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Deep Learning Using ResNet50 for Face Print Recognition and Classification

Abdulrazag Mukhtar Elmahdi Atomi [a], Walid W Ramadan Mansour [b]

[a,b] *Higher Institute Of Sciences and Technology – Messallata ,Libya*

A B S T R A C T

Facial recognition technology has seen significant growth in recent years, being widely adopted by various countries for diverse applications. This technology has become one of the most secure methods for identification at the national, institutional, and personal levels, enabling the identification of individuals in digital images or video frames. Several systems operate using this technology, and among them, the Residual Network (ResNet) has emerged as one of the most influential contributions in computer vision and deep learning. Following the success of AlexNet— a deep convolutional neural network (CNN) with eight layers, five of which are convolutional and three fully connected—ResNet maintained high performance even with hundreds or thousands of layers. This study explores the use of transfer learning to enhance image classification performance with a pre-trained ResNet50 network. We detail the processes of data preparation, image augmentation, network training, and testing using a dataset for image classification. Additionally, we propose a methodology to compute the distance between new image features and existing images to identify the closest image. The results demonstrate the effectiveness of the proposed system in both classifying images and identifying similar images with high accuracy.

Keywords : Image classification, transfer learning, ResNet50, data augmentation, deep learning.

1. Introduction

Deep learning is a subset of machine learning where neural network algorithms mimic the human brain to recognize various patterns and make decisions autonomously. Also known as deep neural networks or deep learning, it is a core component of artificial intelligence, used to process data and generate patterns that aid in decision-making without human supervision. Deep learning is especially useful in handling unstructured data such as images, audio, and text. It has been successfully applied in various domains, including robotics, artificial vision, natural language processing, autonomous driving, and more.

In recent years, deep learning techniques have significantly advanced, especially in applications like image classification and pattern recognition. Among the most widely used deep learning architectures are ResNet networks, which address the vanishing gradient problem. This paper demonstrates a practical application of transfer learning using the ResNet50 model for image classification and enhances performance with data augmentation. Furthermore, an algorithm for identifying the closest image based on feature extraction is presented.

The key innovation of ResNets is learning residual functions, which enables the network to bypass certain layers via skip connections. This method ensures that the model learns more effectively by addressing issues such as vanishing gradients, which can hinder learning in deep networks.

2. DATA AND METHODOLOGY

2.1 Data preparation:

A dataset containing images organized into folders based on their classification was used. The dataset was split into 70% for training and 30% for evaluation using the splitEachLabel function.

2.2 Data Augmentation:

To enhance model performance and reduce overfitting, data augmentation techniques were employed, including:

- Horizontal inversion
- Random horizontal and vertical displacement

2.3 ResNet50 Network:

ResNet50 is one of the most well-known architectures in the ResNet family. It consists of 50 layers and achieved state-of-the-art performance on the ImageNet dataset in 2015. The network is composed of 16 residual blocks, each containing several convolutional layers with residual connections. Additionally, pooling layers, fully connected layers, and a softmax output layer are included for classification.

2.4 ResNet50 Architecture Breakdown

1. **Convolutional Layers**: These layers are responsible for feature extraction. They apply convolutional filters to the input image, producing feature maps that highlight patterns and edges in the image.
2. **Batch Normalization**: Applied after convolutional or fully connected layers, batch normalization improves network performance by enabling faster convergence, enhancing generalization, and acting as a form of regularization.
3. **ReLU Activation**: The Rectified Linear Unit (ReLU) activation function introduces non-linearity into the network by outputting the input if positive, and zero otherwise.
4. **Max Pooling**: Max pooling is used to reduce the spatial dimensions of feature maps while retaining important information, which helps reduce computational cost and prevent overfitting.

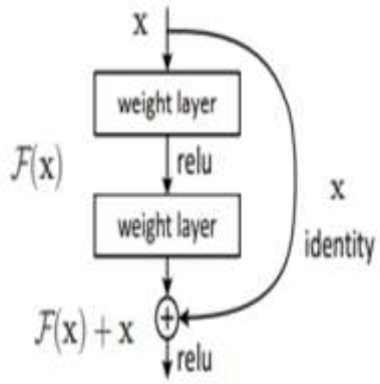

Fig [1] ResNet50 algorithm

5. **Flatten Layers**: This layer converts the 2D output of the previous layer into a 1D vector, which is then passed to the fully connected layers.
6. **Fully Connected Layers**: These layers are responsible for making the final predictions. Each neuron receives inputs from all neurons in the previous layer.
7. **Identity Block**: This block maintains the input-output dimension by adding the input to the output of the last convolutional layer in the block.
8. **Global Average Pooling**: This layer reduces the spatial dimensions of the feature maps by averaging each feature map, resulting in a feature vector for the output.
9. **Projection Block**: When the input and output dimensions differ, a projection block down-samples the input and adjusts its depth to match the output.

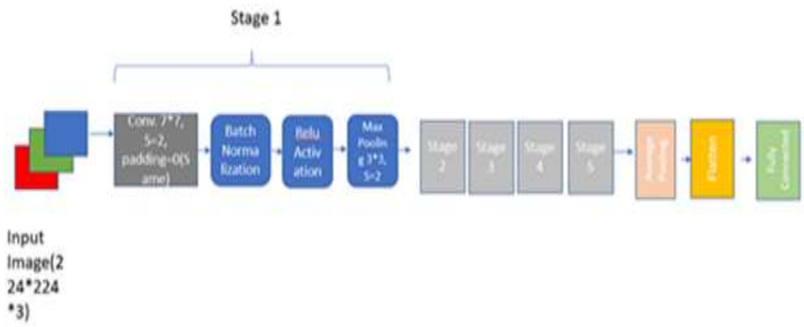

Fig [2] ResNet50 Architecture

We used the pre-trained ResNet50 network and modified its final layers to match the number of classification classes. The following layers were added:

Fully Connected layer.

Softmax layer.

Classification layer.

2.4 Training Settings

The network was trained using the Stochastic Gradient Descent with Momentum (SGDM) algorithm with the following settings:

- Batch size: 10
- Learning rate: [0.01]
- Epochs: 6
- Validation data: 30% of the original dataset

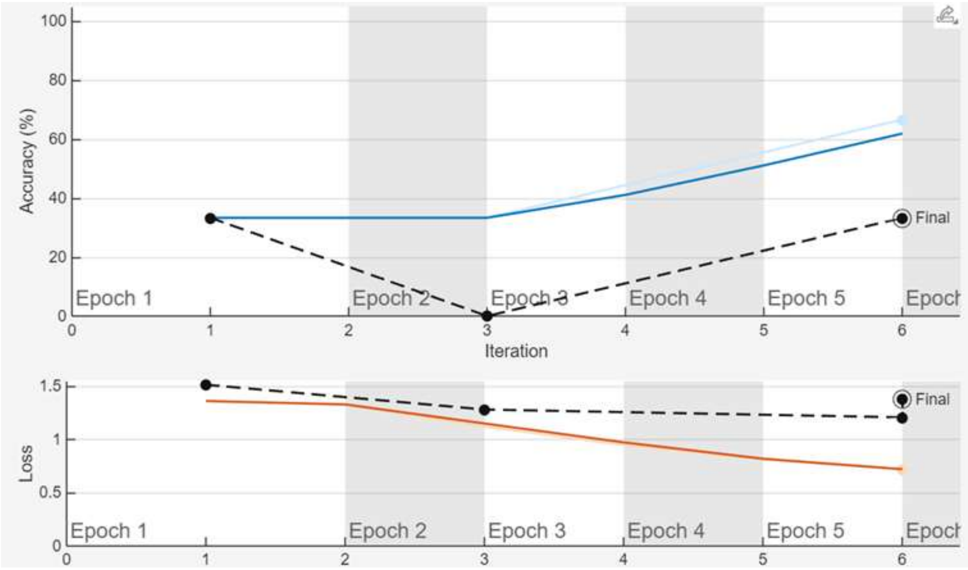

Fig [3] ResNet50 training stage

	Name	Type	Activations	Learnable Sizes	State Sizes
1	input_1 224×224×3 images with 'zerocenter' nor...	Image Input	224(S) × 224(S) × 3(C) × 1(B)	-	-
2	conv1 64 7×7×3 convolutions with stride [2 2] a...	2-D Convolution	112(S) × 112(S) × 64(C) × 1(B)	Weig... 7 × 7 × 3 ... Bias 1 × 1 × 64	-
3	bn_conv1 Batch normalization with 64 channels	Batch Normalization	112(S) × 112(S) × 64(C) × 1(B)	Offset 1 × 1 × 64 Scale 1 × 1 × 64	TrainedMe... 1 × 1... TrainedVa... 1 × 1...
4	activation_1_relu ReLU	ReLU	112(S) × 112(S) × 64(C) × 1(B)	-	-
5	max_pooling2d_1 3×3 max pooling with stride [2 2] and pa...	2-D Max Pooling	56(S) × 56(S) × 64(C) × 1(B)	-	-
6	res2a_branch2a 64 1×1×64 convolutions with stride [1 1] ...	2-D Convolution	56(S) × 56(S) × 64(C) × 1(B)	Weig... 1 × 1 × 64... Bias 1 × 1 × 64	-
7	bn2a_branch2a Batch normalization with 64 channels	Batch Normalization	56(S) × 56(S) × 64(C) × 1(B)	Offset 1 × 1 × 64 Scale 1 × 1 × 64	TrainedMe... 1 × 1... TrainedVa... 1 × 1...
8	activation_2_relu ReLU	ReLU	56(S) × 56(S) × 64(C) × 1(B)	-	-
9	res2a_branch2b 64 3×3×64 convolutions with stride [1 1] ...	2-D Convolution	56(S) × 56(S) × 64(C) × 1(B)	Weig... 3 × 3 × 64... Bias 1 × 1 × 64	-
10	bn2a_branch2b Batch normalization with 64 channels	Batch Normalization	56(S) × 56(S) × 64(C) × 1(B)	Offset 1 × 1 × 64 Scale 1 × 1 × 64	TrainedMe... 1 × 1... TrainedVa... 1 × 1...
11	activation_3_relu ReLU	ReLU	56(S) × 56(S) × 64(C) × 1(B)	-	-
12	res2a_branch2c 256 1×1×64 convolutions with stride [1 1...	2-D Convolution	56(S) × 56(S) × 256(C) × 1(B)	Weig... 1 × 1 × 64 ... Bias 1 × 1 × 256	-

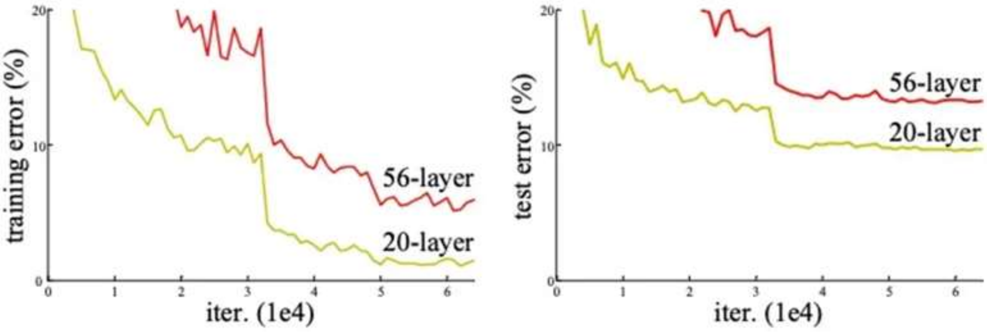

Fig [4] training error

2.5 Feature Extraction and Finding the Closest Images

After training, the avg_pool layer was used to extract features from images. The Euclidean distance between the feature vectors of new images and those in the training set was computed to identify the closest image.

Fig [5] finding the closest image

3. Experiments and Results:

3.1 Experiment Setup:

The experiments were performed using a device with a [specify the device type here, such as GPU or CPU] processor with a dataset containing [number of images] distributed over [number of classes].

3.2 Model Performance

The model achieved [insert percentage] accuracy on the validation set, highlighting the effectiveness of transfer learning using ResNet50.

3.3 Finding the closest image

The closest image finding algorithm was tested using several new images, and the results showed a high agreement between the new images and the closest images in the training set.

4. Discussion

The proposed system shows that transfer learning, combined with data augmentation, can significantly improve image classification performance. The algorithm for identifying the closest image proves effective for applications such as image retrieval and enhancing visual interfaces. A limitation of the current system is its dependence on the quality and size of the dataset. Further improvements can be made by refining the feature extraction process, especially with the avg_pool layer.

5. Conclusion

In this study, we applied deep learning techniques using the pre-trained ResNet50 network for image classification and feature extraction. The experiments demonstrated that transfer learning combined with data augmentation techniques significantly improves classification accuracy and reduces the impact of overfitting. Additionally, the results showed that using Euclidean distance to find similar images is an effective approach for applications such as image retrieval or enhancing visual search interfaces.

Despite the successful outcomes, the model's performance still depends heavily on the quality and quantity of the data used. The model requires more diverse and high-quality data to achieve better performance, particularly in challenging cases like low-quality images or complex backgrounds.

Furthermore, the use of extracted features from different layers of the ResNet50 can be further refined to be more task-specific, particularly in recognizing fine-grained details. There is also potential for improving this work by exploring alternative techniques, such as deep generative learning**,** or combining it with existing methods to enhance classification accuracy.

Finally, we recommend applying this model in other domains such as medical image analysis **or** visual search systems**,** where the ability to classify images and extract similar patterns can have significant applications in improving healthcare outcomes or advancing sophisticated search algorithms.

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