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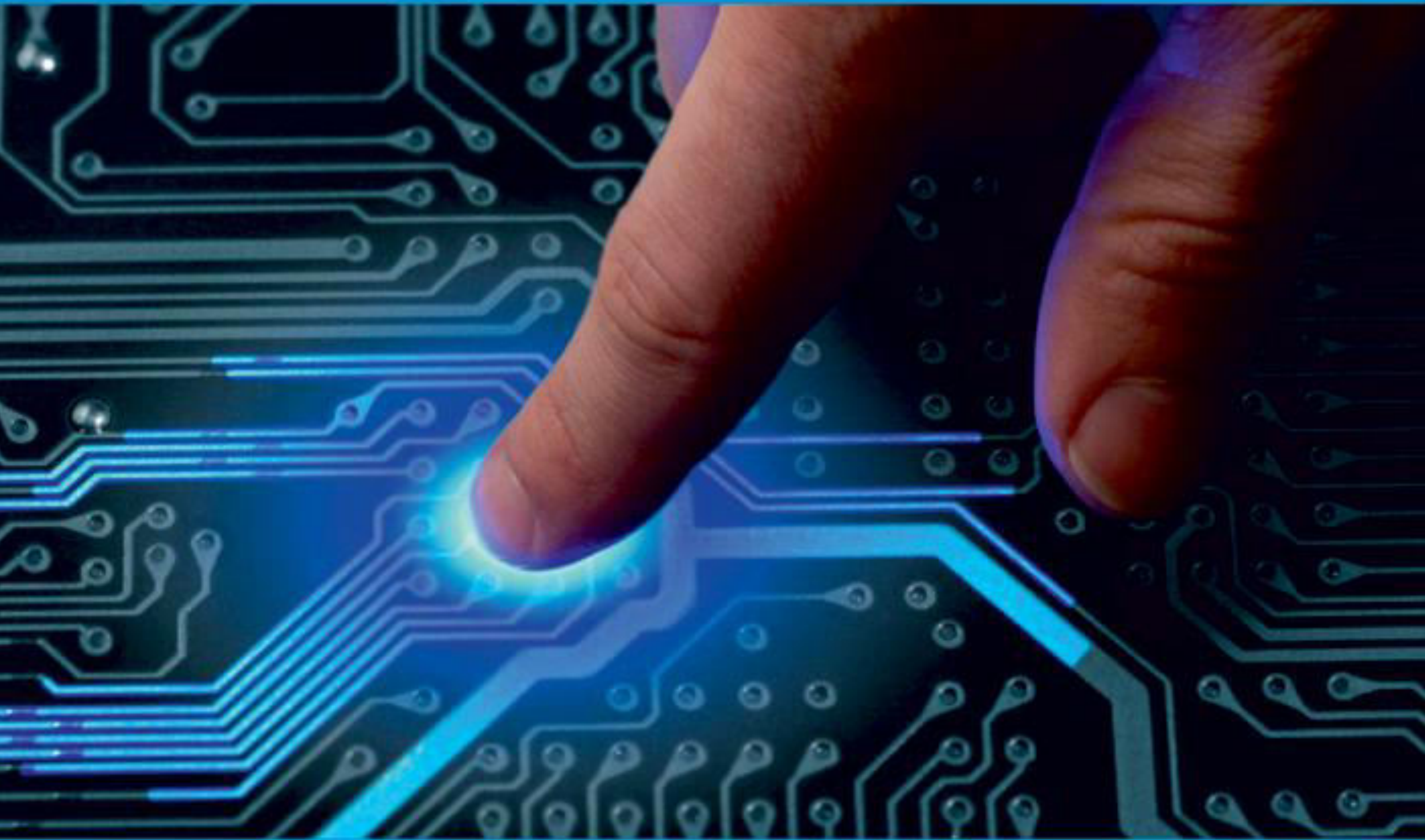

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Image Classification Using Machine Learning

Arti Panchal[1], Richa Sapre [2], Sunil Wankhade[3]

UG Students, Dept. of I.T., Rajiv Gandhi Institute of Technology, Versova, Mumbai, Maharashtra, India[1,2]

Professor, Dept. of I.T, Rajiv Gandhi Institute of Technology, Versova, Mumbai, Maharashtra, India[3]

ABSTRACT: Artificial intelligence is what the modern world will be made of. A common use of machine learning is image classification, where the aim is to develop a model for digital image analysis. This research of CNN and image classification models intends to give readers with an analysis of an image classification model. In order to classify photos, meaningful attributes must be extracted from the images and used to forecast the label of the image. Convolutional neural networks (CNNs) are a common method for classifying images and have been demonstrated to be highly effective in image recognition applications.

KEYWORDS: Digital image analysis; Image classification model; Convolution neural network.

I. INTRODUCTION.

Convolutional Neural Networks, often known as CNNs, are a subset of deep learning algorithms that are employed in machine learning and artificial intelligence. While other types of grid-like data can also be processed and analyzed using CNNs, its primary application is the processing and analysis of visual data, such as photos and videos.

A computer can be taught to identify objects, patterns, or other features in images and classify them into specified groups or labels using the technique of image classification. CNNs are a popular choice for this purpose since they have revolutionized image classification by automatically learning characteristics from photos. A number of convolutional and pooling layers are followed by one or more fully linked layers to make up the CNN architecture.

Convolutional Neural Networks (CNNs) are artificial neural networks that learn and extract significant features from images automatically. These features are then used to classify the images into specified groups or classes. Automating feature extraction and pattern detection from images is how CNNs classify images. Due to this automation, CNNs may perform at the cutting edge in a variety of computer vision tasks, including object recognition, facial recognition, and handwritten digit recognition, without expending a great deal of manual Labor.

II. RELATED WORK.

Author made use of In order to blur, sharpen, detect edges, and other effects on the input image, the Conv2D layer applies a convolution matrix or mask. With only two layers in this model, fully linked layers come after convolutional layers. A global average pooling layer in the top layer reduces overfitting by bringing the number of model parameters down overall. Dense layer with sigmoid activation makes up the second and last layer. By averaging all of the values in each feature map to produce a single number, the Global Average Pooling 2D layer decreases the dimensionality of the feature maps. The dot product of the input, weights matrix, and bias vector is processed by the Dense layer using an operation that applies the activation function.. This model has a total of 2,68,47,234 parameters, with 2,68,45,058 trainable parameters and 2176 non-trainable parameters. Authors have used a Feature Map (also known as a Convolved Map or an Activation Map), feature detectors (also known as kernel or filter) are used. This makes patterns in the image visible and preserved, and also reduces the image's file size for faster processing. Feature Maps are produced using related photos are multiplied and added element-by-element using filters containing a variety of Feature Detectors. This makes it possible to create several maps of features. Here, author also mentions about Convolution neural networks are given Rectifier Functions to promote nonlinearity (break up linearity). This is a crucial step in using CNNs for image identification. Because of the sharp transitions between pixels, the variety of colors, etc., images are typically nonlinear. The non-linearity of pictures is enhanced by ReLU functions, Consequently, the ML model finds patterns more quickly.

Author uses Convolution , Max pooling , flattening and full connection to create a convolution neural network. Author mentions about To build a Feature Map (also known as Convolved Map or Activation Map), which is used for image identification, we convolve the input image with Feature Detectors (also known as Kernel or Filter). This makes patterns in the image visible and keeps them intact while also compressing them for faster processing.

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III. PROPOSED ALGORITHM

A. *Design Considerations:*

- Taking the input size which is accepted by CNN.
- Specific CNN architecture for efficient analysis.
- Optimal dropout should be 0.2 to 0.5
- Batch size should be 32-128
- 50-100 ephocs for better training.

B. *Description of the Proposed Algorithm:*

Convolutional Neural Networks (CNNs) are designed with the primary objective of automatically and effectively learning hierarchical and discriminative features from data, especially structured data such as pictures and grids. The proposed algorithm is consists of three main steps.

[1] Step 1: Convolution and Activation:-
Mathematically, the convolution operation (denoted by *) between an input image I and a convolutional kernel K at a specific location (i, j) can be represented as:

$$(I * K) (i ,j) = \sum m \sum n \ I(I + m ,j + n) * K (m ,n)$$

I(i+m, j+n) represents the pixel values in the input image, and K(m, n) represents the values in the convolutional kernel. This operation calculates the dot product between the kernel and the local region of the image centered at (i, j).

Rectified Linear unit (ReLU) :- The network is given non-linearity via this process, enabling it to understand intricate, non-linear correlations in the data.

$$ReLU (x) = max (0,x)$$

[2] Step 2: Pooling Operation and weight matrix

The feature maps can be downsampled using mathematical functions for pooling operations like average or maximum pooling. It can be said to be expressed as:

$$MaxPooling(x)=max(x1,x2,\ldots,xn)$$

Here, x1,x2,…,xn are values in a local region, and the operation retains the maximum value.

[3] Step 3: Flattening and weight updation (Training)

Convolutional or pooling layer feature maps must be reshaped from a multidimensional tensor into a 1D vector in order to be flattened. CNNs frequently process data in groups. A matrix with each row denoting a single data sample can be used to represent a batch of data with N samples, such as X.
Through optimization algorithms like gradient descent, CNNs train to determine the ideal weights (kernels) and biases. The weight updates can be stated mathematically as:

$$New\ Weight = Old\ Weight + Learning\ Rate * Gradient$$

The chain rule of calculus is used to compute the gradients.

IV. PSEUDO CODE.

Step 1: Initialize an empty CNN model
Step 2: Add a convolutional layer with 32 filters, each with a 3x3 kernel and ReLU activation
Step 3: Conduct max pooling and flattening

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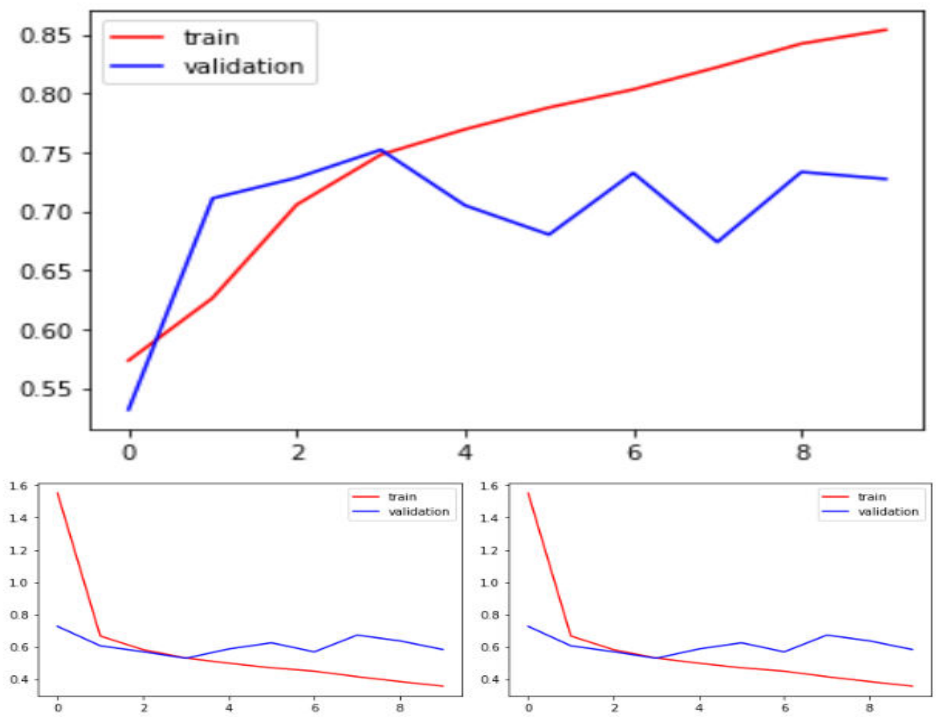
Step 4: Load and preprocess your image dataset
Step 5: Train the compiled CNN model with data, epochs, batch size
Step 6: Evaluate the trained CNN model
Step 7: Calculate the test loss and accuracy
Step 8: Return the test loss and accuracy as results.

V. SIMULATION RESULTS.

Due to the model's initial use of random weights and predictions, both training loss and validation loss are initially significant. The training loss normally reduces as training progresses. This is as a result of the model changing its weights to more closely match the training set of data. The validity loss, however, could not always follow the same pattern. It might start out declining, but eventually, it might start rising or plateau. The graph's focal point is this area. The model is overfitting if the training loss keeps declining while the validation loss picks up speed or plateaus. When a model becomes very specialized in fitting training data and struggles to generalize to new data, it is said to be overfit. The ideal situation is to observe a simultaneous drop in training and validation loss and an increase in both training and validation accuracy. This shows that the model is effectively learning to generalize without overfitting. It is possible to decide when to end training by keeping an eye on this graph. When the validation loss starts to rise or plateaus, you should stop because more training could result in overfitting. During each training iteration (epoch), the model's performance on the training data is measured by the training loss. It often shows the error or difference between the training dataset's actual target values and the outputs that were expected. Minimizing this loss is the aim of training. The validation loss is estimated using a different dataset called the validation dataset and is comparable to the training loss. The validation dataset is used to test how effectively the model generalizes to fresh, untested data rather than for model training. The validation loss is useful in evaluating the model's generalizability to data that it hasn't been specifically trained on. Training Accuracy is a metric that counts the number of examples in the training dataset that were properly categorized. It is a typical classification task statistic that shows how well the model fits the training set of data. Similar to training accuracy, validation accuracy quantifies the proportion of examples in the validation dataset that were correctly categorized. It gives information on how well the model generalizes to fresh data.



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VI. Conclusion and Future Work.

Convolutional Neural Networks (CNNs) have shown to be an effective and adaptable tool for image classification problems, in conclusion. They have transformed the field of computer vision by allowing machines to accurately identify and classify objects in photographs. CNNs have been used in a variety of fields, such as facial recognition, driverless vehicles, and medical imaging, and have significantly impacted both technology and society. Future CNN image categorization improvements should result in improved accuracy and effectiveness. Transfer learning will continue to be crucial for expanding the use of previously trained models. In order to allay worries about model transparency, interpretability will increase. Applications for real-time edge computing will proliferate, and CNNs will merge with different data modalities. The development and application of the technology will be significantly influenced by ethical issues. Customization and personalization will provide bespoke solutions, and AI's contribution to creativity will only grow, fostering more creative and forward-thinking applications. All things considered, CNNs will be crucial in transforming various businesses and our visual interactions with the outside world, emphasizing ethical AI development.

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