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Detection and Classification of Gender-Type Using Convolution Neural Network

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Abstract*: Deep learning has a vital role in computer vision to discover things. Deep learning techniques, especially convolutional neural networks, are being exploited in identifying and extracting relevant features of a specific set of images. In this research we suggested that it could help in detecting the gender-type of individuals and classifying them using convolutional neural networks, as it achieved superior predictive performance in classifying individuals according to gender, and the experimental results showed that the proposed system works accurately and efficiently, which gives an accuracy rate of 97.76%.*

Keywords: Machine learning, Deep learning Image classification Machine learning.

I. INTRODUCTION

The face is one of the most important features of practical biometrics. An image of a person's face can be obtained easily without physical contact with the biometric system.

The information that can be obtained from the face is of great importance because it helps people communicate with each other and convey ideas, such as gender, race, age and facial expressions. Knowing the gender of people and recognizing them from the face is easy for humans, but complicated for a machine.

Machine learning [1] is a subset of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

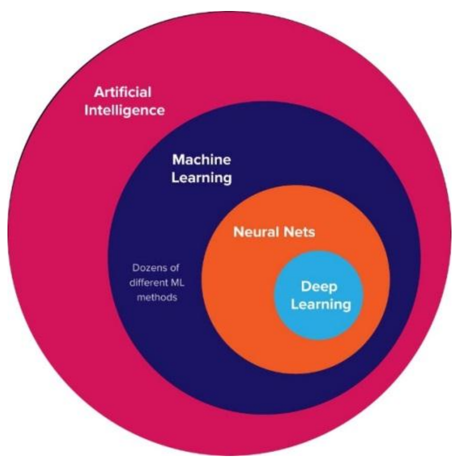

Figure 1: Artificial Intelligence vs. Machine Learning vs. Deep Learning

Machine Learning Methods:

- Supervised
  Algorithms can apply what has been learned in the past to new data using labeled examples to predict future events.
- Unsupervised
  Used when the information used to train is neither classified nor labeled.
- Semi-supervised machine learning
  Algorithms fall in between supervised and unsupervised learning (both labeled and unlabeled data for training).
- Reinforcement machine learning algorithms
  learning method that interacts with its environment by producing actions and discovers errors or rewards.

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, natural language processing, brain-computer interfaces, and financial time series[6-13].

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme[14-17].

Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage[18-25].

CNNs Architecture

A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of a series of convolutional layers that convolve with a multiplication or other dot product. The activation function is commonly a ReLU layer, and is subsequently followed by additional convolutions such as pooling layers, fully connected layers and normalization layers, referred to as hidden layers because their inputs and outputs are masked by the activation function and final convolution[26-31].

Convolutional: When programming a CNN, the input is a tensor with shape (number of images) x (image height) x (image width) x (input channels). Then after passing through a convolutional layer, the image becomes abstracted to a feature map, with shape (number of images) x (feature map height) x (feature map width) x (feature map channels). A convolutional layer within a neural network should have the following attributes[32-35]:

Convolutional kernels defined by a width and height (hyper-parameters).

The number of input channels and output channels (hyper-parameter).

The depth of the Convolution filter (the input channels) must be equal to the number channels (depth) of the input feature map.

Convolutional layers convolve the input and pass its result to the next layer. This is similar to the response of a neuron in the visual cortex to a specific stimulus. Each convolutional neuron processes data only for its receptive field. Although fully connected feedforward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons would be necessary, even in a shallow (opposite of deep) architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable. For instance, a fully connected layer for a (small) image of size 100 x 100 has 10,000 weights for each neuron in the second layer. The convolution operation brings a solution to this problem as it reduces the number of free parameters, allowing the network to be deeper with fewer parameters. For instance, regardless of image size, tiling regions of size 5 x 5, each with the same shared weights, requires only 25 learnable parameters. By using regularized weights over fewer parameters, the vanishing gradient and exploding gradient problems seen during backpropagation in traditional neural networks are avoided[36-38].

Pooling: Convolutional networks may include local or global pooling layers to streamline the underlying computation. Pooling layers reduce the dimensions of the data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer. Local pooling combines small clusters, typically 2 x 2. Global pooling acts on all the neurons of the convolutional layer. In addition, pooling may compute a max or an average. Max pooling uses the maximum value from each of a cluster of neurons at the prior layer. Average pooling uses the average value from each of a cluster of neurons at the prior layer[39-42].

Fully connected: Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional multi-layer perceptron neural network (MLP). The flattened matrix goes through a fully connected layer to classify the images[43].

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Receptive field: In neural networks, each neuron receives input from some number of locations in the previous layer. In a fully connected layer, each neuron receives input from every element of the previous layer. In a convolutional layer, neurons receive input from only a restricted subarea of the previous layer. Typically the subarea is of a square shape (e.g., size 5 by 5). The input area of a neuron is called its receptive field. So, in a fully connected layer, the receptive field is the entire previous layer. In a convolutional layer, the receptive area is smaller than the entire previous layer. The subarea of the original input image in the receptive field is increasingly growing as getting deeper in the network architecture. This is due to applying over and over again a convolution which takes into account the value of a specific pixel, but also some surrounding pixels[44-48].

Weights: Each neuron in a neural network computes an output value by applying a specific function to the input values coming from the receptive field in the previous layer. The function that is applied to the input values is determined by a vector of weights and a bias (typically real numbers). Learning, in a neural network, progresses by making iterative adjustments to these biases and weights[49-52].

The vector of weights and the bias are called filters and represent particular features of the input (e.g., a particular shape). A distinguishing feature of CNNs is that many neurons can share the same filter. This reduces memory footprint because a single bias and a single vector of weights are used across all receptive fields sharing that filter, as opposed to each receptive field having its own bias and vector weighting[53-56].

II. RELATED WORKS

Many applications and algorithms have been used to detect faces and extract features and information from images such as Viola and Jones algorithms [2], It was given by Open Source Computer Vision (OpenCV) libraries, HOG, Linear SVM, Single Shot Detectors (SSDs) [3].In 2019, Alajrami et al. used the Haar Cascade. Classifier in human and face detection to improve surveillance systems effeciency [4], Jhilik Bhattacharya et al. used real-time DNN-based face identification for visually impaired persons [5]

In this paper, deep neural networks, especially convolutional neural networks which are one of the basic algorithms for deep learning, are used to determine and verify the gender of individuals by obtaining performance of classification tasks directly from images and evaluating them using a dataset of images of real people.

III. MATERIAL AND METODS

Deep learning approach using convolutional neural network (CNN) is an excellent method for image recognition and is one of the neural network techniques that deals with computer vision in artificial intelligence, such as image and video processing.

Three types of main layers are there in a CNN: (a) Convolution layer, (b) Pooling layer, and (c) Output layer. Feed-forward structure is used to arrange these layers in the network.

Each convolution layer is followed by a pooling layer, whereas last convolution layer is followed by output layer. Convolution and pooling layers are 2-D layers whereas output layer is 1-D layer. The general architecture CNN is shown in Figure2.

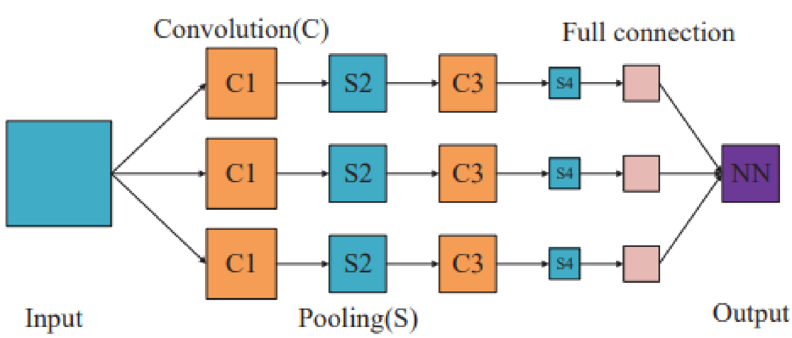

Figure 2 : General CNN architecture

The proposed CNN architecture is VGG16 with input image size 64x64 As follows (as shown in Figure 3):

First and Second Layers:

The input for Gender classification is a 64x64x3 RGB image which passes through first and second convolutional layers with 64 feature maps or filters having size 3×3 and same pooling. The image dimensions changes to 64x6x64. Then the VGG16 applies

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maximum pooling layer or sub-sampling layer with a filter size 3×3 and a stride of two. The resulting image dimensions will be reduced to 32x32x64.

Third and Fourth Layer:

Next, there are two convolutional layers with 128 feature maps having size 3×3 and a stride of 1. Then there is again a maximum pooling layer with filter size 3×3 and a stride of 2. This layer is same as previous pooling layer except it has 128 feature maps so the output will be reduced to 16x16x128.

Fifth and Sixth Layers:

The fifth and sixth layers are convolutional layers with filter size 3×3 and a stride of one. Both used 256 feature maps. The two convolutional layers are followed by a maximum pooling layer with filter size 3×3, a stride of 2 and have 256 feature maps so the output will be reduced to 8x8x256.

Seventh to Twelfth Layer:

Next are the two sets of 3 convolutional layers followed by a maximum pooling layer. All convolutional layers have 512 filters of size 3×3 and a stride of one. The final size will be reduced to 2x2x512.

Thirteenth Layer:

The convolutional layer output is flatten through a fully connected layer with 2048 feature maps each of size 1×1.

Fourteenth and Fifteenth Layers:

Next is again two fully connected layers with 1026 units.

Output Layer:

Finally, there is a softmax output layer ŷ with 2 possible values.

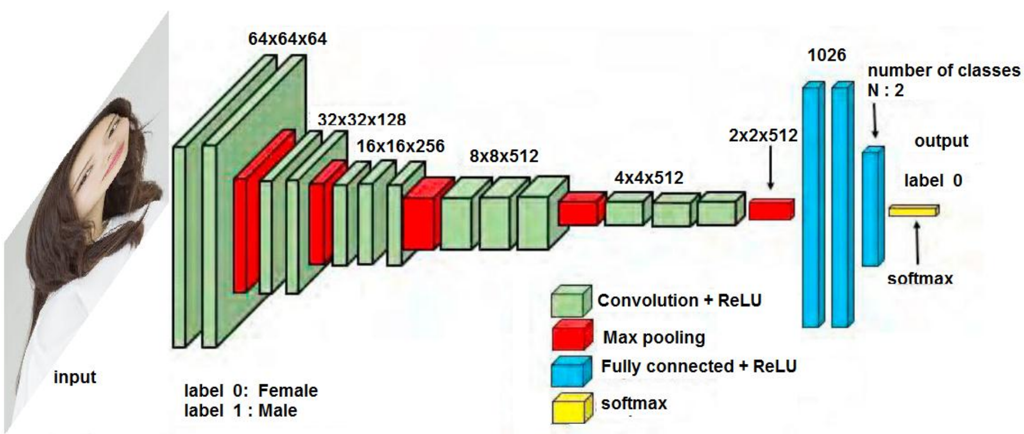

Figure 3: The VGG16 Architecture used in our proposed model

IV. EXPERIMENTS AND RESULTS

The model is built using the Python programming language, and it comes with support from a wide range of libraries

A. Dataset

The 200K Celebrity Face Images for Gender Classification dataset [57] was used in our research. The dataset was divided on pictorial data for training, validating, and testing, and in each of them it was divided into two categories (male and female), where each of them contained personal photos of the same type.

160,000 images were used for the training process, 22598 images were for validation and 20001 images were for the testing. All the images in the dataset were preprocessed into the size of 64(width) * 64(Height)* 3(color Channel).

B. Evaluation of proposed solution

The training model is used to find out the accuracy and loss after 20 epochs, and it has 5,000 steps per epoch for the 200K Celebrity Face Images for Gender Classification dataset data set.

Here are the results we have got after doing 20 epochs (as shown in table1 and figures 4 and 5):

Table1: Training and validation Accuracy and Loss

Model	F1-Accuracy		F1-Loss	
Name	Training	Validation	Training	Validation
VGG16	99.77%	97.76%	0.007	0.098

From this figure 4 and 5, the results training and validation is very high and we did not have the problem of over fitting because the dataset samples is very big.

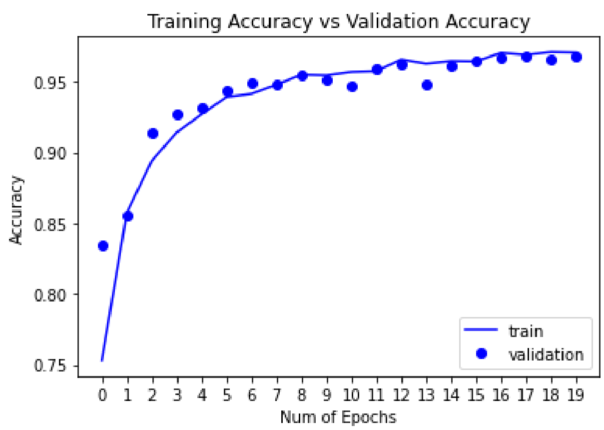

Figure 4 : Training and validation accuracy

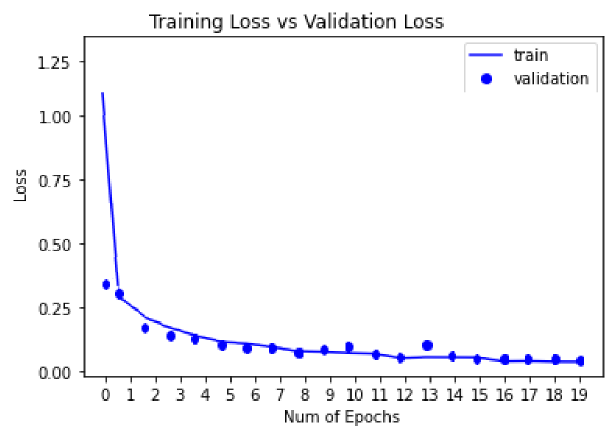

Figure 5: Training and validation loss

C. Performance of the model:

We tested our proposed model using the un-seen dataset (test dataset). We had 20001 images kept aside for testing(i.e. the proposed model did not see the images during trading and validation) our proposed model. The F-1 measure accuracy we achieved as in table 2.

Table2: Accuracy of testing the proposed model

Model	Testing Accuracy		
Name	Male	Female	Overall Average
VGG16	97.32%	98.09%	97.76%

The Accuracy of our proposed model achieved 97.76% as seen in Table2 which is very high.

V. CONCLUSION

Gender prediction is very important for determining a person's identity. In this study, we proposed an approach that uses deep learning-based learning of images of people obtained from Kaggle website under the name 200K Celebrity Face Images for Gender. In this paper, we trained and validated the proposed model the tested its performance with un-seen dataset for testing. The Accuracy rate we achieved was 97.76%. This indicates that our proposed model can effectively predicate and classify Gender from the Face Images.

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