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Face Detection Algorithm Generation Using Artificial Neural Networks

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Abstract

This study examines research and literature reviews on Deep Neural Networks. In the realm of biometrics, authentication, access control, compliance, digital cards, surveillance systems, and facial recognition (FR), the process of identifying individuals using facial imaging has a variety of practical applications. Convolutional neural networks (CNNs) have shown efficacy in facial recognition, a kind of deep networks. Certain preprocessing measures, like as sampling, must be implemented for real-time systems prior to use in CovNets. Nonetheless, whole pictures (all pixel values) are sent to Cov-Nets as input, and all processes are executed by the network (feature extraction, function filtering, training). Consequently, Cov-Nets are often challenging and time-consuming to install. Cov-Nets are in the developmental phase, exhibiting little accuracy, hence possessing significant potential for future advancement. This research presents a novel approach to use a deep neural network for face recognition. This study presents a novel method. This method utilizes extracted face characteristics instead of raw pixel values as input. This minimizes complexity and yields an accuracy of 97.05% for the Yale Faces dataset.

Keywords: DNN, Cov-Nets, ANN, AI, Yale, CNN, Facial Recognition.

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I. INTRODUCTION

Facial recognition (FR) detects a face by comparing it to a facial database. Significant advancements have been made in recent years owing to enhanced design, application learning, and face recognition models. It will be astonishing when individuals can recognize another irrespective of age, lighting circumstances, and diverse gestures. The researchers want to create an RF device that can match or exceed the roughly 97.5 percent human identification rate. The methodologies used in optimal face detection systems will depend on the application's context. Face recognition systems may be classified into two broad categories:

Identify an individual by their facial features within an extensive facial database (e.g., a law enforcement database). The deep neural network for recognizing human features in these systems (64-bit) provides search information individually. Typically, just one photograph per individual is accessible. Real-time recognition is often unnecessary.

Identify an individual in the real world. We are employed in systems that facilitate and restrict access for certain groups of individuals. Multifaceted photos are often accessible for each individual for training and real-time identification purposes. The concept is suggested for the secondary system with distinct face measurements, characteristics, and angles. The concept of an ideal face feature continues to be an unresolved issue.

The conventional pipeline for facial recognition consists of four stages: facial identification, facial alignment, facial representation, and classification. The input picture extracts facial traits using a newly developed approach, resulting in the formation of a deep neural network. This includes a SoftMax layer. The network design is adaptable, and optimal results may be achieved by including or eliminating DNNs. Numerous libraries, functionalities, and interfaces have lately been created and enhanced for a network. CovNets are advanced neural networks with an effective framework of spaced bars architecture for data processing. These networks are very effective for practical applications, including time series data that can be seen as a one-dimensional grid, and picture data that can be interpreted as a two-dimensional framework of evenly spaced pixel bars. Convolutional networks are basic neural networks that use convolutional operations instead of conventional matrix multiplication in at least one layer. The mathematical procedure signifies a network that symbolizes convolution. A “convolutional neural network” is a specialized linear procedure.

II. LITERATURE SURVEY

Numerous convolutional networks or deep convolutional networks have lately shown effective results in face verification. Recent findings by Yi Sun et al. indicate that existing methods typically address the face recognition (FR) problem in two phases: feature extraction (designing or learning features from each facial image) and recognition (calculating the similarity of features between two faces using a representation).

To reduce the dimensions of Self-Organizing Maps (SOM), which is an effective algorithm, transformation techniques are used for SOM and Karhunen-Loeve (KL). Master Component Analysis (PCA) has already been successfully utilized for the same purpose. Despite CovNets demonstrating encouraging outcomes for facial recognition, the formulation of an optimal CovNet architecture remains unclear due to the absence of theoretical guidelines for specific classification tasks. AI agencies report that the CovNet Restricted Boltzmann Machine (RBM) has shown a 97.08% accuracy in matching two photographs of the same person in a controlled environment.

The geometric characteristics, including mouth breadth and position, noise placement, and facial dimensions and chin shape, were established by Brunelli and Poggio. In a sample of 47 individuals, a recognition rate of 90% was recorded. We disclosed that a simple matching strategy achieves 100% recognition for the analogous dataset. The mixing distance approach, developed by Cox et al., achieved a 95% detection rate using an interrogative database of 95 photos, each represented by 30 manually derived features corresponding to individual faces.

Optimal results are shown on an extensive database by Pentland et al, achieving 95 percent identification accuracy from 200 out of 3000 instances. Breakthrough discoveries are problematic since a significant proportion of images of individuals seem identical. Meanwhile, Lades et al. presented a dynamic architecture whereby the closest stored graph employs elastic graph matching for invariant object detection under distortion. We demonstrated favorable outcomes with a sample of 87 individuals and test photographs, aged 150 years, including diverse motions and facial expressions. A parallel system with 23 transducers employs a comparable methodology that incurs computational costs, requiring about 25 years in comparison to 87 stored items. Eigenfaces provide a rapid, straightforward, and effective method. Nevertheless, the pixel intensity for the training and test pictures may be decreased, since the ideal result requires a high degree of correlation. Graphics matching is an alternative method for facial recognition.

In the Face Recognition Technology (FERET) database, Wikott et al. used an enhanced approach and compared 300 images of various sides of the same individuals. Their awareness score has been documented as 97.3 percent. The handmade outcomes in the FR have proved commendable in constrained settings such as Local Binary Patterns and Local Phase Quantization. Moreover, when applied to images captured in uncontrolled circumstances, such as varying face postures, speech, and lighting, performance deteriorates significantly.

High-level recognition often relies on many processing stages, shown by the Marr processing paradigm, which transitions from pictures to surfaces and culminates in 3D models. Turkaand and Pentland contend that a two-dimensional image processing mechanism is also implemented. They devised a technique for identifying facial images by projecting the primary features of the original trainers' photographs. Unlike recognized individuals, the resultant Eigenfaces are evaluated. None of the prior methodologies exclusively used the derived functionality for the FR study in deep neural networks. The article suggests preprocessing photos intended for input into deep neural networks for face recognition, using Haar cascades instead of directly transferring pixel values to convolutional networks.

III. DEEP NEURAL NETWORKS

A neural network, inspired by the human brain, is engineered to discern patterns in numerical information. Real-world data, including photos, text, audio, and videos, is used by neural networks and converted into numerical vectors. A neural network has many layers, each containing a certain number of nodes. Depending on the model type, the neural network endeavors to ascertain the weight of each input data given into a node. The input data and weight determine the value of the final outcome. The weighted total of the input values is calculated, and the output for the node is determined based on certain threshold biases.

An activation function is used to transform input into output. The objective of a neural network is to approximate a certain function "f". A fundamental function that classifies, y = af(x)a, serves to categorize the input data x into class y, while the neural network classifies a parameter β, resulting in y = f(x).

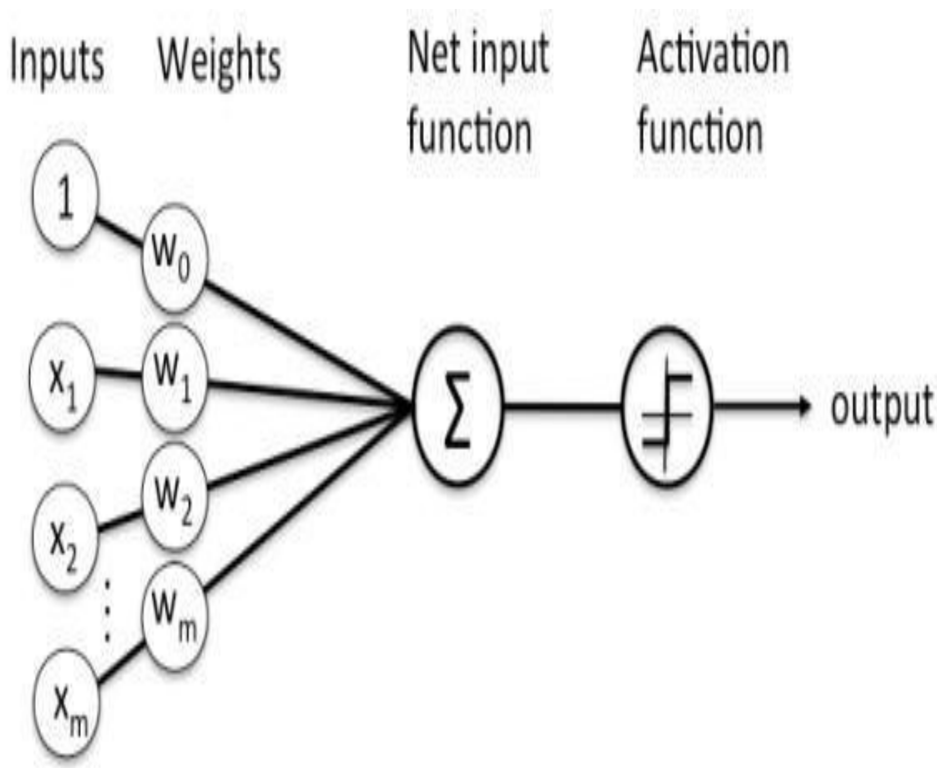

FIG 1: Artificial Neural Network

The interconnection of these functions may be expressed as f(x) = f4(f2(f1(xa))), constituting a singular neural network. In the sequence, the first layer is designated as f1, and correspondingly, the subsequent layer is referred to as f2, and so on. The depth of the neural network is dictated by the length of the chain. The output layer is designated as the terminal layer. The representation of the neural network is seen in Fig. 2. The output of the target layer is not visible during exercise, so the central layers are referred to as the secret layer. A deep neural network (DNN) is an artificial neural network (ANN) characterized by several hidden layers and greater levels of abstraction.

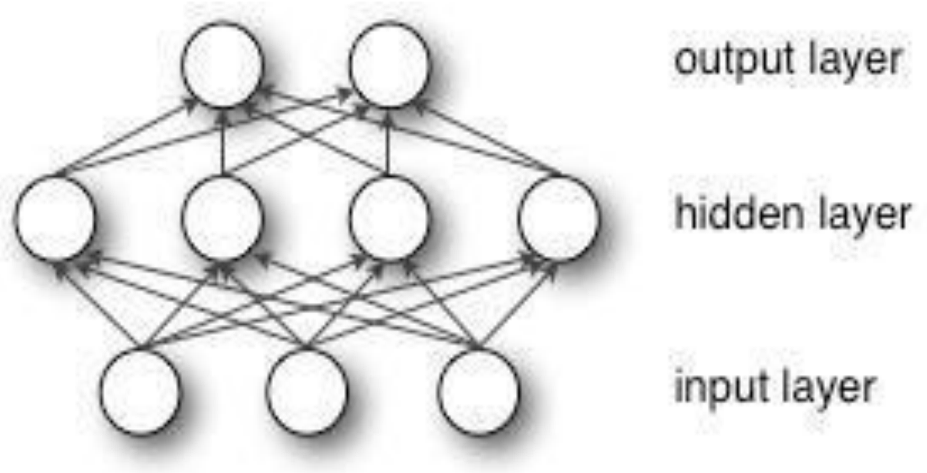

FIG 2: Small Neural Network

The dimensionality of the hidden layer determines the breadth of the deep neural network (DNN). The calculation is performed using the active features of the hidden layer values. Training deep neural networks entails minimizing the expenditure feature, since the discrepancy between the product and the label pertains to the cost categorization feature. This function often employs gradient descent. The Rectilinear Unit, or ReLU, should be used as an activation function in contemporary neural networks. The activation of the secret device : h () =5(()) μ

If (μ) represents the tangent function, then w(i) denotes the unit encompassed by the weight vector, and x signifies the entry. Excessive passing in DNN often results in constrained data issues. This decline is mitigated by using weights. It randomly eliminates some nodes based on their probability of occurrence. "Drop out" signifies the temporary removal of units together with their incoming and outgoing edges. It is seen in Figure 3.

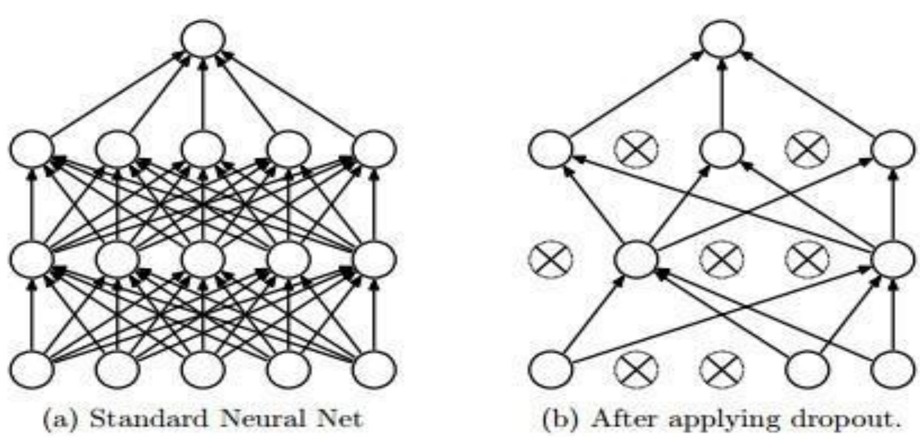

FIG 3: Dropout Neural Net

IV. ALGORITHM

Based on the research literature reviews we have done a new algorithm can be proposed:

- Pixel values are loaded into the dataset from all the images.
- By using hair cascade identify the presence of facial features in all images
- According to the output of before step ,crop face to cross validate in the ratio 9:1 we have to split data
- Design the following Neural Network Algorithm:

This Model contains four layers of Neural Network

A. 512 outputs with reactivation and dropout of 0.2 are given by the First-layer that is dense layer.

B. 512 outputs with reactivation and dropout of 0.2 are given by the Second-layer that is dense layer.

C. 256 outputs with reactivation and dropout of 0.2 are given by the Third-layer that is dense layer.

D. 15 outputs with SoftMax activation and dropout of 0.2 are given by Fourth-layer or output layer which is densed layer.

- ✓ Training the Neural Network with the value epoch=50.
- ✓ By using training and testing accuracy, plot the graph.
- ✓ Calculate the final average accurate result.

V. CONCLUSION

Deep neural networks are a type of artificial neural network with multiple hidden layers, which makes them more complex and resource-intensive compared to conventional neural networks. Instead of raw pixel values, hair cascading is used in the extraction of and feeding of facial features to reduce the complexity of the neural network-based recognition process with a lower number of redundant entry features. The use of DNN rather than CovNets lightens and fasten the process. In addition, in the proposed method, the exactness is not compromised since the average accuracy obtained is 97.05%. Although a further step is being taken in extracting facial features from each file, the method for small datasets is still better.

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