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Classifying Images Using ConvolutionalNeural Networks (CNNS)

T.Naga Navya[1]*, Bolla Susmitha[2] , Saripudi Sri Tirisha[3], Naredla Pallavi[4],Sadhu Naga Meenashi[5]
1*Assistant Professor: Vignan's Nirula Institute of Technology and Science for Women.
2,3,4,5 B.Tech Scholar: Vignan's Nirula Institute of Technology and Science for Women.

ABSTRACT

Recently, deep learning has been used in picture categorization, word detection and recognition, object tracking, posture estimation, scene labeling, and visual saliency detection. Models like Auto Encoder, Sparse Coding, Restricted Boltzmann Machine, Deep Belief Networks, and Convolutional Neural Networks are frequently used in deep learning. In comparison to previous models, convolutional neural networks have demonstrated strong performance in picture classification. In this paper, a simple convolutional neural network for image classification was constructed. This simple convolutional neural network completed the image classification. We also looked at a number of learning rate setting strategies and other optimization algorithms built on top of the Convolutional neural network to find the optimal parameters that have the biggest impact on image classification.

Keywords: Deep learning, Convolutional Neural Network (CNN), image classification, MINIST Image Datasets, Machine Learning.

1. INTRODUCTION

In essence, image classification [1-10] is a type of task that attempts to comprehend the image and classify the image into a specific category. While this may seem like a very simple task for humans to manually decide the class of various images, image classification [11] in the data science field means automatically processing a huge number of images in parallel and providing the classification results simultaneously. Meanwhile, while judging an image that is commonly viewed, such as an animal, may be simple for humans to judge, the image classification task may be significantly difficult for most people if such an image requires specific knowledge [12-20] to classify, like the x-ray photo. In this scenario, the image classification task for a machine means to completely comprehend images as data, and classify the image based on information.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image classification tasks. CNNs, inspired by biological processes, employ different layers [21-30] for feature extraction and classification, significantly improving accuracy and efficiency in image recognition tasks. Various studies have explored CNNs' application in different domains, from hyperspectral image analysis to underwater fish recognition and quality assessment of materials like wood.

This project aims to leverage deep learning algorithms, specifically CNNs, to enhance the accuracy and efficiency of image classification. By automating tasks typically performed by the human visual system, this project seeks to address the limitations of traditional image processing methods and contribute to advancements in visual information [31-35] indexing and retrieval systems. Through the integration of supervised and unsupervised learning techniques, the project will explore different strategies for feature extraction and classification, ultimately improving the capability of computers to understand and process visual information effectively.

2. LITERATURE SURVEY

In recent years there have been great strides in building classifiers for image detection and recognition on various datasets using various machine learning algorithms. Deep learning, in particular, has shown improvement in accuracy on various datasets. Some of the works have been described below:

Norhidayu binti Abdul Hamid et al.[1]Evaluated the performance on MNIST datasets using 3 different classifiers: SVM (support vector machines), KNN (KnearestNeighbor) and CNN (convolutional neural networks). The Multilayer perceptron didn't perform well on that platform [36-40] as it didn't reach the global minimum rather remained stuck in the local optimal and couldn't recognize digit 9 and 6 accurately. Other classifiers, performed correctly and it was concluded that performance on CNN can be improved by implementing the model on Keras platform.

Mahmoud M. Abu Gosh et al.[2]Implement DNN (Deep neural networks), DBF (Deep Belief networks) and CNN (convolutional neural networks) on MNIST dataset [41-50] and perform a comparative study. According to the work, DNN performed the best with an accuracy of 98.08% and other had some error rates as well as the difference in their execution time.

Youssouf Chherawalaet al.[3]Built a vote weighted RNN (Recurrent Neural networks) model to determine the significance of feature sets. The significance is determined by weighted votes and their combination and the model is an application of RNN. It extracts features from the Alex word images and then uses it to recognize handwriting.

Alex krizhevsky uses a[4] 2-layer Convolutional Deep belief network on the CIFAR-10 dataset. The model built classified the CIFAR-10 dataset with an accuracy of 78.90% on a GPU unit. Elaborative differences in filters and their [51-55] performance is described in the paper which differs with every model.

Yehya Abouelnagaet al.[5]Built an ensemble of classifiers on KNN. They used KNN in combination with CNN and reduce the Overfitting by PCA (Principal Component Analysis). The combination of these two classifiers improved the accuracy to about 0.7%.

Yann le Cunnet al.[6]Give a detailed introduction to deep learning and its algorithms. The algorithms like Backpropagation with multilayer perceptron, Convolutional neural networks, and Recurrent neural networks are [56-63] discussed in detail with examples. They have also mentioned the scope of unsupervised learning in future in Artificial intelligence.

Li Deng[7] details a survey on deep learning, its applications, architectures, and algorithms. The generative, discriminative and hybrid architectures are discussed in detail along with the algorithms that fall under the respective categories. CNN, RNN, Autoencodes, DBN's, RBM's (Restricted Boltzmann machines) are discussed with their various applications.

3.PROPOSED METHODOLOGY

Data Preparation:

Dataset: You need a dataset of labeled images (e.g., CIFAR-10, MNIST, etc.).

Preprocessing: Resize, normalize, and possibly augment the images (rotation, flipping, etc.).

CNN Architecture:

A CNN typically consists of several layers

Input Layer: The raw image is input as a tensor (e.g., 32x32x3 for CIFAR-10 images).

Convolutional Layers: Apply convolution filters to the input image, extracting features like edges, textures, or more complex patterns. The key parameters are the size of the filters (e.g., 3x3 or 5x5) and the stride.

Activation Function: After each convolution, an activation function (typically ReLU) is applied to introduce non-linearity.

Pooling Layer: Perform downsampling (e.g., MaxPooling) to reduce the spatial dimensions and focus on important features.

Fully Connected Layer: After the convolutional layers, flatten the data and feed it into one or more fully connected layers, where each neuron connects to every other neuron.

Output Layer: The final layer should have as many neurons as the number of classes (e.g., 10 neurons for CIFAR-10) and often uses a softmax activation to convert the logits into probabilities.

Forward Propagation:

During forward propagation, the input image passes through each layer in sequence, where:

- Convolutions capture spatial features.

- Pooling reduces the size of the data.

- Fully connected layers learn global patterns from the extracted features.

Loss Function:

For classification tasks, the cross-entropy loss function is commonly used:

[text{Loss} = - sum_{i=1}^{n} y_i log(p_i)] where (y_i) is the true label, and (p_i) is the predicted probability.

Backpropagation and Optimization:

After computing the loss, the gradients of the loss with respect to the network's weights are computed using backpropagation. The optimizer (e.g., SGD, Adam) updates the weights to minimize the loss.

Training: The model is trained over several epochs (iterations over the entire dataset). At each epoch, the model adjusts its parameters to better classify the images based on the backpropagated gradients.

Evaluation:

After training, evaluate the model on a separate test set to measure its accuracy. Common metrics include accuracy, precision, recall, and F1-score

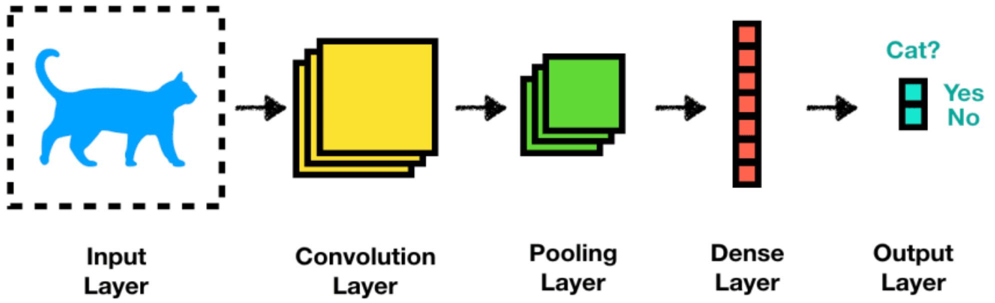

Fig:1 Flow chart

3. RESULTS

The project's conclusions are quite satisfactory. The technology detected images with a 93 percent accuracy rate. The results indicate that Convolutional Neural Networks(CNNs) may effectively detect images using deep learning approaches, outperforming conventional neural networks. The systemmixes several training data intelligently for calculating and lowering false alarm rates with completely.The network is connected. Although there are small detecting issues in some photographs, the overall performanceStatistics are quite efficient. The only disadvantage is that it is a little slow because it requires more. computational capability to generate results. Cleaning may minimize the false alarm score.

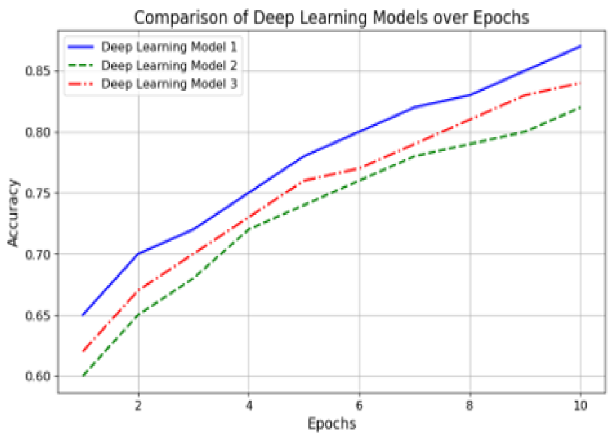

Fig:2 Comparison of DL Models

We trained and tested photos from the cifar-10 keras dataset to determine their classification. We categorized the photographs into three categories: automobile, airplane, and birds. We used Python Notebook to import all libraries and begin creating. After creating the model, we tested it for accuracy based on sample size and epochs. We employed CNN and layers to improve accuracy. We adopted the sequential technique in this paper [8][9][10].

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 32)        896
_________________________________________________________________
batch_normalization (BatchNo (None, 32, 32, 32)        128
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 30, 30, 32)        9248
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 15, 15, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 15, 15, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 15, 15, 64)        18496
_________________________________________________________________
batch_normalization_1 (Batch (None, 15, 15, 64)        256
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 13, 13, 64)        36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 6, 6, 128)         73856
_________________________________________________________________
batch_normalization_2 (Batch (None, 6, 6, 128)         512
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 4, 4, 128)         147584
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 2, 2, 128)         0
_________________________________________________________________
dropout_2 (Dropout)          (None, 2, 2, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 3)                 1539
=================================================================
Total params: 289,443
Trainable params: 288,995
Non-trainable params: 448
_________________________________________________________________
```

Fig 3:Layers used in CNN Model

We used the sequential mode and the different layers which can be used for classification of images.

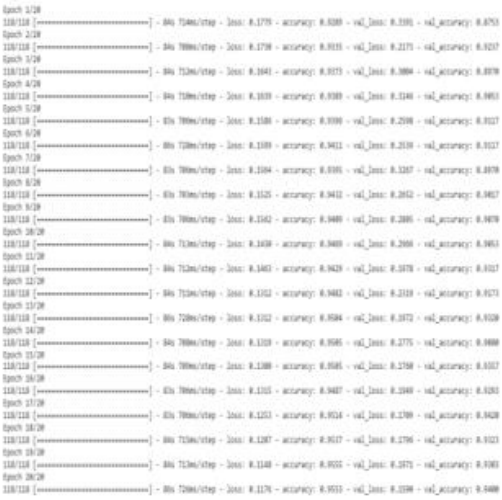

Fig 4:20 Epochs with the Validation Accuracy

After training the model, we achieved validation accuracy of 94.2%. We then loaded the model and classified sample photos using the classification model.

We established a folder to contain the best models, as well as classes for picture storage, training, classification, and testing.We used sequential mode and several layers to classify photos.We utilized a batch size of 64 photos to train each lot. Our primary goal was to appropriately classify and name the majority of the photos.

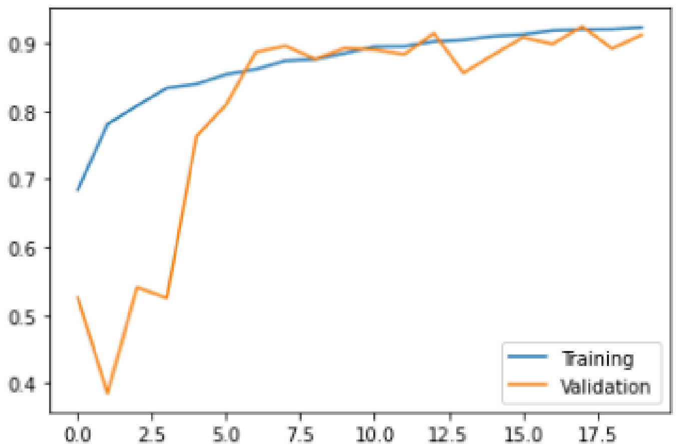

Fig:5Training and Validation Accuracy Graph

5.CONCLUSION

After using the CNN method, we were able to obtain 93 percent validation accuracy of our model. We trained and then tested the images and used the CNN method for the classification. This study focused on the CNN model and the accuracy of validation. After 20 epochs, the CNN model reached 90 percent accuracy of validation and then we loaded that model to label the images. We did the literature survey and found that different CNN techniques are been used to perform different operations and based on the computational power of any particular project or the complexity different methods of CNN can be compared.

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