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Classification of Age and Gender Using Deep Learning by Inception

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Abstract: *Age and gender classification has extended its number of uses, despite of the rise of social platforms and social media. However, this stands in stark contrast to the large performance increases explained previously for the strongly linked task of audio. In this study, we show that deep convolutional neural networks may be used to learn representations and significantly enhance performance on tasks (CNN). Where we get in the inception the training accuracy was 99%, validation accuracy 97%, testing accuracy 98%. A testing dataset with 1676 audio files related to 39 age and gender categories and 40 epochs is combined into a single section titled "age-gender-test."*

Keywords: Age and gender Classification, Deep Learning, Classification

1. 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.

2. 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)

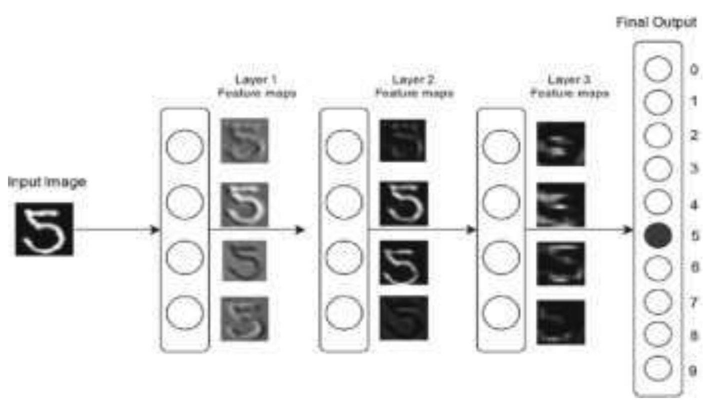

Figure 1: A deep neural network for digit classification

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.

3. 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].

4. INCEPTION V3:

A typical image useful for the detection has been shown to obtain larger than 78.1 percent accuracy on the ImageNet dataset. To use its 48 layers, the network can classify images into the more than a 1000 different object classes. There are many tools, notebooks, pen, and animals on view. The system has created a collection of deep image features for a selection of images as a result. The input image size for the network is 299 by 299 pixels. Among the symmetric and asymmetric basic components in the model are convolutions, average pooling, max pooling, concats, dropouts, and fully linked layers. The model highly depends on batch normalization, which is applied to the inputs for the activation. Softmax used to evaluate cost.

4. AGE AND GENDER CLASSIFICATION:

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).

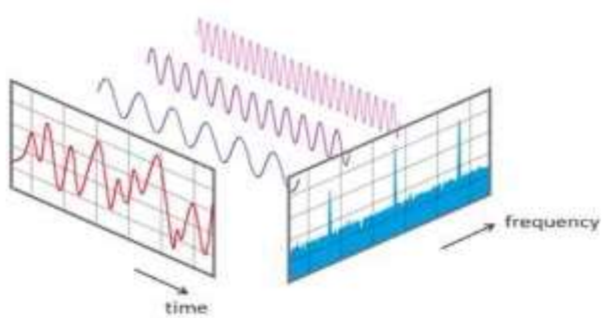

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Figure 3: Typical audio signal

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].

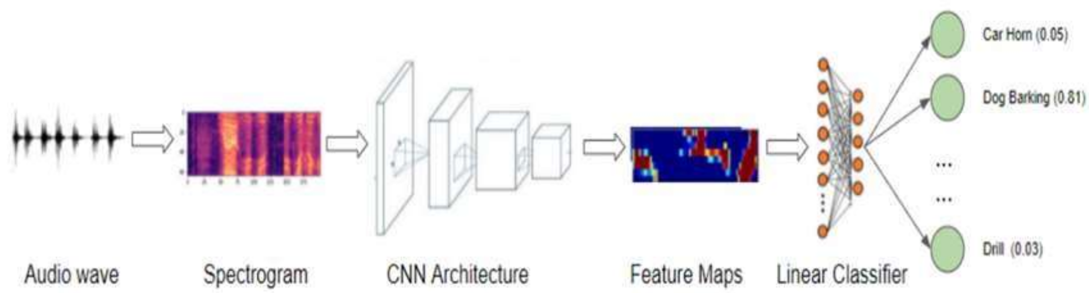


Figure 4: Audio Classification application

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.

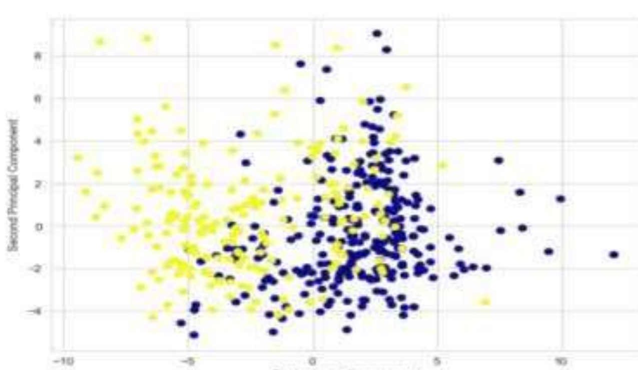


Figure5: original data plotting through SVM

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**

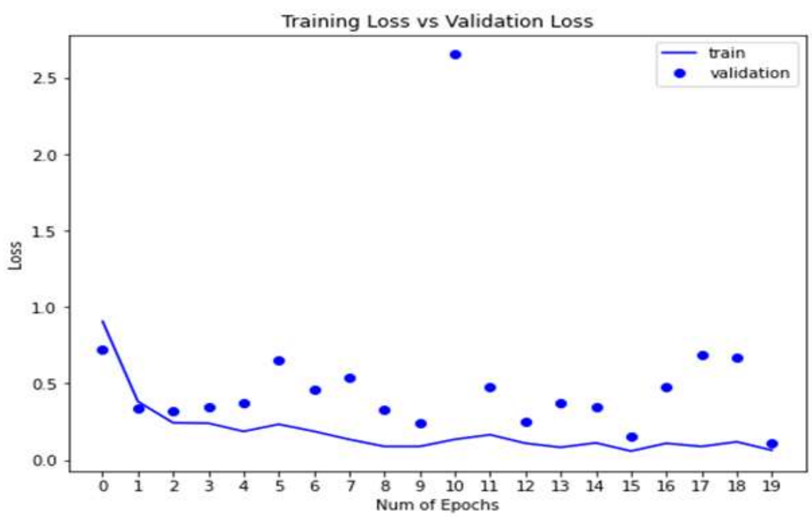
6. Inception:

On top of InceptionV3 (conv base), we add GlobalMaxPooling2D layer and Dense layer with Softmax activation function, and run the whole thing end-to-end on the input data. In addition, we use various augmentation strategies on our model to make the most of our limited training data, avoid over-fitting, and improve accuracy.

6.1 Training and validation of Inception Model

We have trained and validated the 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: 98.64%, 97.24%, 0.04699, and 0.11317.

Progress for training loss and accuracy as shown in Figure 6 below:



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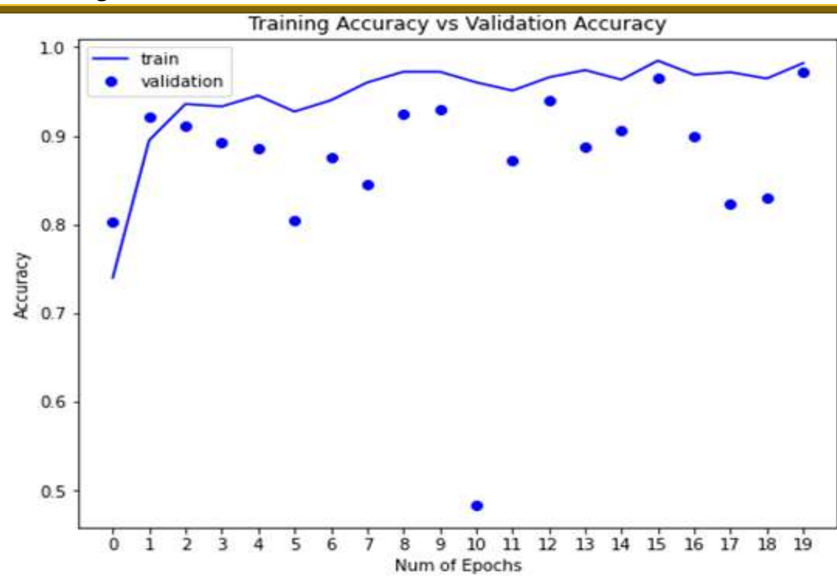

Figure 6: Progress for Inception training, validation loss and accuracy

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

```
Epoch 1/20
41/41 [==============================] - 8s 186ms/step - loss: 3.5485 - accuracy: 0.0899 - fscore: 0.0205 - val_loss: 3.6882 - val_accuracy: 0.0172 - val_fscore: 0.0000e+0
Epoch 2/20
41/41 [==============================] - 7s 160ms/step - loss: 3.3044 - accuracy: 0.1273 - fscore: 0.0405 - val_loss: 3.7917 - val_accuracy: 0.0172 - val_fscore: 0.0000e+0
Epoch 3/20
41/41 [==============================] - 7s 162ms/step - loss: 3.2233 - accuracy: 0.1357 - fscore: 0.0445 - val_loss: 3.8823 - val_accuracy: 0.0172 - val_fscore: 0.0000e+0
Epoch 4/20
41/41 [==============================] - 8s 201ms/step - loss: 3.0594 - accuracy: 0.1501 - fscore: 0.0624 - val_loss: 4.0290 - val_accuracy: 0.0172 - val_fscore: 0.0000e+0
Epoch 5/20
41/41 [==============================] - 7s 182ms/step - loss: 2.9828 - accuracy: 0.1814 - fscore: 0.0774 - val_loss: 4.2097 - val_accuracy: 0.0268 - val_fscore: 0.0275
Epoch 6/20
41/41 [==============================] - 7s 163ms/step - loss: 2.8218 - accuracy: 0.2163 - fscore: 0.1151 - val_loss: 3.6111 - val_accuracy: 0.0403 - val_fscore: 0.0478
Epoch 7/20
41/41 [==============================] - 7s 163ms/step - loss: 2.7293 - accuracy: 0.2393 - fscore: 0.1401 - val_loss: 3.0644 - val_accuracy: 0.1700 - val_fscore: 0.0698
Epoch 8/20
41/41 [==============================] - 7s 161ms/step - loss: 2.5434 - accuracy: 0.2835 - fscore: 0.1859 - val_loss: 3.2435 - val_accuracy: 0.1693 - val_fscore: 0.1276
Epoch 9/20
41/41 [==============================] - 7s 178ms/step - loss: 2.4548 - accuracy: 0.3011 - fscore: 0.2349 - val_loss: 2.5337 - val_accuracy: 0.2878 - val_fscore: 0.2243
Epoch 10/20
41/41 [==============================] - 7s 159ms/step - loss: 2.4342 - accuracy: 0.3010 - fscore: 0.2218 - val_loss: 2.4135 - val_accuracy: 0.2670 - val_fscore: 0.1769
Epoch 11/20
41/41 [==============================] - 7s 161ms/step - loss: 2.2837 - accuracy: 0.3399 - fscore: 0.2603 - val_loss: 2.3579 - val_accuracy: 0.3050 - val_fscore: 0.2713
Epoch 12/20
41/41 [==============================] - 7s 162ms/step - loss: 2.1462 - accuracy: 0.3849 - fscore: 0.3014 - val_loss: 2.1251 - val_accuracy: 0.3796 - val_fscore: 0.2695
Epoch 13/20
41/41 [==============================] - 7s 175ms/step - loss: 2.0642 - accuracy: 0.3986 - fscore: 0.3139 - val_loss: 2.0031 - val_accuracy: 0.4556 - val_fscore: 0.3607
Epoch 14/20
41/41 [==============================] - 7s 160ms/step - loss: 2.0860 - accuracy: 0.4085 - fscore: 0.3229 - val_loss: 2.2791 - val_accuracy: 0.3296 - val_fscore: 0.3442
Epoch 15/20
41/41 [==============================] - 7s 162ms/step - loss: 2.0237 - accuracy: 0.4062 - fscore: 0.3585 - val_loss: 2.2195 - val_accuracy: 0.3676 - val_fscore: 0.3439
Epoch 16/20
41/41 [==============================] - 7s 162ms/step - loss: 1.8055 - accuracy: 0.4796 - fscore: 0.4357 - val_loss: 2.1083 - val_accuracy: 0.4087 - val_fscore: 0.4088
Epoch 17/20
41/41 [==============================] - 7s 174ms/step - loss: 1.8193 - accuracy: 0.4710 - fscore: 0.4150 - val_loss: 1.9177 - val_accuracy: 0.4497 - val_fscore: 0.4040
Epoch 18/20
41/41 [==============================] - 7s 161ms/step - loss: 1.7475 - accuracy: 0.4958 - fscore: 0.4695 - val_loss: 1.6145 - val_accuracy: 0.5377 - val_fscore: 0.4560
Epoch 19/20
41/41 [==============================] - 7s 162ms/step - loss: 1.6071 - accuracy: 0.5419 - fscore: 0.5032 - val_loss: 1.8570 - val_accuracy: 0.4497 - val_fscore: 0.3933
Epoch 20/20
41/41 [==============================] - 7s 163ms/step - loss: 1.5957 - accuracy: 0.5343 - fscore: 0.5041 - val_loss: 2.0810 - val_accuracy: 0.3706 - val_fscore: 0.3332
CPU times: user 4min, sys: 12.2 s, total: 4min 12s
Wall time: 2min 39s
```

Figure 7: Loss and Accuracy rate

International Journal of Academic Information Systems Research (IJAISR)
ISSN: 2643-9026
Vol. 6 Issue 9, September - 2022, Pages: 1-9

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:

```
print(confusion_matrix(y_testclass, classpreds))

[[34  0  0 ...  0  0  0]
 [ 0 49  0 ...  0  0  0]
 [ 0  0 52 ...  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, As a result of using recent deep learning algorithms, the methodology was assessed. The models on the training dataset were evaluated using the accuracy rate and normal F1-score. In Figure 9, the model inception achieved decreased rates of false positives and negatives, showing the efficiency.

```
print(classification_report(y_testclass, classpreds, target_names=c_names))
```

	precision	recall	f1-score	support
Female-15	0.94	1.00	0.97	34
Female-16	0.96	1.00	0.98	49
Female-24	0.96	0.96	0.96	54
Female-25	1.00	1.00	1.00	47
Female-26	1.00	1.00	1.00	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	0.94	1.00	0.97	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	0.95	1.00	0.97	37
Male-16	1.00	0.68	0.81	44
Male-25	0.79	0.96	0.86	46
Male-26	0.96	0.88	0.92	56
Male-27	0.95	1.00	0.98	41
Male-28	0.97	0.97	0.97	36
Male-29	1.00	1.00	1.00	51
Male-30	1.00	1.00	1.00	38
Male-31	1.00	0.92	0.96	38
Male-32	1.00	1.00	1.00	47
Male-33	0.98	1.00	0.99	51
Male-34	1.00	1.00	1.00	47
Male-35	1.00	0.97	0.99	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	1.00	1.00	1.00	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	0.98	1.00	0.99	44
Male-65	1.00	1.00	1.00	42
accuracy			0.98	1676
macro avg	0.98	0.98	0.98	1676
weighted avg	0.98	0.98	0.98	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 crossentropy 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 Inception 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 Inception 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 Inception model using the test dataset provided by Kaggle. Accuracy of model Inception used in the training 99%, validation 97% and testing 98%

10. 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 (Inception).

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