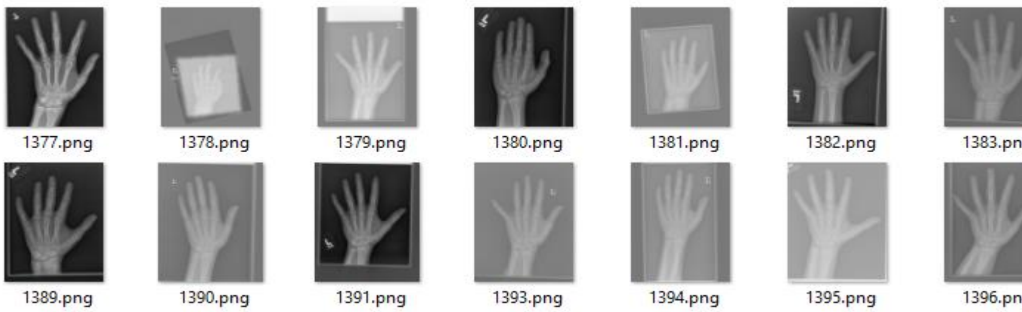

Figure 5. RSNA sample bone image (age)

3.5.2. Model building

The Figure 6 illustartes the over all process flow for the determination of age and gender by using the bone image data set. It provides the sequence of operation carried out in the research. It illustrates the flowof operation as input, modeling, training, and testing. After creating a model, the model is tested with the test sample images to predict the age and gender.

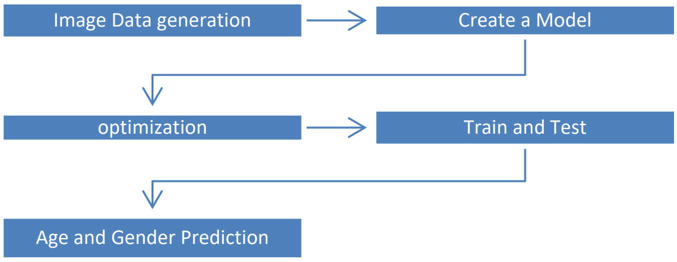

Figure 6. Overall process

4. RESULT AND DISCUSSION

4.1. Building model for age and gender estimation

A function that returns a Keras model object of a convolutional neural network has the input parameters set as arguments. The fully connected layer, convolutional layer, max layer, and pooling layer make up the CNN model. The image that was used has a size of 224.224.3. There are 4 convolutional layers with a [32,64,128,128] convolution filter size. The convolutional filter should have the shape [3,3]. ReLU is the activation function for the hidden layer, and Softmax is the final activation function. There are 128 buried layer neurons. This model uses 40 epochs, a 40-batch size, and a 50-step validation process.

```
val_generator = val_data_generator.flow_from_dataframe(
    dataframe = df_valid,
    directory = '/content/drive/MyDrive/Project_phase_2/dataset/boneage-training-dataset/boneage-training-dataset',
    x_col = 'id',
    y_col = 'bone_age_z',
    batch_size = 32,
    seed = 42,
    shuffle = True,
    class_mode = 'raw',
    flip_vertical = True,
    color_mode = 'rgb',
    target_size = (img_size, img_size))

#test data generator
test_data_generator = ImageDataGenerator(preprocessing_function = preprocess_input)

test_generator = test_data_generator.flow_from_directory(
    directory = '/content/drive/MyDrive/Project_phase_2/dataset/boneage-test-dataset/boneage-test-dataset',
    shuffle = True,
    class_mode = None,
    color_mode = 'rgb',
    target_size = (img_size,img_size))
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from  keras.applications.xception import preprocess_input

img_size = 256

train_data_generator = ImageDataGenerator(preprocessing_function = preprocess_input)
val_data_generator = ImageDataGenerator(preprocessing_function = preprocess_input)

train_generator = train_data_generator.flow_from_dataframe(
    dataframe = df_train,
    directory = '/content/drive/MyDrive/Project_phase_2/dataset/boneage-training-dataset/boneage-training-dataset',
    x_col= 'id',
    y_col= 'bone_age_z',
    batch_size = 32,
    seed = 42,
    shuffle = True,
    class_mode= 'raw',
    flip_vertical = True,
    color_mode = 'rgb',
    target_size = (img_size, img_size))
```

Figure 7. Model building

In order to determine accuracy, categorical loss, categorical accuracy, validation loss, validation accuracy, and multiclass area under the curve (AUC), a model with 40 epochs is shown in Figure 7. Following is a list of the three metrics that are displayed to evaluate how well the model performs:
- loss -> the loss function's value for each epoch.
- Calculates the frequency with which predictions match one-hot labels.
- The multiclass AUC function "computes the approximate AUC via a Riemann sum for each label and then takes the average.

The Figure 8 model analysis and evaluation provides the number of females and males considered for the determination of age and gender. The sample code provides the sequence of operation for train and testing model. The trained network to predict the labels of previously images contained in the test folder. The evaluation of loss function, categorical accuracy and categorical AUC of the test dataset be shown below. Figures 9 and 10 provides the final image as the result, where the gender and age of the corresponding image is obtained.

```
[ ] train_df = pd.read_csv('./boneage-training-dataset.csv')
    test_df = pd.read_csv('./boneage-test-dataset.csv')
    train_df['id'] = train_df['id'].apply(lambda x: str(x)+'.png')
    test_df['Case ID'] = test_df['Case ID'].apply(lambda x: str(x)+'.png')

    train_df.head()
```

	id	boneage	male
0	1377.png	180	False
1	1378.png	12	False
2	1379.png	94	False
3	1380.png	120	True
4	1381.png	82	False

```
male      6833
female    5778
Name: gender, dtype: int64
<matplotlib.axes._subplots.AxesSubplot at 0x7f78a7c10d30>
```

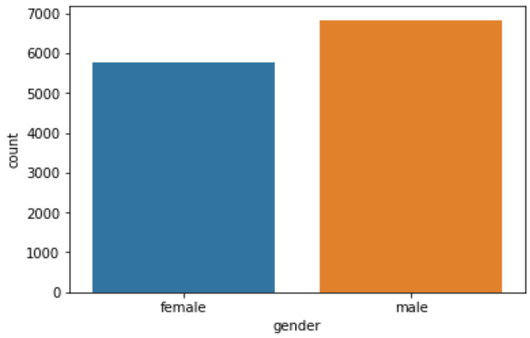

Figure 8. Model analysis and evaluation

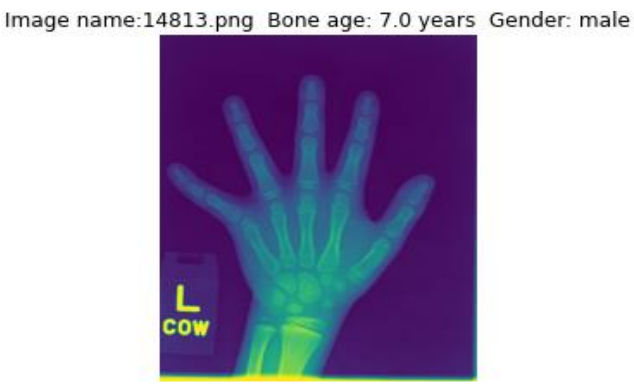

Figure 9. Depicting age and gender

Figure 10. Final result

5. CONCLUSION

The automatic feature learning of age and gender classification using multimodal approaches has been tested using the proposed deep learning method employing convolutional networks. The results of the empirical study also showed that pre-processing, subject-separated data partitioning, hyper-parameter selection, and dataset size may all have an effect on the final performance of the deep learning classifier. In this study, deep learning convolutional neural network models were developed to identify the age and gender of an interactive modal more accurately. In the coming work, hybrid techniques will be used, and their performances will be examined.

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