

# Image Recognition Algorithm Based on Improved AlexNet and Shared Parameter Transfer Learning

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**Abstract:** With the development of artificial intelligence technology, the basic judgment of students learning state can be realized through the comprehensive analysis of students face, expression, behavior posture and other multi-modal data. In this paper, we present a new image recognition algorithm based on improved AlexNet and shared parameter transfer learning. The main idea of the proposed method is to apply the technique of shared parameter transfer learning (SPTL) to improve the performance of deep neural network architectures such as AlexNet. Compared with conventional methods, SPTL has several advantages: 1) it can be applied for non-convex optimization problems; 2) it can provide better training speed and robustness; 3) it can achieve high accuracy in both training and testing stages. In addition, our method is easy to implement which it does not require any special preprocessing. After the completely associated layer comes to 10, the acknowledgment rate can be near to 98%.

**Keywords:** Affective Computing; Deep Reinforcement Learning; Expression data; Learning Status

## 1. Introduction

AlexNet may be a classical profound convolutional neural network for picture classification, but utilizing it directly for expansive scale picture recovery isn't productive. To address this issue propose a novel system to make strides its capacity for highlight extraction and its productivity for likeness estimation [1]. Tending to volunteer potato control in sugar beets, the point was to control more than 95% of volunteer potatoes and guarantee less than 5% of undesired control of sugar beet plants [2]. Adams et. al., recommend that as amazing as perceiving breaks is for a DCNN, comparative learning can be accomplished by top-performing medically-naïve people with less than 1 hour of perceptual preparing [3]. Agreeing to the surprising execution of convolutional neural network (CNN) in restorative space, Yang et. al., hypothesized that a profound learning calculation can accomplish tall precision in recognizing the World Wellbeing Organization (WHO) moose brain and tall review gliomas [4]. The point of Lu et. al., is to consequently distinguish obsessive brain in attractive reverberation pictures (MRI) based on profound learning structure and exchange learning [5]. Zhang et. al., started a high-performance numerous sclerosis classification show [6]. Pointing at the issues of as well numerous parameters of the AlexNet demonstrate and single highlight scale, a worldwide pooling expanded convolutional neural network (GPD CNN) is proposed for plant illness recognizable proof by combining expanded convolution with worldwide pooling [7]. Wang et. al., proposed a novel liquor addiction recognizable proof approach that can help radiologists in understanding conclusion [8]. Yang et. al., build up an picture semantic division show utilizing two neural network structures, FCN-AlexNet, and SegNet, whose impacts are investigated within the elucidation of different question sizes and computation productivity [9]. Convolutional Neural Network (CNN) has empowered perplexing include recognizable proof and classification of pictures. In this scope, an effective classification strategy utilizing wavelet change and AlexNet CNN is displayed to classify the ECG signals into three diverse categories, to be specific: Arrhythmia (ARR), Congestive Heart disappointment (CHF) and Ordinary Sinus Beat (NSR) [10].

To this conclusion, Gupta et. al., proposed a shared subspace learning system to use a auxiliary source to move forward recovery execution from a essential dataset [11]. In spite of the significance of the issue, generally less endeavors have been made to ponder the issue. Choe et. al., extended the

estimate of preparing dataset in different ways to move forward the exactness and strength of confront acknowledgment [12]. Cong et. al., proposed calculations and strategies to quicken preparing of profound neural systems for activity acknowledgment on a cluster of GPUs [13]. This can be astounding as the precision of profound learning models for TSC seem possibly be improved if the show is fine-tuned from a pre-trained neural organize rather than preparing it from scratch. Fawaz et. al., filled this hole by examining how to exchange profound CNNs for the TSC assignment. Typically caused by distinctive conditions when taking the photographs, such as points, separations, light conditions, nourishment holders, and foundation scenes [14]. To ease such a semantic crevice, Meng et. al., displayed a cross-modal arrangement and exchange organize (ATNet), which is persuaded by the worldview of learning utilizing advantaged data (LUPi). Bhole et. al., conducted a case think about for person distinguishing proof of Holstein cattle, characterized by dark, brown and white designs, in collaboration with the Dairy campus in Leeuwarden. The acknowledgment strategy for little test ferrographic pictures based on the convolutional neural network(CNN) and exchange learning(TL) is proposed [15]. Ramesh et. al., analyze the execution of the pre-trained organize and the result is compared with a profound convolution organize with customized layers on the same dataset [16]. Aich et. al., investigated the thought of weight sharing over different scales in convolutional systems [17]. After pre-processing the knuckle design picture, plan a pre-training arrange show of the Vgg-16 engineering to perform relocation learning on the knuckle design information set [18].

In this paper, we have discussed how to improve the performance of AlexNet and improve its accuracy. We will use a shared parameter transfer learning method which is based on the improved AlexNet. The Improved AlexNet (I-Alexnet) model was trained with a different set of random initialization weights for each layer and hyper-parameters: number of layers, number of neurons in each layer, activation function etc. The I-Alexnet model has been implemented in Keras and Tensorflow respectively. In this paper, we will only focus on the implementation using Tensorflow as it is more efficient than Keras .

## 2. Proposed method

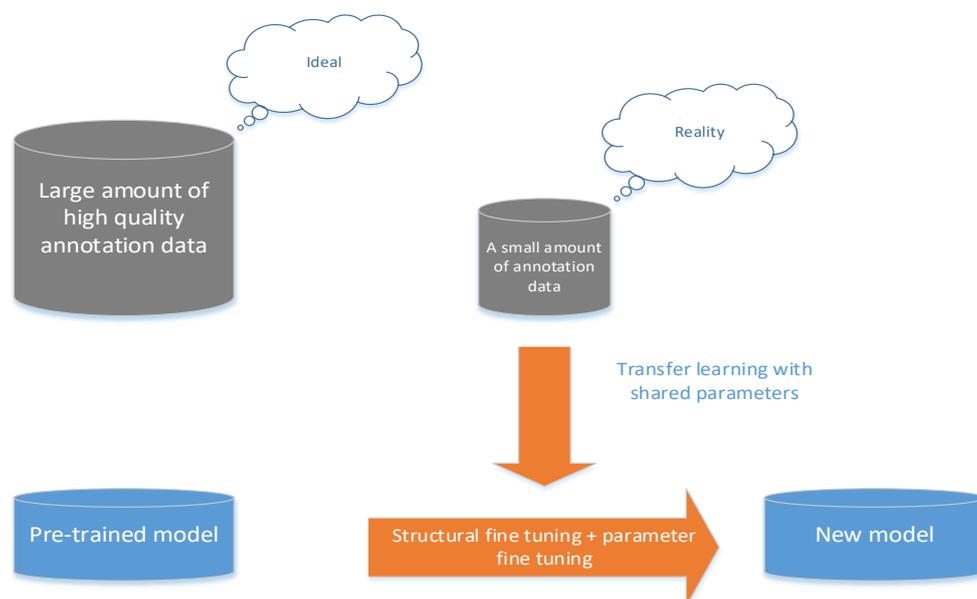


Figure 1: Schematic diagram of transfer learning with shared parameters

Deep convolutional neural networks (CNNs) area unit a special style of neural networks that have incontestible current best results on a spread of competition benchmarks. The super learning capability of deep CNN is especially achieved by victimisation multiple nonlinear feature extraction stages, which may mechanically learn hierarchic representations from information [19]. The provision of huge amounts of information and enhancements in hardware process units have accelerated CNN analysis, and extremely attention-grabbing deep CNN architectures have conjointly been according recently. In recent years, the high performance achieved by deep CNN architectures in difficult benchmark task competitions has shown that innovative subject field concepts, still as parameter optimisation, will improve CNN performance on a spread of vision-related tasks. The improved AlexNet architecture is

based on the original AlexNet architecture. It uses a new loss function that combines both softmax and cross-entropy losses. The shared parameter transfer learning method is used to train the model with data from ImageNet. This method uses a pre-trained CNN model as an initial condition for training the new network. Transfer learning may be a machine learning technique that permits information scientists to profit from information gained from machine learning models antecedently used for similar tasks. This type of learning is exemplified by the power of kinsfolk to transmit information. If you find out how to ride a bicycle, you'll find out how to drive different two-wheelers a lot of simply. Similarly, a trained self-driving model of a automotive may also be used for self-driving of a truck. Wikipedia defines transfer learning as follows: Transfer learning may be a analysis drawback in machine learning that focuses on storing the information gained in determination and applying it to a unique however connected problem. This technology is applicable to several machine learning models, as well as deep learning models like artificial neural networks and reinforcement models [20]. As shown in Figure 1, the goal is to leverage the information of the pre-trained model once acting completely different tasks.

Shared parameter transfer learning is a technique to learn parameters of one model from another. It uses the fact that neural networks are very good at approximating functions with many parameters, and it can be used to train models with different architectures using only a small amount of data. It can be seen that the hidden state probability at time  $t$  is only calculated at time  $T-1$ , so the state reuse theory in online planning can be applied to the Viterbi algorithm to reduce the time and space complexity. In the data set generation stage, the researcher combines the capabilities of a large language model (GPT-3) and a text-to-image model (Stable Diffusion) to generate a multimodal training data set containing text editing instructions and corresponding images before and after editing [21]. This process consists of the following steps: Fine-tune GPT-3 to generate a text edit content set: Given a prompt describing an image, generate a text instruction describing the change to be made and a prompt describing the changed image; Use the text-to-image model to convert two text prompts (i.e., before and after editing) into a pair of corresponding images [22].

Inspired by the application of twin network in the field of image detection, we propose a novel image recognition algorithm based on Improved AlexNet and Shared Parameter Transfer Learning (as shown in Figure 2). The proposed method is able to improve the performance of Image Recognition Algorithm (IRA) by improving its accuracy in object detection and classification tasks. It also improves the speed of IRA by reducing the number of training samples required for each iteration step [23-25]. To achieve these goals, we use shared parameters between two CNNs that are trained independently: one for classifying images into different classes using Convolutional Neural Networks (CNN), while another one trains an improved version of AlexNet to classify images into different classes using shared parameter transfer learning. The recognition algorithm is based on the improved AlexNet and shared parameter transfer learning. The network architecture has been modified to include a new layer between the convolutional and fully connected layers, which can be used for feature extraction [26].

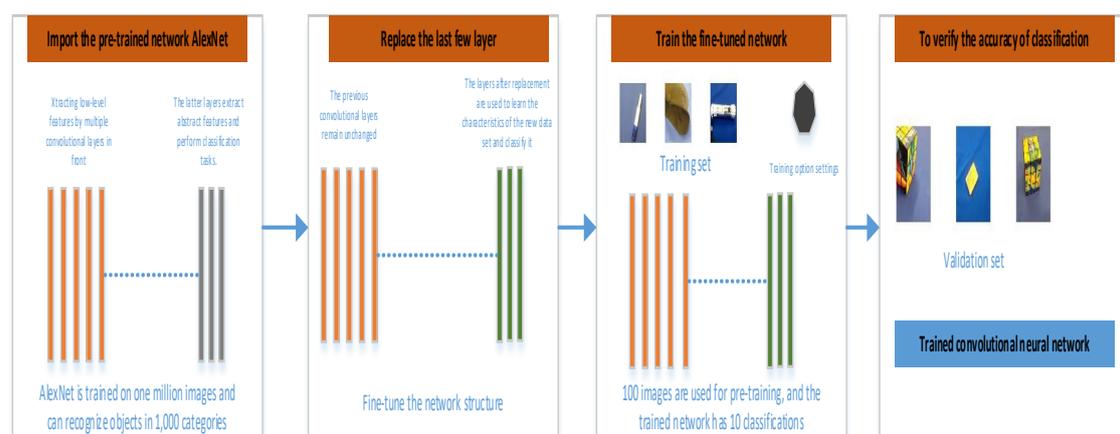


Figure 2: Image recognition realization process

The current version of Image Recognition Algorithm based on AlexNet is a result of the combined efforts of researchers from Google Brain Team and DeepMind. The algorithm is called as Inception-v3, which has been improved upon in comparison with its previous versions. It uses four different layers to build up the final model. To obtain the coaching knowledge, this paper combines 2 giant pre-trained models, the language model (GPT-3) and also the text-to-image generative model (Stable Diffusion), to

get an oversized pairwise coaching dataset of image redaction examples [27]. Researchers trained a brand new model InstructPix2Pix on this massive knowledge set and generalized it to real pictures and user-written directions once reasoning. InstructPix2Pix may be a conditional diffusion model that generates associate degree emended image given associate degree input image and a text instruction to edit the image. The model performs image redaction directly within the aerial with none further example pictures, full descriptions of the input/output pictures, or fine-tuning of every example, that the model quickly edits pictures in exactly a couple of seconds.

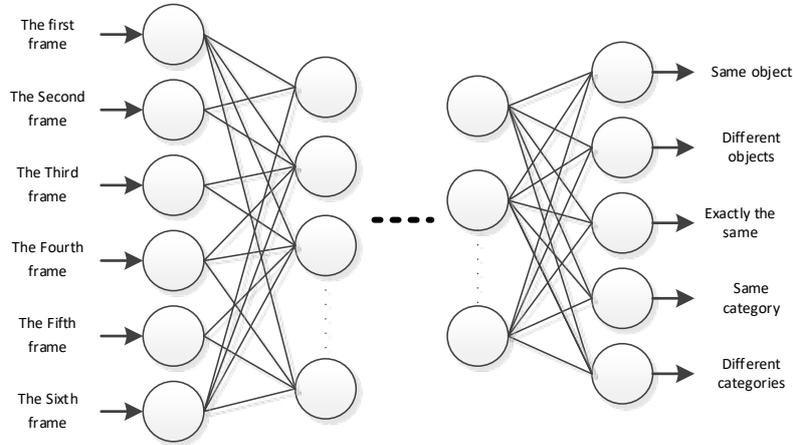


Figure 3: Neural network structure

This layer consists of multiple convolutional layers. The output layer has 64 filters that are applied to an image and then it is passed through a pooling operation before being sent out for further processing by other layers. As shown in Figure 3, according to the RBM algorithm formula, there are 6 visible units in layer V of the RBM connected with the input layer in the hidden layer, and there are 5 visible units in layer V of the RBM connected with the output layer in the hidden layer, and a layer of RBM is added in the middle to realize data transition cache, so the energy of RBM in the model is:

$$E_1(v, h | \theta) = -\sum_{i=1}^6 a_i v_i - \sum_{j=1}^t b_j h_j - \sum_{i=1}^6 \sum_{j=1}^t v_i W_{ij} h_j \quad (1)$$

$$E_2(v, h | \theta) = -\sum_{i=1}^t a_i v_i - \sum_{j=1}^t b_j h_j - \sum_{i=1}^t \sum_{j=1}^t v_i W_{ij} h_j \quad (2)$$

$$E_3(v, h | \theta) = -\sum_{i=1}^5 a_i v_i - \sum_{j=1}^t b_j h_j - \sum_{i=1}^5 \sum_{j=1}^t v_i W_{ij} h_j \quad (3)$$

The above three formulas represent the energy calculation of the hidden layer, the middle layers and the last layer respectively. In formulas 1, 2 and 3,  $v_i$  is the value of unit I in the visible layer;  $h_j$  is the value of unit J in the hidden layer. When the value is 0, it means that the unit is in an inactive state, and when the value is 1, it means that the unit is in an active state. The parameters a, B and W of RBM are abbreviated as  $\theta$ , where a is the bias vector of layer V, and B is the bias vector of the hidden layer. The energy joint probability distribution based on the improved RBM can be expressed as Equation 4:

$$P(v, h | \theta) = \frac{e^{-E(v, h | \theta)}}{Z(\theta)} \quad (4)$$

Where  $\theta$  is the normalization factor, i.e., the partition function, then the likelihood function of can be expressed as Equation 5:

$$P(v | \theta) = \frac{1}{Z(\theta)} \sum_h e^{E(v, h | \theta)} \quad (5)$$

### 3. Experimental process

All the experiments are carried out on the workstation, the equipment parameters are intel I9-10900k, 64GB, 2 \* RTX3090, 1 T pcie3.0 SSD, and the experimental platform is Matlab 2016b. During the experiment, the CIFAR-10 data set was used to train the constructed convolutional neural network.

#### 3.1 Stack Information

Decompresses modern pictures and loads them for capacity as picture information. The imageData store naturally explains pictures based on the organizer title and stores the information as an ImageData store question. Through picture information capacity, huge picture information can be put away, counting information that cannot be put into memory, and pictures can be examined effectively in clusters amid the preparing handle of the convolutional neural organize. The information is separated into a preparing information set and a approval information set. 70% of the pictures were utilized for preparing and 30% for approval. SplitEachLabel parts the pictures datastore into two unused datastores. This exceptionally little dataset presently contains 55 preparing pictures and 20 approval pictures.

#### 3.2 Load pre-trained network

Load the pre-trained AlexNet neural network. As shown in Figure 4, AlexNet has been trained on over 1,000,000 pictures and may classify pictures into a thousand object classes (such as keyboard, mouse, pencil, and numerous animals). Therefore, the model has learned a fashionable feature illustration supported an oversized variety of pictures. Here, analyzeNetwork is employed to interactively and visually gift the specification and details regarding the network layer.



Figure 4: Sample Dataset

#### 3.3 Replace the final layer

The last three layers of the pre-trained network net are configured for 1000 classes [28]. These three layers must be fine-tuned for the new classification problem. All but the last three layers are extracted from the pre-trained network. Migrate the layers to the new classification task by replacing the last three layers with a fully connected layer, a softmax layer, and a classification output layer. Specify options for a new fully connected layer based on the new data. Set the fully connected layer to the same size as the number of classes in the new data. To make learning in the new layer faster than in the migrated layer, increase the WeightLearnRateFactor and BiasLearnRateFactor values for the fully connected layer.

#### 3.4 Training network

As shown in Figure 5, the network needs the scale of the input image to be 227\*227\*3, however the photographs within the image knowledge store have totally different sizes [29]. The coaching pictures could also be mechanically resized mistreatment the improved image knowledge store. Specifies the sweetening operations to be in addition performed on the coaching image: willy-nilly flipping the coaching image on the vertical axis, and willy-nilly translating the coaching image by up to thirty

pixels in each the horizontal and vertical directions. Knowledge sweetening helps forestall network overfitting and learning of specific details of coaching pictures.

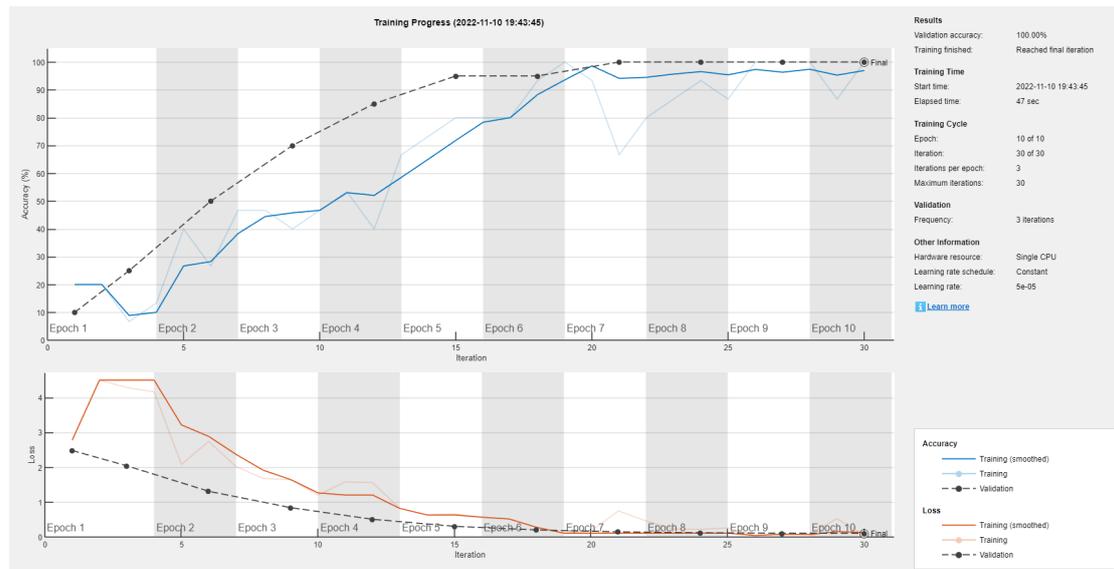


Figure 5: Training Progress

#### 4. Experimental result

The main component of most image recognition systems is the feature extraction module that extracts features from an input image using certain pre-defined algorithms like histogram matching or edge detection techniques. For transfer learning, the options (transferred layer weights) within the shallower layer of the pre-trained network square measure preserved, whereas to cut down the educational speed within the transferred layer, the initial learning rate is about to alittle worth. within the previous step, we have a tendency to raised the educational rate issue for the totally connected layer to hurry up learning within the new final layer [30]. This mix of learning rate settings solely quickens learning within the new layer and slows down learning for the opposite layers. once transfer learning is performed, the amount of coaching rounds needed is comparatively tiny. One spherical coaching|of coaching} may be a complete coaching cycle for the whole training knowledge set. It may be found that the accuracy will increase considerably with the rise of the amount of epochs. Specify the tiny batch size and verify the info. The package validates the network each Validation Frequency iteration throughout the coaching method.

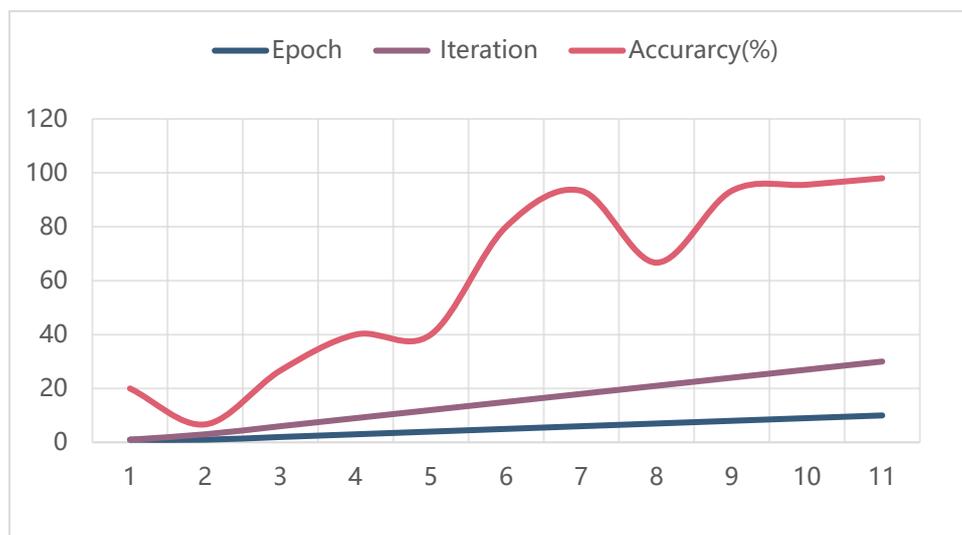


Figure 6: Verify the result trend chart

As shown in Figure 6, with the adjustment of the parameters of the fully connected layer and the

hidden layer, the image recognition rate changes. After the fully connected layer reaches 10, the recognition rate can be close to 98%.



Figure 7: Recognition result

It can be seen from Figure 7 that, after testing, the objects that the system needs to identify can be accurately identified from the test set, but some pictures have the problem of incomplete identification. Each column of the perplexity lattice speaks to a anticipated category, and the entire number of each column speaks to the number of information anticipated to be in that category; each push speaks to the genuine category to which the information has a place, and the overall number of information in each push speaks to the number of occasions of the information in that category. As shown in Figure 8, within the picture precision assessment, it is primarily utilized to compare the classification comes about with the real measured values, and the precision of the classification comes about can be shown in a perplexity framework.

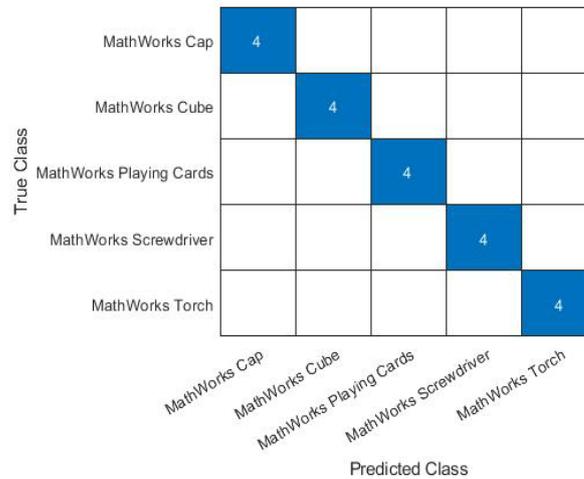


Figure 8: Confusion matrix diagram

## 5. Conclusion

Image recognition is the process of identifying objects in an image. It can be used to identify a person, object, or scene from a single image. Image recognition systems are used for many applications such as surveillance and security, automatic face detection and tracking, object identification in images (e.g., faces), and smart phone applications such as photo tagging. The image recognition algorithm is based on the improved AlexNet architecture and shared parameter transfer learning. The improved AlexNet has been trained with a larger dataset, which contains more data points in each layer of the network, compared to the original AlexNet. This leads to better accuracy when training with large datasets. In addition, we have also used transfer learning for improving the performance of the model. Transfer learning helps us by taking features from one object class and using them as features for another object class that shares similar characteristics with it. In this paper, the recognition algorithm is based on the improved AlexNet and shared parameter transfer learning. The network architecture has

been modified to include a new layer between the convolutional and fully connected layers, which can be used for feature extraction. This technique also improves performance by using both CNNs simultaneously as well as improving accuracy through sharing parameters of the two networks.

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