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Age and Gender Classification Using Deep Learning - VGG16

Aysha I. Mansour and Samy S. Abu-Naser

Department of Information Technology,
Faculty of Engineering & Information Technology,
Al-Azhar University, Gaza, Palestine

Abstract: *Age and gender classification has been around for a long time, and efforts are still being made to improve the findings. This has been the case since the inception of social media platforms. Visible understanding has become more important in the computer vision society with the emergence of AI increase in performance and help train a model to achieve age and gender classification. Although these networks built for the mobile platform are not always as accurate as the larger, more resource-intensive networks we've come to know and love, they stand out when it comes to the accuracy trade-off. Despite the importance of these attributes in our daily lives, the ability to estimate them efficiently from face images is still far from meeting the requirements of commercial applications.*

Keywords: Age and gender Classification, Deep Learning, Classification

INTRODUCTION: However, unlike many other computer vision applications, age and gender classification is an inherently difficult problem. The type of data needed to train these kinds of systems is the main cause of the difficulty difference Compare to datasets without age and gender tags, which often number in the thousands or, at best, tens of thousands, general object classification tasks frequently have access to thousands, if not millions, of images for training. The reason for this is because we need access to the personal information of the persons in the images in order to create labels for such images. Age and gender classification tasks, in my experience, are more efficient for large than other classification tasks.

1. BACKGROUND:

DEEP LEARNING: is an Artificial Intelligence branch of machine learning that has networks with the ability to learn from unlabeled or unstructured data. Deep learning is a technique can be used for age and gender classification from audio files [1-10]. Deep learning algorithms have mostly been used to improve the capabilities of computers so that they can comprehend what humans can do, such as speech recognition. Voice, as the main mode of human communication has got researchers' attention over the past five decades dating back to the advent of Artificial Intelligence [11-20].

Instead of any type of deeper understanding that can be obtained using the approach, "deep learning" refers to various layers of representations. The number of layers that comprise up a data model is referred to as the depth of the model[21-30]. The topic could have been labeled as learning multilayer representations or learning classification tasks. Tens, sometimes even hundreds, of representation layers are typically included in deep learning techniques used nowadays. These layers are actively trained by being subjected to training data. Representations learnt by a deep network for digit classification during the first pass. Network structural changes can be incorporated that result in desired representations at various layers (see Figure1)

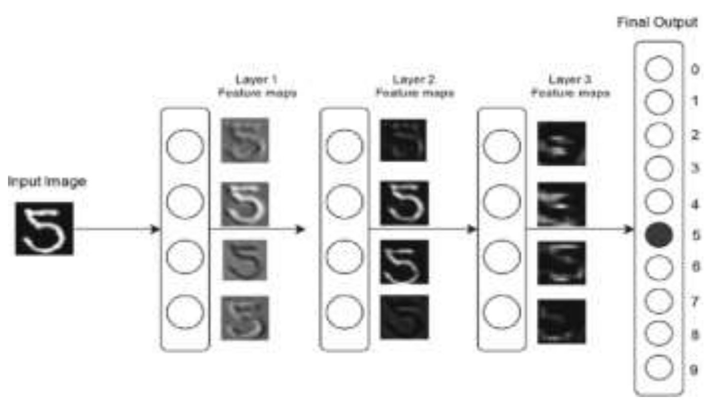

Figure1:A deep neural network for digit classification

As you can see in figure 2: The network transforms the digital image into more different from the original representations that provide additional details about the result. Believe of a deep network as a multiple stage information distillate where data is passed through simpler processes until it is suitable for a given task.

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2. CONVOLUTIONAL NEURAL NETWORK (CNN):

A neural network is a network of connected synthetic "neurons" that communicate with one another. An effectively trained network will function accurately when given an image or example to detect since the associations have numeric levels that are set during the preparation process. Complex structures are checked for organization issues by building different and unique layers in a CNN. Convolution layers, pooling/subsampling layers, non-straight layers, and totally related layers are the four types of layers that are the most frequent. Although neural systems and other case Identification techniques have been around for up to five years, convolutional neural systems have made important advancement.

The features of using CNN for image assertion are discussed in this section. Tenacity in the form of changes and mutilation in the image, lower system needs, best and easier management.

A CNN employs a system similar to a multilayer perceptron that has been optimized for low processing requirements [31-40].

3. VGG 16 Architecture:

Convolutional neural network foundation The VGG 16 is a basic convolutional neural network that helps in learning basic design concepts. VGG16 was found to be the design with the best performance on the ImageNet dataset. Let's analyse the basic architecture of this system.

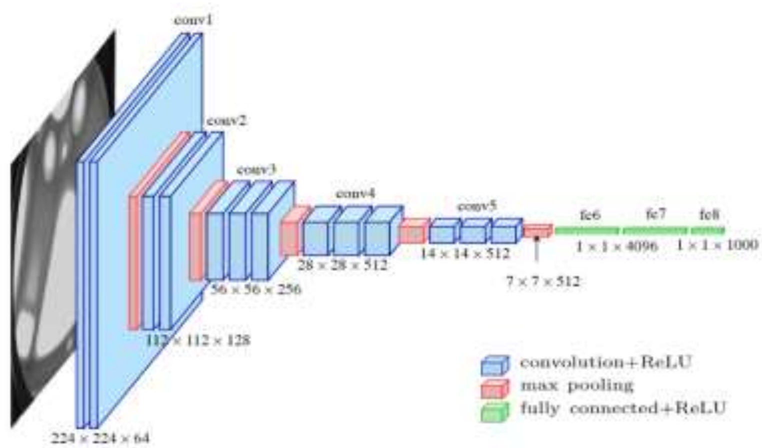

Figure 2: VGG16 Architecture

The input to the cov1 layer is a 224 by 224 RGB image with a fixed size (as can be seen in Figure 2). The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configuration, it additionally includes 1×1 convolution filters, which can be understood as a linear change of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. After convolution, the spatial resolution of the layer input is preserved, i.e. the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. Layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2.

Three Fully-Connected (FC) layers follow a stack of convolutional layers (which has a different depth in different architectures): the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one 16 for each class). The final layer is the soft-max layer. In all networks, the completely connected levels are configured in the same way.

The rectification option is available on all hidden layer non-linearity. It is also noted that none of the networks (except for one) contain Local Response Normalization (LRN), this type of normalization has no effect on performance on the ILSVRC dataset, but leads to increased memory consumption and computation time[4].

4. AGE AND GENDER CLASSIFICATION:

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Age and gender play fundamental roles in social interactions. Different salutations and grammar structures are held for men and women in different languages, and different dialects are frequently employed when addressing older compared to young people. Despite the importance of these attributes in our daily lives, the ability to estimate them efficiently from face images is still far from meeting the requirements of commercial applications. Age and gender classification have been around for a time, but improvements are still being developed. Since the creation of social media platforms, this has been the situation. With the rise of artificial intelligence came an increase in performance and the capacity to train a model to achieve age and gender classification, visible intelligence has become more important in the computer vision industry. Although the accuracy of the these networks developed for mobile devices is not always high as that of the larger, more knowledge networks we've came to appreciate, they stand out in respect of the resource/accuracy trade-off [5].

4.1 AUDIO:

One of the most common applications of Audio Deep Learning is sound classification. It entails learning to classify sounds and predict which category they belong to. In my deep learning class, we have looked at a few articles that were found to be useful. They explained how we prepare audio data for deep learning, why Mel Spectrograms are used in deep learning models, and how they are produced and optimized. This type of problem can be applied to a variety of practical scenarios, such as classifying music clips to determine the genre of the music or classifying short utterances by a group of speakers to determine the speaker based on the voice. We'll start with sound files, convert them to spectrograms, feed them into a CNN Classifier model, and then predict which class the sound.

Audio is represented as audio signal with properties including frequency, bandwidth, and decibel level. The amplitude and time of a typical audio signal can be expressed as a function of each other (as in Figure 3).

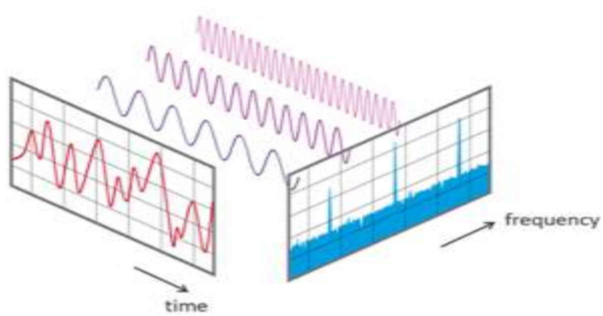

Figure 3: Typical audio signal

There are tools developed to help you in collecting these noises and convert them into a computer-readable format. Examples of these formats are

- wav (Waveform Audio File) format
- mp3 (MPEG-1 Audio Layer 3) format
- WMA (Windows Media Audio) format

The collection of audio features important to the job at hand is followed by decision-making techniques that include detection, classification, and knowledge fusion in a typical audio processing process (as in Figure 4). Well, we have some helpful Python modules to help us with this.

Several approaches for application of CNNs to speech recognition studies have been proposed. applied their original functionally extended CNNs for sound spectrogram inputs and demonstrated that their CNN architecture outperformed earlier basic forms of fully connected DNNs on phone recognition and large vocabulary speech recognition tasks[42-50].

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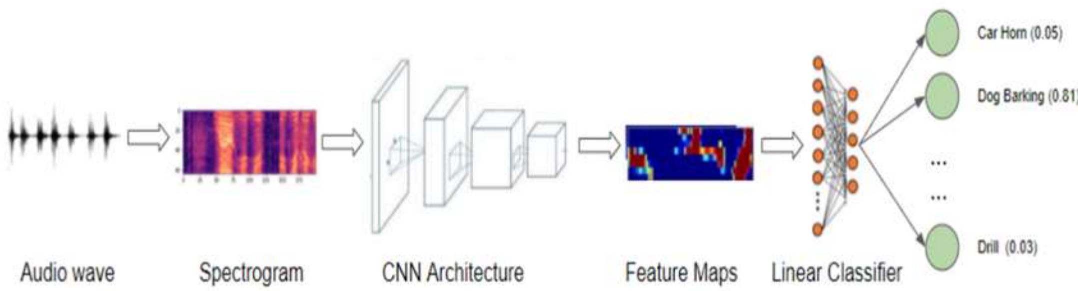


Figure 4: Audio Classification application

5. METHODOLOGY:

In the fenced field of computer science called as artificial edging, statistical techniques are used to provide computer systems the capacity to "learning and adapt" (i.e., keep improving performance on a specific assignment) given data, without being directly customized.

One of the most image analysis techniques is Support vector machine (SVM). One of the best classifiers is it. It is a classification that can be used when there seem to be a lot of features and training data. SVM can be limited to cases where the problem's feature set is very high. For problems involving a large number of elements, such as image classification, etc., it performs incredibly well. It works best for problems involving document classification where features and examples are often quite feature set is high. It is a high classification because it uses a machine learning technique called optimal border based classification. Figure 5 shows how the data collected was plotted using SVM.

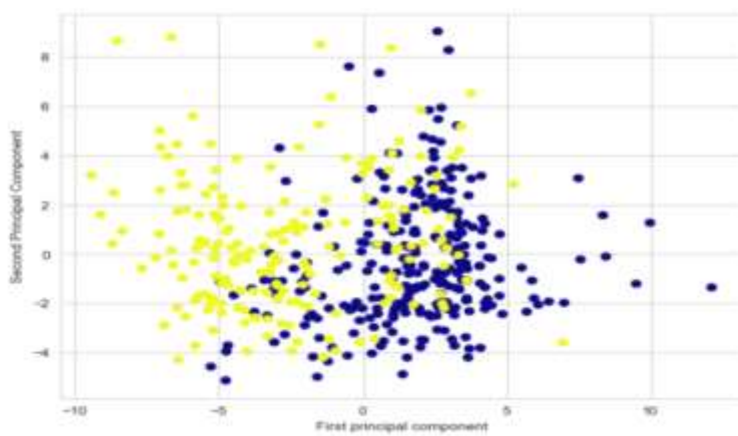


Figure5: original data plotting through SVM

Also known as deep structured learning, is a subset of a more relatives of deep learning techniques that are based on data from special projects rather than doing specific calculations. Unsupervised, partially supervised, or supervised learning are all possible. Powerful learning data are related to preparation for training and matching sequences in an artificial nervous system, such as neural coding that creates a connection between different lifts and related neuronal experiences in the mind. Important learning architecture includes machine learning algorithms, multi-layer perceptron, and neuron[51-64].

5.1 DATASET:

The dataset for age and gender classification was collected from Kaggle website. The dataset consists of 39 categories. These categories represents the speaker gender and age. The dataset contain 8380 audio files of type wav for age and gender classification.

The dataset divided into three datasets (60%, 20%, 20%). The first dataset for training, the second dataset for validating, and the third for testing. Table 1 shows the number of sample of each dataset.

Table1: shows the distribution of samples for the datasets

Dataset	Number of samples
Training Dataset	5028
Validation Dataset	1676
Testing Dataset	1676

5.2 EVALUATION:

Testing dataset organized into one folder (age-gender-test) and contains 1676 audio files related to 39 of age and gender categories (as seen Table 2). Audio files were converted into images using (PNG) format. These images are different from the images that was used in original dataset for training and validation.

Table2: shows the distribution of samples over the 39 categories for testing

S.N.	Category	Number of audio files
1	Female-15	34
2	Female-16	49
3	Female-24	54
4	Female-25	47
5	Female-26	48
6	Female-27	33
7	Female-28	49
8	Female-29	42
9	Female-30	50
10	Female-35	40
11	Female-43	34
12	Female-54	44
13	Female-56	45
14	Female-57	39
15	Male-14	47
16	Male-15	37
17	Male-16	44
18	Male-25	46
19	Male-26	56
20	Male-27	41
21	Male-28	36
22	Male-29	51
23	Male-30	38
24	Male-31	38
25	Male-32	47
26	Male-33	51
27	Male-34	47

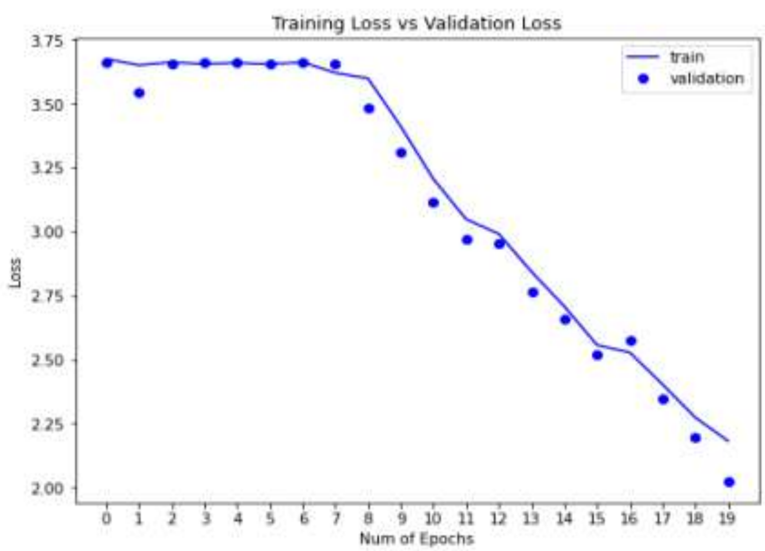
28	Male-35	39
29	Male-36	38
30	Male-37	35
31	Male-38	53
32	Male-40	37
33	Male-41	48
34	Male-43	39
35	Male-45	41
36	Male-48	38
37	Male-51	35
38	Male-57	44
39	Male-65	42
	Total	**1676**

6. VGG16

We used a pre-trained VGG16 network with 16 convolutional layers followed by a fully connected hidden layer, as well as dropout layers in between. Dropout regularizes the networks to prevent over fitting, and all layers except the output layer have ReLU activations.

6.1 Training and validation of VGG16 Model

We have trained proposed model for 40 epochs with batch size 32, optimizer Adam, and learning rate 0.0001. The training accuracy, validation accuracy, training loss, and validation loss were determined after the 40 epochs as follows respectively: 100%, 98.58%, 0.00014, and 0.10671.Progress for training loss and accuracy as shown in Figure 6 below:



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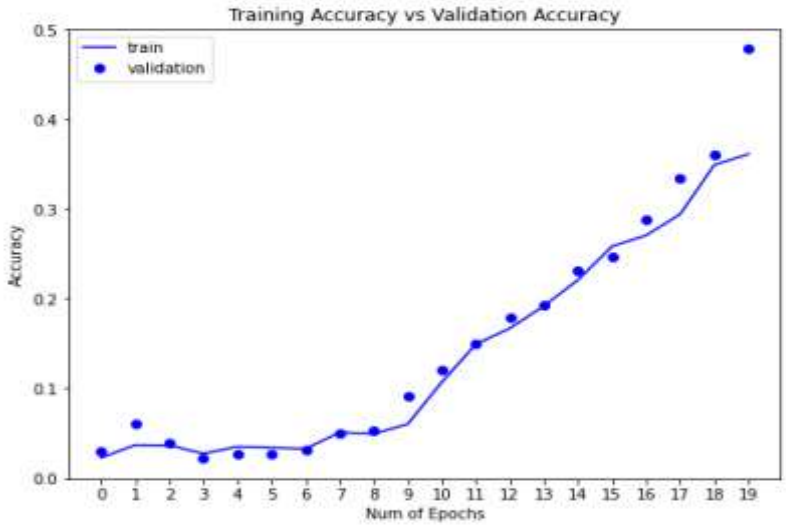

Figure 6: Progress for VGG16 training, validation loss and accuracy

7. Loss and Accuracy rate:

The loss versus accuracy curve is a useful feature in terms of how much time and memory the model training process uses. The results of a convolution neural networks loss rate in the training and test sets after 20 repetitions are shown in Figure 7. Which suggests that the convolutional neural network successfully learned the input and can act as a good model for understanding classification of age and gender

Figure 7: Loss and Accuracy rate

```
Epoch 1/20
41/41 [==============================] - 10s 234ms/step - loss: 3.7637 - accuracy: 0.0236 - fscore: 0.0000e+00 - val_loss: 3.6
Epoch 2/20
41/41 [==============================] - 5s 111ms/step - loss: 3.6055 - accuracy: 0.0579 - fscore: 0.0000e+00 - val_loss: 3.47
Epoch 3/20
41/41 [==============================] - 5s 126ms/step - loss: 3.3559 - accuracy: 0.1170 - fscore: 0.0390 - val_loss: 3.2095 -
Epoch 4/20
41/41 [==============================] - 5s 119ms/step - loss: 3.1121 - accuracy: 0.1570 - fscore: 0.0500 - val_loss: 2.9997 -
Epoch 5/20
41/41 [==============================] - 5s 133ms/step - loss: 2.9897 - accuracy: 0.1623 - fscore: 0.0559 - val_loss: 2.8290 -
Epoch 6/20
41/41 [==============================] - 5s 117ms/step - loss: 2.7401 - accuracy: 0.2425 - fscore: 0.0917 - val_loss: 2.6311 -
Epoch 7/20
41/41 [==============================] - 5s 118ms/step - loss: 2.5848 - accuracy: 0.2957 - fscore: 0.1810 - val_loss: 2.4382 -
Epoch 8/20
41/41 [==============================] - 9s 213ms/step - loss: 3.6207 - accuracy: 0.0511 - fscore: 0.0000e+00 - val_loss: 3.6
Epoch 9/20
41/41 [==============================] - 9s 215ms/step - loss: 3.5989 - accuracy: 0.0495 - fscore: 0.0000e+00 - val_loss: 3.4
Epoch 10/20
41/41 [==============================] - 9s 215ms/step - loss: 3.4120 - accuracy: 0.0602 - fscore: 0.0041 - val_loss: 3.3104 -
Epoch 11/20
41/41 [==============================] - 9s 214ms/step - loss: 3.2061 - accuracy: 0.1070 - fscore: 0.0440 - val_loss: 3.1170 -
Epoch 12/20
41/41 [==============================] - 9s 216ms/step - loss: 3.0487 - accuracy: 0.1494 - fscore: 0.0461 - val_loss: 2.9702 -
Epoch 13/20
41/41 [==============================] - 9s 217ms/step - loss: 2.9895 - accuracy: 0.1671 - fscore: 0.0549 - val_loss: 2.9544 -
Epoch 14/20
41/41 [==============================] - 9s 214ms/step - loss: 2.8429 - accuracy: 0.1921 - fscore: 0.0608 - val_loss: 2.7665 -
Epoch 15/20
41/41 [==============================] - 9s 215ms/step - loss: 2.7077 - accuracy: 0.2210 - fscore: 0.0911 - val_loss: 2.6575 -
Epoch 16/20
```

```
Epoch 17/20
41/41 [==============================] - 5s 129ms/step - loss: 1.5914 - accuracy: 0.5595 - fscore: 0.5064 - val_loss: 1.6288 -
Epoch 18/20
41/41 [==============================] - 5s 121ms/step - loss: 1.4333 - accuracy: 0.6043 - fscore: 0.5857 - val_loss: 1.4211 -
Epoch 19/20
41/41 [==============================] - 5s 118ms/step - loss: 1.4230 - accuracy: 0.6037 - fscore: 0.5859 - val_loss: 1.2216 -
Epoch 20/20
41/41 [==============================] - 5s 122ms/step - loss: 1.2543 - accuracy: 0.6585 - fscore: 0.6493 - val_loss: 1.1877 -
CPU times: user 2min 55s, sys: 4.05 s, total: 2min 59s
Wall time: 2min 26s
```

In this work, the age and gender classification dataset was used to train the deep neural network CNN. The model was then analyzed, and the results showed that it performed efficiently. The confusion matrix of the classification results is shown in Figure 8, where each row shows the real category so each column gives the intended result.

8. Confusion Matrix:

```
[[34  0  0 ...  0  0  0]
 [ 0 48  0 ...  0  0  0]
 [ 0  0 54 ...  0  0  0]
 ...
 [ 0  0  0 ... 35  0  0]
 [ 0  0  0 ...  0 44  0]
 [ 0  0  0 ...  0  0 42]]
```

Figure 8: confusion matrix

9. Comparison of Classification Performance:

To evaluate the effectiveness of these models, the proposed method was evaluated with modern techniques for recent deep learning. The accuracy rate and average F1-score were used to evaluate the models on the test set. In Figure 9, the model VGG16 achieved lower false positive and false negative rates, which demonstrates the effectiveness.

	precision	recall	f1-score	support
Female-15	1.00	1.00	1.00	34
Female-16	0.98	0.98	0.98	49
Female-24	0.96	1.00	0.98	54
Female-25	1.00	1.00	1.00	47
Female-26	0.96	0.94	0.95	48
Female-27	1.00	1.00	1.00	33
Female-28	1.00	1.00	1.00	49
Female-29	1.00	1.00	1.00	42
Female-30	1.00	1.00	1.00	50
Female-35	1.00	1.00	1.00	40
Female-43	1.00	1.00	1.00	34
Female-54	1.00	1.00	1.00	44
Female-56	1.00	1.00	1.00	45
Female-57	1.00	1.00	1.00	39
Male-14	1.00	1.00	1.00	47
Male-15	1.00	1.00	1.00	37
Male-16	0.95	0.91	0.93	44
Male-25	1.00	0.96	0.98	46
Male-26	0.94	0.91	0.93	56
Male-27	1.00	1.00	1.00	41
Male-28	1.00	1.00	1.00	36
Male-29	1.00	1.00	1.00	51
Male-30	0.95	1.00	0.97	38
Male-31	1.00	1.00	1.00	38
Male-32	1.00	1.00	1.00	47
Male-33	1.00	1.00	1.00	51
Male-34	1.00	1.00	1.00	47
Male-35	1.00	1.00	1.00	39
Male-36	1.00	1.00	1.00	38
Male-37	1.00	1.00	1.00	35
Male-38	1.00	1.00	1.00	53
Male-40	0.93	1.00	0.96	37
Male-41	1.00	1.00	1.00	48
Male-43	1.00	1.00	1.00	39

Male-45	1.00	1.00	1.00	41
Male-48	1.00	1.00	1.00	38
Male-51	1.00	1.00	1.00	35
Male-57	1.00	1.00	1.00	44
Male-65	1.00	1.00	1.00	42
accuracy			0.99	1676
macro avg	0.99	0.99	0.99	1676
weighted avg	0.99	0.99	0.99	1676

Figure 9: Comparison of Classification Performance

9.1 Fully Connected Layer:

Each neuron in a neural network receives information from a number of different sites in the preceding layer. Every neuron in a fully linked layer receives input from the previous layer's elements. Neurons in a convolutional layer receive input from only a subset of the previous layer. Typically, the subarea is square in shape (e.g., size 5 by 5). The receptive field of a neuron is its input area. As a result, in a fully connected layer, the receptive field encompasses the previous layer in its full. The receptive area in a convolutional layer is smaller than the previous layer in its full [40].

The CNN process starts with convolution and pooling, which break down the image into features that can be analyzed independently. This process's output is fed into a fully connected neural network structure, which drives the final classification decision [41].

9.2 Testing the model:

We want our classification to be as close as possible to the actual ones and we have 39 classes, thus, we used the categorical cross-entropy loss function with softmax as the last layer's activation function.

We had to use transfer learning with a set of pre-trained models, with the VGG16 model.

To apply these previously trained models to our new dataset, we must change the last fully connected layer in addition to output the classes of the new inputs.

In our case, we replaced the last fully-connected layer with GlobalMaxPooling2D layer and fully-connected dense layer with a softmax activation function, and we added Batch Normalization layer, Relu activation function, Flatten layer, and dense layer with Softmax activation function to the pre-trained networks. The pre-trained layers are then all retrained after a maximum of 40 epochs. A test dataset containing 39 classes and 1676 audio samples was used to evaluate the model.

9.3 -Result and Discussion:

We trained the VGG16 model on the training dataset and validation dataset for 40 epochs and we recorded all important data like model accuracy, loss, time used, F1 score, recall, and precession.

After that, we tested the VGG16 model using the test dataseting provided by Kaggle.

Accuracy of model VGG16 used in the training 100%, validation 97% and testing 99%

Conclusion

In this research, we conclude a deep, easy, fast, and effective learning method to discover age and gender classification using audio files.

This model was created using the Python programming language, which is available on the Google Colab platform which are high-level languages with a user interface that is simple and free.

We have trained our dataset on age and gender classification using a pre-trained deep learning model (VGG16).

References:

[1] Abu-Jamie, T. N., et al. (2022). Classification of Sign-language Using VGG16. International Journal of Academic Engineering Research (IJAER), 6(6): 36-46.
[2] Abu Nada, A. M., et al. (2020). "Age and Gender Prediction and Validation through Single User Images Using CNN." International Journal of Academic Engineering Research (IJAER) 4(8): 21-24.
[3] Abu Nada, A. M., et al. (2020). "Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach." International Journal of Academic Information Systems Research (IJAISR) 4(8): 6-9.
[4] Abu-Saqer, M. M., et al. (2020). "Type of Grapefruit Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 4(1): 1-5.
[5] Afana, M., et al. (2018). "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City." International Journal of Advanced Science and Technology 124: 51-59.
[6] Al Barsh, Y. I., et al. (2020). "MPG Prediction Using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 4(11): 7-16.
[7] Alajrami, E., et al. (2019). "Blood Donation Prediction using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(10): 1-7.
[8] Alajrami, E., et al. (2020). "Handwritten Signature Verification using Deep Learning." International Journal of Academic Multidisciplinary Research (IJAMR) 3(12): 39-44.
[9] Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31.
[10] Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 74-81.
[11] Alfarra, A. H. et al. (2022). "Classification of Pineapple Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 5(12): 37-41.
[12] Alghoul, A., et al. (2018). "Email Classification Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 8-14.
[13] Alkahlout, M. A. et al. (2022). "Classification of Fruits Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 5(12): 56-63.
[14] Al-Kahlout, M. M., et al. (2020). "Neural Network Approach to Predict Forest Fires using Meteorological Data." International Journal of Academic Engineering Research (IJAER) 4(9): 68-72.
[15] Alkronz, E. S., et al. (2019). "Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network." International Journal of Academic and Applied Research (IJAAR) 3(2): 1-8.
[16] Almadhoun, H. et al. (2021). "Classification of Alzheimer's Disease Using Traditional Classifiers with Pre-Trained CNN." International Journal of Academic Health and Medical Research (IJAHMR) 5(4):17- 21.
[17] Al-Madhoun, O. S. E.-D., et al. (2020). "Low Birth Weight Prediction Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 8-14.
[18] Al-Masawabe, M. M. et al. (2022). "Papaya maturity Classification Using Deep Convolutional Neural Networks." International Journal of Engineering and Information Systems (IJEAIS) 5(12): 60-67.
[19] Al-Massri, R., et al. (2018). "Classification Prediction of SBRCTs Cancers Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 1-7.
[20] Al-Mobayed, A. A., et al. (2020). "Artificial Neural Network for Predicting Car Performance Using JNN." International Journal of Engineering and Information Systems (IJEAIS) 4(9): 139-145.
[21] Al-Mubayyed, O. M., et al. (2019). "Predicting Overall Car Performance Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAR) 3(1): 1-5.
[22] Alshawwa, I. A., et al. (2020). "Analyzing Types of Cherry Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 4(1): 1-5.
[23] Al-Shawwa, M., et al. (2018). "Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(9): 1-6.
[24] Ashqar, B. A., et al. (2019). "Plant Seedlings Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 3(1): 7-14.
[25] Bakr, M. A. H. A., et al. (2020). "Breast Cancer Prediction using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(10): 1-8.
[26] Barhoom, A. M., et al. (2019). "Predicting Titanic Survivors using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(9): 8-12.
[27] Belbeisi, H. Z., et al. (2020). "Effect of Oxygen Consumption of Thylakoid Membranes (Chloroplasts) From Spinach after Inhibition Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 1-7.
[28] Dalffa, M. A., et al. (2019). "Tic-Tac-Toe Learning Using Artificial Neural Networks." International Journal of Engineering and Information Systems (IJEAIS) 3(2): 9-19.
[29] Dawood, K. J., et al. (2020). "Artificial Neural Network for Mushroom Prediction." International Journal of Academic Information Systems Research (IJAISR) 4(10): 9-17.
[30] Dheir, I. M., et al. (2020). "Classifying Nuts Types Using Convolutional Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(12): 12-18.
[31] El-Habil, B. et al. (2022). "Cantaloupe Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 5(12): 7-17.
[32] El-Khatib, M. J., et al. (2019). "Glass Classification Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(2): 25-31.
[33] El-Mahelawi, J. K., et al. (2020). "Tumor Classification Using Artificial Neural Networks." International Journal of Academic Engineering Research (IJAER) 4(11): 8-15.
[34] El-Mashharawi, H. Q., et al. (2020). "Grape Type Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 41-45.
[35] Elzamly, A., et al. (2015). "Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process." International Journal of Advanced Science and Technology 81: 35-48.
[36] Elzamly, A., et al. (2015). "Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods." Int. J. Adv. Inf. Sci. Technol 38(38): 108-115.
[37] Elzamly, A., et al. (2017). "Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations." International Journal of Information Technology and Electrical Engineering 6(2): 40-45.
[38] Habib, N. S., et al. (2020). "Presence of Amphibian Species Prediction Using Features Obtained from GIS and Satellite Images." International Journal of Academic and Applied Research (IJAAR) 4(11): 13-22.
[39] Harz, H. H., et al. (2020). "Artificial Neural Network for Predicting Diabetes Using JNN." International Journal of Academic Engineering Research (IJAER) 4(10): 14-22.
[40] Hassanein, R. A. A., et al. (2020). "Artificial Neural Network for Predicting Workplace Absenteeism." International Journal of Academic Engineering Research (IJAER) 4(9): 62-67.
[41] Heriz, H. H., et al. (2018). "English Alphabet Prediction Using Artificial Neural Networks." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 8-14.
[42] Jaber, A. S., et al. (2020). "Evolving Efficient Classification Patterns in Lymphography Using EasyNN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 66-73.
[43] Kashf, D. W. A., et al. (2018). "Predicting DNA Lung Cancer using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(10): 6-13.
[44] Khalil, A. J., et al. (2019). "Energy Efficiency Predicting using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(9): 1-8.
[45] Kweik, O. M. A., et al. (2020). "Artificial Neural Network for Lung Cancer Detection." International Journal of Academic Engineering Research (IJAER) 4(11): 1-7.
[46] Maghari, A. M., et al. (2020). "Books' Rating Prediction Using Just Neural Network." International Journal of Engineering and Information Systems (IJEAIS) 4(10): 17-22.
[47] Mettleq, A. S. A., et al. (2020). "Mango Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 22-29.
[48] Metwally, N. F., et al. (2018). "Diagnosis of Hepatitis Virus Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 1-7.
[49] Mohammed, G. R., et al. (2020). "Predicting the Age of Abalone from Physical Measurements Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAR) 4(11): 7-12.
[50] Musleh, M. M., et al. (2019). "Predicting Liver Patients using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(10): 1-11.
[51] Oriban, A. J. A., et al. (2020). "Antibiotic Susceptibility Prediction Using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(11): 1-6.
[52] Qwaider, S. R., et al. (2020). "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza." International Journal of Academic Information Systems Research (IJAISR) 4(8): 16-22.
[53] Sadek, R. M., et al. (2019). "Parkinson's Disease Prediction Using Artificial Neural Network." International Journal of Academic Health and Medical Research (IJAHMR) 3(1): 1-8.
[54] Salah, M., et al. (2018). "Predicting Medical Expenses Using Artificial Neural Network." International Journal of Engineering and Information Systems (IJEAIS) 2(20): 11-17.
[55] Saleh, A. et al. (2020). "Brain Tumor Classification Using Deep Learning." 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech). IEEE, 2020.
[56] Salman, F. M., et al. (2020). "COVID-19 Detection using Artificial Intelligence." International Journal of Academic Engineering Research (IJAER) 4(3): 18-25.
[57] Samra, M. N. A., et al. (2020). "ANN Model for Predicting Protein Localization Sites in Cells." International Journal of Academic and Applied Research (IJAAR) 4(9): 43-50.
[58] Shawarib, M. Z. A., et al. (2020). "Breast Cancer Diagnosis and Survival Prediction Using JNN." International Journal of Engineering and Information Systems (IJEAIS) 4(10): 23-30.
[59] Zaqout, I., et al. (2015). "Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology." International Journal of Hybrid Information Technology 8(2): 221-228.
[60] Aldammagh, Z., Abdeljawad, R., & Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Financial Internet Quarterly, 17(3), 35-46.
[61] Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Available at SSRN 3761669.
[62] Jouda, H., Abu Jarad, A., Obaid, T., Abu Mdallalah, S., & Awaja, A. (2020). Mobile Banking Adoption: Decomposed Theory of Planned Behavior with Perceived Trust. Available at SSRN 3660403.
[63] Obaid, T., Abdaljawad, R., & Mdallalahc, S. A. (2020). Factors Driving E-Learning Adoption In Palestine: An Integration of Technology Acceptance Model And IS Success Model. Available at SSRN 3686490.
[64] Obaid, T. F., & Eneizan, B. M. (2016). Transfer of training and post-training on job performance in Middle Eastern countries. Review of Public Administration and Management, 400(3786), 1-11.
[65] Obaid, T. F., Zainon, M. S., Eneizan, P. D. B. M., & Wahab, K. A. Transfer Of Training And Post-Training On Job Performance