Deep Learning Approaches for Image Recognition and Classification

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Abstract- Picture processing, computer vision, and machine learning all have their own unique approaches to solving the age-old issue of picture categorization. In this research, we investigate the use of deep learning to classify images. For this, we make use of the Alex Net architecture in conjunction with convolution neural networks. For the purpose of categorization, the Image Net database provides the choice of four photos to use as test cases. In addition to carrying out studies, we cropped the photos to isolate different part locations. The findings demonstrate that Alex Net's deep learning-based picture categorization method produces accurate results. Women Deep learning is a subfield of machine learning that has seen increasing use in recent years. Depending on the kind of learning being done, many methodologies, such as unsupervised, semi-supervised, and supervised learning, have been presented as possible solutions. In the areas of image processing, computer vision, and pattern recognition, the deep learning systems performed far better than their more traditional machine learning counterparts, as shown by a number of the experimental findings. This article offers a concise summary of the Deep Learning field, starting with Deep Neural Networks (DNN). The Convolution Neural Network (CNN) and its designs are the next topic to be discussed in this study. Some examples of CNN architectures are LeNet, AlexNet, GoogleNet, VGG16, VGG19, Resnet50, and others. Transfer learning has been included into the CNN via the use of its pre-trained architectures. These designs are evaluated using significant amounts of data from ImageNet.

Indexed Terms- Deep Learning, Image Recognition,

I. INTRODUCTION

Classification involves categorising things by their traits. Image classification uses real-world examples to help computers see like humans. The picture is categorised based on its content. This study examines deep learning for picture classification. Machine learning—a subject of artificial intelligence (AI)—includes classical picture categorization methods. Machine learning has a feature extraction module that extracts edges and textures and a classification module that classifies based on those features.[1] Machine learning systems use these components. Machine learning can only extract a limited number of features from photographs and cannot derive differentiating traits from the training set. Machine learning's biggest limitation. Deep learning overcomes this drawback. Deep learning (DL) uses its own calculation algorithm to learn. Like a human, a deep learning model continually dissects information into a homogeneous structure.[2,3] Deep learning uses an artificial neural network (ANN) with several algorithms to attain this aim. ANNs are modelled after biological neural networks like the brain. Deep learning outperforms typical machine learning methods. Deep learning considers neural networks that recognise a picture by its properties. This is done to build a feature extraction model that can overcome the problems of existing methods. The integrated model extractor must learn to effectively extract differentiating characteristics from the training batch of photos. GIST, gradient-oriented and Local Binary Pattern histograms, and SIFT can classify the picture's feature descriptors. Section-II covers artificial neural network basics. Section III covers AlexNet. Section-IV discusses implementation and results. Section V concludes with references.[4]

- Artificial Neural Networks

A neural network may be defined as "a combination of hardware bonded or separated by the software system that operates on the small component in the human brain known as a neuron." This is one description of what a neural network is.[5] Another definition of what a neural network is can be found here. Utilising a neural network that contains several layers is one option to consider in lieu of the scenario that was discussed previously.[6] When the resolution is exceedingly high, the training picture samples need to have more than nine times the amount of parameters that are necessary for accurate tuning of the traditional classification. Due to the intricate nature of the network's construction, the task of putting into practise a neural network with several layers in the real world is extremely challenging.[7] The current expression for the multi-layered neural network that has been constructed is called "deep learning." Every node in a deep neural network is responsible for calculating its own basic inputs and then passing that information along to the subsequent layer in lieu of the layer that came before it.[8]

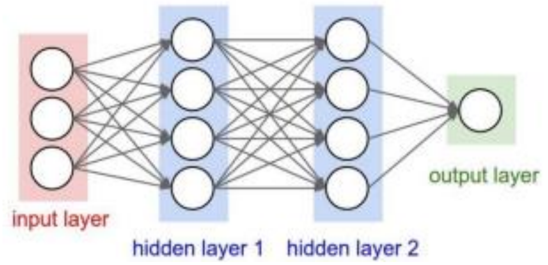

Fig. 1: The Most Primitive Deep Neural Network[9]

In order to train the data that is contained in the networks, we first give them an image to work from as input, and then we tell them what the network has produced as its output. The total depth of a neural network, in addition to the number of layers that were utilised in the process of generating the network's inputs and outputs, may be used as a metric to determine how sophisticated a neural network is. [10,11] Neural networks are critically significant components of a wide variety of methodological frameworks, such as fuzzy logic, evolutionary algorithms, and Bayesian techniques, amongst others. The term "hidden layers" is used to describe these levels the vast majority of the time when people are discussing them. They are expressed in terms of the number of hidden nodes as well as the number of inputs and outputs that are contained within each individual node.[12] Convolution Neural Networks, or ConvNets for short, are the most popular approach that is used to put the deep learning strategy into action. This method is sometimes abbreviated as ConvNet.[13] In addition to classification layers, the ConvNet incorporates feature detection layers into its architecture. Convolutional layers, maxpooling or average-pooling layers, and fully-connected layers are the three types of layers that make up a Convolutional Neural Network, often known as a ConvNet.[14]

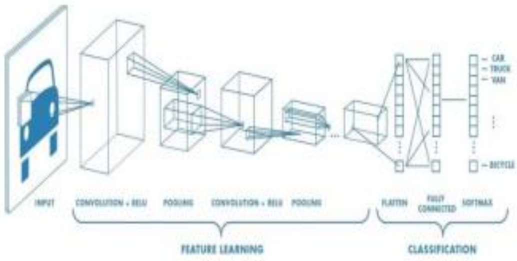

Fig. 2: Architecture of CNN[15]

II. CONVOLUTIONAL NEURAL NETWORKS (CNN)

The objective of picture categorization required the creation of a Convolutional Neural Network, which was accomplished with the assistance of a number of layers. The analysis and categorization of photos was delegated to this network as its responsibility.[16] CNN's structure is made up of a number of levels, which may be broken down into the following categories according to their functions:

1. Input Layer: This layer is responsible for receiving raw images and passing them on to the layers that come after it so that features may be retrieved from them.
2. The Convolution Layer: The next layer, which is known as the convolution layer, is the one that follows the input layer. Within this layer, a number of different filters are applied to the photographs in order to identify features that may be found within the pictures. During the phase of testing, these qualities are what are used to compute the matches with the candidates.[17]

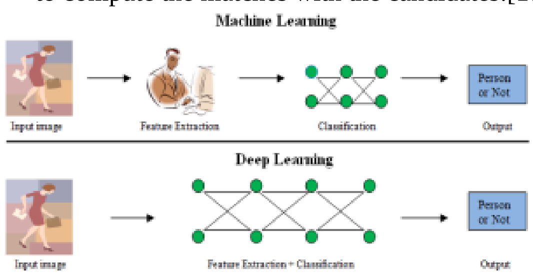

Fig. 1: Machine Learning vs. Deep Learning [18]

3. ReLU (Rectified-Linear Unit): The Rectified Linear Unit or is the next layer to be added after the convolution layer.ReLU. This layer allows

for quicker and more effective training by replacing the negative integer in the convolution layer with zero (0).

4. Pooling: The pooling layer receives the features that were extracted. This layer takes in enormous photos, scales them down, and then adjusts the parameters such that the vital information is not lost in the process. It maintains the highest possible value from each window..
5. Fully Connected Layer: The last layer is a completely linked one that takes in pictures that have been filtered at a high level and transforms them into labels that correspond to categories.
6. Softmax Layer: This layer is the one that appears shortly before the output layer. At this level, the probabilities for each class are expressed as decimal values. These decimal probabilities fall somewhere in the range of 0 to 1, inclusive.

"Figure 2 depicts the first four steps, which are known as the feature extraction stages, and the final two stages, which are known as the classification stages.

- Transfer learning

During the training phase of deep learning, the model is presented with a considerable quantity of data and is instructed on how to alter its own model weight and bias. During this phase, deep learning is also referred to as "supervised learning." After that, these weights are put into a variety of different network models so that those models may be evaluated. The newly developed network model can get started with weights that have already undergone pre-training.[19,20]

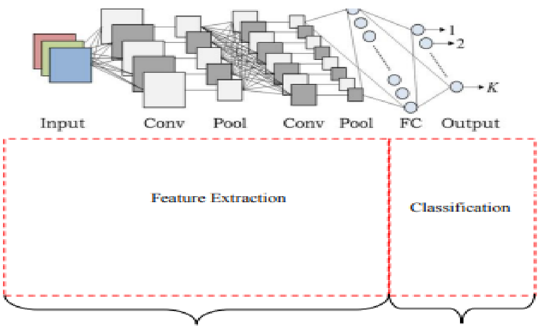

Fig. 2: CNN layers [21]

One definition of a model that has been pre-trained is one that has had its training done on the same domains as other models.[22,23] There is a wide variety of pre-trained architectures that may be exploited; some of the arguments for the utilisation of pre-trained models include the following: To begin, there is a requirement for a bigger quantity of processing power in order to train the gigantic models on the massive datasets. Second, training the network might take many weeks or perhaps a large amount of time, which is a disadvantage.[24] By training the new network with weights that have already been taught, the learning process may be sped up and become more efficient. Table-1 is a listing of the error rates that CNN's architecture experiences the majority of the time.[25]

Table-1: top-5 error rates of network Architectures [26]

CNN Architectures	Top-5 error rate (%)
LeNet	28.2
AlexNet	16.4
VGG	7.30
GoogleNet	6.70
ResNet	3.57

The pre-trained models are explained as follows:

- LeNet:

The design of LeNet is based on a convolutional architecture as its primary component. It starts with one convolutional layer, then it moves on to another convolutional layer that flattens the image, then it moves on to two fully-connected layers, and lastly it ends with one softmax layer.[27]In comparison to the LeNet, the neural network known as the AlexNet represents a significant technological advancement.[28,29] Rectified Linear Units, sometimes referred to as ReLUs, are used in this network to create non-linearity, which in turn speeds up the network. This process is known as "recursive rectification." In addition to having an output layer, this network is made up of 62.3 million parameters and has five convolutional layers, three fully connected layers, and finally an output layer. After that, the network has an output layer .[30]

- VGG:

Visual Geometry Group is the full name of the organisation that VGG stands for as an acronym. Nodes with the identifiers VGG16 and VGG19 are often found in a VGG network. Because the big size kernels in this network have been replaced with a multiple number of 3x3 filters, we are able to extract difficult features at a reduced cost. This is made possible by the fact that the size of the kernels has been lowered .[31]

- Google Net:

This GoogleNet was able to attain a fair degree of accuracy; but, in order for it to do so, a large amount of computing power was necessary. There was a significant amount of order in the computations.[32,33] Instead of having fully-connected layers at the conclusion of the model, GoogleNet has been replaced with average pooling. This change takes place after the last convolutional layer. The number of parameters will become significantly less when this adjustment has been made.

- ResNet:

To this point, increasing the network depth has also automatically resulted in an improvement in accuracy. This has been the case up until this point. Nevertheless, the depth of the ResNet network might potentially cause a few problems on its own.[34,35] The accuracy of the prediction in the initial layers of the network dropped dramatically as a direct result of the increasing depth, which in turn forced a modification in the weights and brought about the end of the network. Another problem was the extremely large amount of parameter space that was required.[36] The implementation of residual modules was done with the goal of avoiding these kinds of complications as much as possible. ResNet50 and ResNet152 are the names of two different types of networks that belong to the ResNet family.[37]

- Alexnet

The ConvNet may be subdivided into two separate versions, which are respectively referred to as the LeNet and the AlexNet. An artificial intelligence system that was built to classify hand-written digits is called the LeNet. This system is also known as the Shallow Convolutional Neural Networks (Shallow CNN).[38,39] The architecture of LeNet contains one output layer, two hidden layers, two convolutional layers, and two subsampling levels in addition to the two convolutional layers. Deep convolutional neural networks, also known as AlexNet, are the networks that are employed to classify the input picture into one of a thousand distinct categories.[40] AlexNet is an expression of deep convolutional neural networks. In the realm of artificial neural intelligence, it is standard procedure to make use of AlexNet for the aim of discovering answers to issues such as indoor sensing classification. One such task is described below. For the purpose of pattern recognition in relation to identifying the qualities of an image, it is an efficient method that makes use of more differential vision in the computer industry.[41,42] This is done for the purpose of recognising the features of a picture. In this particular piece of work, the subject of discussion is the classification of a certain picture size according to a required choice. It is possible to effectively categorise the training sample of photographs that are available in AlexNet, which adds to an improvement in vision. The AlexNet consists of five convolutional layers, three fully connected layers, and three sub sampling layers in total.[43,44] The fundamental way in which LeNet and AlexNet may be distinguished from one another is by examining the Feature Extractors that each network employs. Non-linearity is exploited in the Feature Extractor module of AlexNet, whereas log sinusoid is used in the LeNet module of AlexNet. AlexNet makes use of a protocol known as dropout, which does not appear in any of the other data sets concerned with networking.[45]

- Implementation, Results and Discussions

In order to carry out our experiment, we browsed the images available in the ImageNet database and selected the following four: a photo of a sea anemone, a picture of a barometer, a picture of a stethoscope, and a picture of a radio interferometer (see figure 3). The illustration that follows depicts the implementation of the architecture that is shown in Figure 4, as well as the block diagram of the architecture that is shown in Figure 4.[46,47]

Fig. 3: Images for testing (a) (a) A sea anemone measuring 375 by 500 by 3 (b) A barometer measuring 500 by 375 by 3 (c) A stethoscope measuring 375 by 500 by 3 (d) Radio interferometer measuring 375 by 500 by 3 millimetres[48]

The first layer makes use of 96 11x11 filters overall, and stride 4 is the point at which those filters are implemented. 55 centimetres on each side and 96 centimetres in height and width define the output volume.[49] The AlexNet is trained on a graphics processing unit (GPU) with the designation

GTX580, which only has 3GB of RAM available for use. Therefore, the output of CONV1 will be split in two and supplied to two different GPUs; more specifically, each GPU will get 55x55x48. As shown in the accompanying graphic, there is just a link that has to be made between the bits of the second, fourth, and fifth convolutional layers and the component maps of the layer that came before them. These bits and maps are stored on the same GPU.[50,51] All of the kernel mappings that are present in the second layer are connected in some way to the kernels that are present in the third convolutional layer. The neurons in each layer that have full connectivity are coupled to every other neuron in each layer that was there before them. Instead of having layers of pooling or standardisation in between them, the third, fourth, and fifth convolutional layers are directly linked to one another. This allows for a more accurate representation of the data.[52] The results of the second convolutional layer are used to construct the third convolutional layer, which consists of 384 sections with sizes of 3 x 3 x 256. [53] These components have been compiled and standardised into a single set. The fourth convolutional layer includes 384 kernels with a dimension of 3 x 3 x 192, whilst the fifth convolutional layer contains 256 kernels with the same size. Both layers are convolutional layers. The first two layers that are fully connected have a combined total of 4096 neurons in each layer. We make advantage of the local response normalisation which is located inside the layer of normalisation.[54] The framework of AlexNet was designed with not one but two layers of normalisation built into its architecture. When compared to training a deep neural network with function tanh units of the same sort, training with nonlinearity has the potential to take place significantly more quickly. The ReLU is able to provide training that is both more efficient and more successful as a result of its ability to reset all of the students' negative ratings to zero while keeping their positive ratings. The response-normalized movement is characterised by the following statement: The response-normalized movement is denoted by the movement of a neuron, which is figured by first applying kernel i at position (x, y), and then applying the ReLU nonlinearity thereafter. This movement serves as a symbol for the response-normalized movement.

$$c^{i}_{(x,y)} = d^{i}_{(x,y)} \Big/ \left(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} \left(d^{j}_{(x,y)}\right)^2 \right)^{\beta} \quad (1)$$

This form of response standardisation brings about a type of parallel impediment that is stimulated by the kind that is seen in genuine neurons. This creates competition for large activities among neuron yields that have been registered using various kernels. The test photographs are cropped to different section areas before being put through the categorization process.[55] The findings are depicted in Figures 5, 6, 7, and 8 respectively. It can be seen from the findings that the categorization is effective in each and every instance of the data that has been cropped.

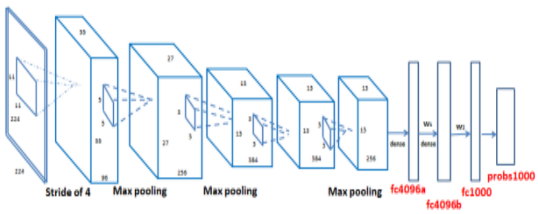

Fig. 4: AlexNet Architecture[56]

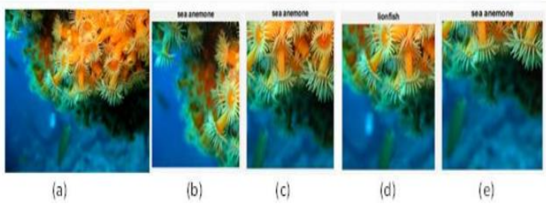

Fig. 5: The sea anemone spread to many different regions.[57]

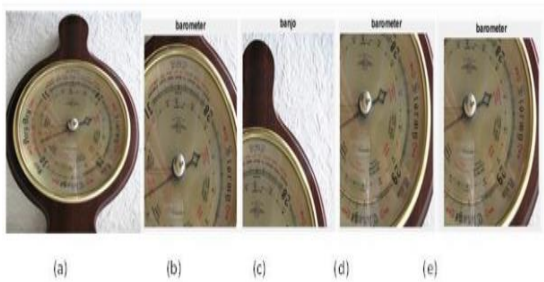

Fig. 6: Barometer with several sections clipped from it [57]

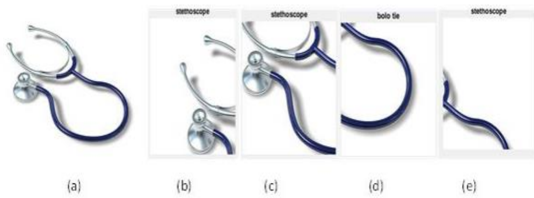

Fig. 7: Various sections of the stethoscope were cut off .[59]

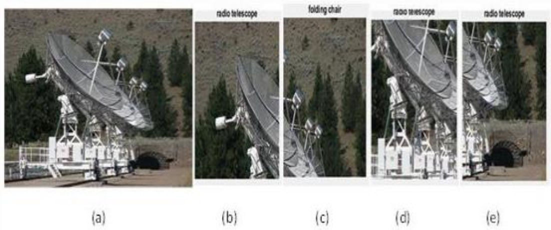

Fig. 8: Radio Interferometer positioned in a number of different regions[60]

CONCLUSION

In order to put deep learning to the test and validate its ability to classify pictures, a search was conducted in the AlexNet database to find four distinct test photos. These test images were of a "sea anemone, a barometer, a stethoscope, and a radio interferometer" respectively. The convolutional neural network that is a component of the architecture of the AlexNet algorithm is responsible for performing the classification task. The results of the tests show that the deep learning algorithm is effective since it correctly classifies the photographs, even for the portions of the test pictures that are included in the studies. This demonstrates that the method is successful.

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