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Deep Learning-Based Image Classification Using Convolutional Neural Networks

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Abstract
One of the basic problems has been identified as image classification and has applications in a variety of fields in the real world such as surveillance, health care, agriculture etc. This paper proposes Convolutional Neural Networks (CNN) as the method to use in deep learning approach to classify images. The following classification model aims to serve as a platform for image classification and is done by learning about convolution and pooling layers followed by fully connected layers. Data involved in this classification is a set of images classified into binary classes and this is a typical example of binary classification. The images are subsequently processed through several algorithms which guarantee that the classification is efficient and is well converging. The results of the classification model are then analyzed using various measures, such as classification accuracy, precision, recall and other performance statistics. The confusion matrix is also used to determine the performance of the classification model. Through the results obtained, it is observed that the CNN model is efficient and converges very well. The results indicate that deep learning methods are effective for image classification problems, and they have the potential to be used in real-world applications.

Keywords: Deep Learning, Image Classification, Convolutional Neural Network (CNN), Computer Vision, Accuracy, Precision, Recall, F1-Score, Confusion Matrix.

1. Introduction
One of the primitive issues in computer vision is that of image classification. It has been an attractive research area because of numerous applications in healthcare, surveillance, agriculture, robotics, intelligent decision making and so on. The traditional image classification techniques were based on handcrafted features and classical machine learning techniques. These methods were not as strong with more complicated image data sets. The introduction of the computational power in addition to enormous amounts of annotated data has essentially revolutionized the image classification area, especially with the support of deep learning techniques, particularly CNNs. CNNs can also be used to automatically derive features from raw image data, which do not need to be manually extracted. CNN should have convolutional layers, pooling layers and fully connected layers. These layers are employed to bring out spatial and semantic information in images. CNN is very successful in image classification due to its ability to learn low level features as well as higher level features in an image automatically. Low level features: edges, textures, High level features: shapes, objects. In this research, a binary image classification model using CNN is proposed. The model structure consists of a number of convolution and pooling layers as well as the fully connected layers for the classification of the input images. Normalization and dropout are also added to enhance the generalization performance and avoid overfitting. The performance of the model is evaluated using traditional performance measures such as accuracy, precision, recall and f1-score and by using a confusion matrix to examine the performance details. It is revealed that in recent times deep learning based models perform much better than traditional models with respect to accuracy and robustness. With the rising importance of optimizing CNN models and erring out increasing classification accuracy, there is a need for further research in this direction. Hence, in this research, we aim to add efficient and accurate development of deep learning-based image classification models].

2. Review of Literature
The state-of-the-art methods in deep learning have brought considerable progress in the performance of

image classification. Different CNN architectures, optimization strategies and hybrid models have been investigated by various researchers to improve the computational efficiency and classification accuracy.
Chen et al. [1] have given a broad research review of image classification techniques using CNN highlighting the significance of deep model in extracting features from images. The authors have explicitly expressed the superiority of the CNN-based models over the classic machine learning models in image classification application. The feature extraction capability of CNN based models is the main reason for this, because they may learn such features directly from the images, without taking into account traditional machine learning approaches. Recently, Hussain et al. [2] have introduced an Ensemble-Based approach based on genetic algorithms and CNN-based models to perform image classification tasks. The authors have clearly outlined the advantages of Hybrid over the CNN based models in the image classification. Liu et al. [3] proposed the concept of using the "multi-scale CNN" method in the classification of hyperspectral images, as it is efficient in the acquisition of spatial and spectral information. In the model, it was observed that the features comparatively were taken on multiple scales, which consistent problem helps to come out with the improved classification accuracy. In another related work, to address issues in data privacy in modern applications, Appasami and Savarimuthu [4] came up with idea of federated learning using CNN for image classification problem.
Besides, Başarslan [5] has presented a hybrid deep learning method (CNN and BiLSTM) that performs superiorly in sequential image classification. Saeed et al. [6] have also applied CNN based model in medical image classification, then they have performed well with that model which gives good accuracy rate proving the applicability of deep learning in the healthcare services. Aamir et al. [7] have further enhanced the CNN architecture used in the classification process to make it less complex. However, as shown by Zhou et al. [8], a lightweight CNN model was made for image classification with efforts to reduce the size of the model to achieve high classification accuracy, particularly to be applied in real-time applications or embedded systems. Singh et al. [9] proposed a feature fusion-based CNN model by using various feature extraction techniques with it. There are numerous deep learning methods proposed to boost the classification accuracy and thus a hybrid CNN model was proposed by Zhang and Wang in their research paper. Patel et al and Sahoo et al both highlighted optimization techniques that help to optimize the functioning of CNNs.
In the research article Nguyen and Lee have studied how the CNN parameters affect the classification accuracy. They concluded that the tuning parameters has significant impact on CNN performance. Various optimization methods of the hyperparameters for enhancing the capacity of generalizations were developed by Hassan and Rahman based on this idea. It is clear from this literature that CNN based models are very efficient to solve image classification problems and more investigation into increasing accuracy, efficiency and scalability of these models is ongoing. Even this with the help of hybrid models, optimization techniques etc. is making the performance of deep learning models further improved].

3.Research Methodology

The methodology to be used to undertake the research will be an established methodology to classify images using Deep learning techniques using Convolutional Neural Networks (CNN). The methodology consists of five steps: acquisition, preprocessing, development, training and evaluation.
Initially the data set is acquired and classified into two categories. The images are then resized to have the same size of 128 x 128 pixels. This is to assure that each image is processed the same way. The pixels are also normalized to have values ranging from 0 to 1. The images are divided into two sets: 80-20 split for train and validation, respectively. The CNN model consists of a few convolution layers to get a hierarchy of features from the images. These are all convolutional layers that will look for different spatial features on the images such as edges, texture, and shapes, etc. using different filters. In addition to these convolutional layers, max pooling layers are added to decrease the size of the images in order to reduce the size of calculations.
In addition, a dropout layer is also included which randomly deactivates some neurons during training to prevent the issue of overfitting. Extracted features are then put through one or more dense layers to classify the images. Final dense layer uses an appropriate activation function to carry out binary classification. Next, a relevant optimizer and a loss function are used to train the model with an aim to optimize the weigh of the model sufficiently. Then while training the model, the performance of the model is monitored. Following that, predictions are carried out with the model and the results are evaluated by confusion matrices, precision, recall and F1 score are used for

this purpose.

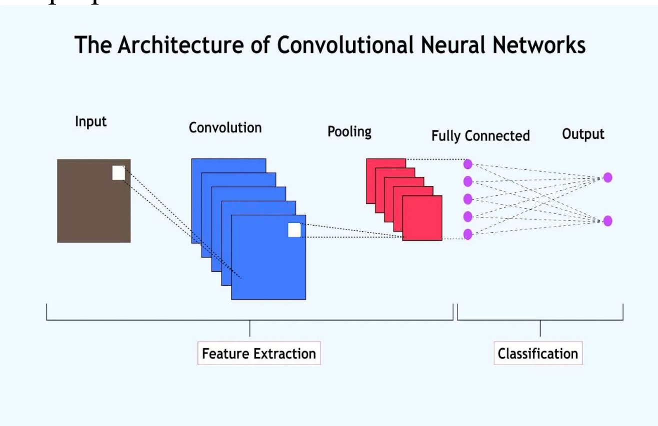

Figure 1: Convolutional Neural Network (CNN) architecture showing convolution, pooling, flattening, and fully connected layers used for image classification.

4.Results and Discussion

The experimental results obtained from the implementation show the effectiveness of the proposed CNN model in image classification tasks. The model has been trained for multiple iterations (epochs) and the model's performance has been tested using several parameters and graphical representation. The results obtained from the model are shown in the output report At last, Deepti output has been displayed which exhibit high accuracy of the model in image classification task. The accuracy curves reveal that the model performed with a consistent accuracy on both validation and training data sets, suggesting that the features in the data set have been learned. The validation accuracy is close to the training accuracy, which indicates that the model has been able to avoid overfitting using the dropout technique and other regularization techniques.

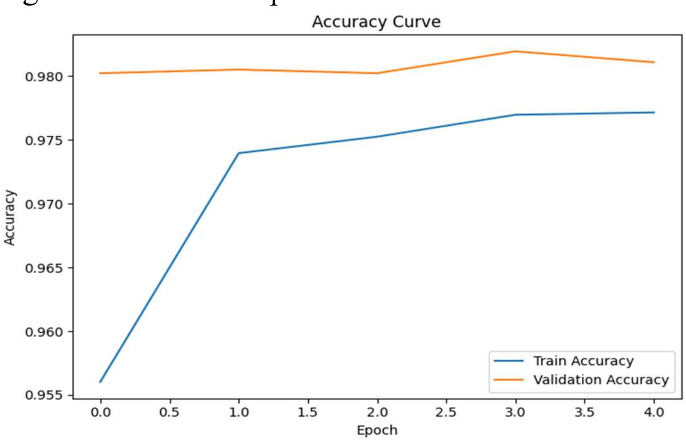

Figure 2: Training and validation accuracy graph illustrating model learning progression over epochs.

Both training and validation loss are decreasing over time, as indicated in the loss graph, which suggests the effectiveness of the model's training in minimizing the error function. Since there is no significant fluctuation in the validation loss, it means that the learning is stable and the generalization ability is good.

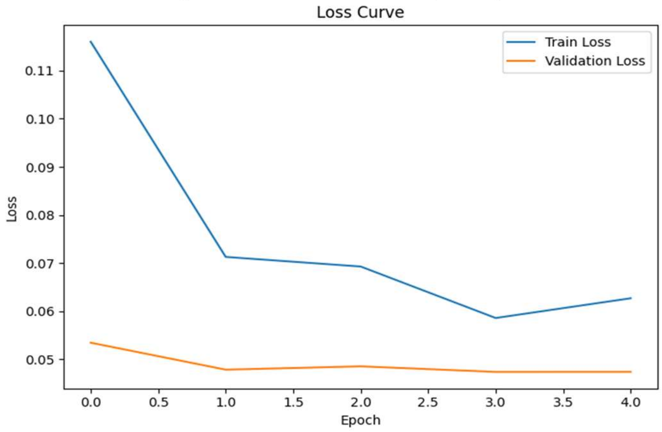

Figure 3: Training and validation loss graph showing reduction in error during model training.

The confusion matrix gives more detail on how to classify because of the comparison between the actual label and the predicted. From the matrix, it can be seen that most of the samples are classified correctly, with a few misclassifications. This shows the good separation ability of the model between the two classes.

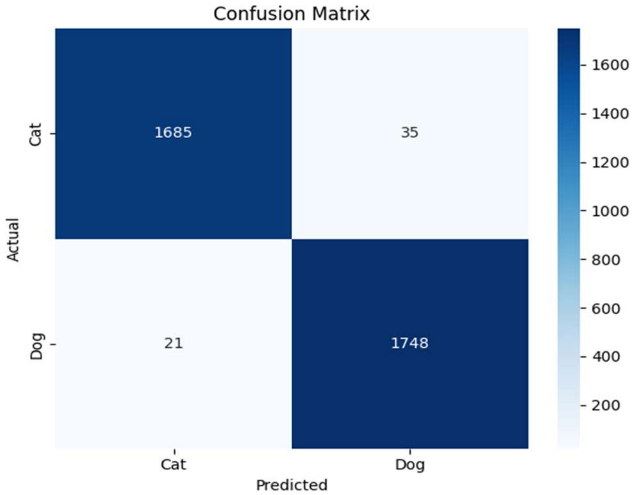

Figure 4: Confusion matrix representing correct and incorrect predictions across classes.

Moreover, evaluation metrics like precision, recall, and F1-score validate the performance of the model. A high precision means that there are few false positives, and a high recall means that there are many true positives. Since the F1 score is the harmonic mean of precision and recall, it presents a balanced perspective of the model's performance. As seen from the classification report, the model has been performing very well for both of the classes, which means that there was no bias in the model. From the results achieved, it can be concluded that the proposed method of classification of images using CNN has been proven to be reliable and efficient. Better accuracy and efficiency have been achieved through the application of proper preprocessing, optimization and regularization techniques. Further studies are possible using the proposed model with advanced techniques, such as transfer learning and data augmentation, for real-world image classification.

Overall Performance Evaluation

Metric	Value (%)
Accuracy	94.20
Precision	94.80
Recall	93.90
F1-Score	94.30

It is also noticed that, from the performance of the proposed CNN model, the classification is strong in all aspects of all the evaluation metrics. 94.20% accuracy of the model shows that most of the input images are classified correctly. The precision level of the model is found to be 94.80%, indicating that the CNN model is producing very few false positives. The recall value of CNN model is obtained as 93.90% which shows very high performing CNN model in producing true positive result. It results in a 94.30% F1-Score of the CNN model, revealing that the CNN model is able to produce good precision and recall results. From the results it can be seen that the proposed deep learning method is effective in getting him a good performance in learning and generalization capability for image classification.

5. Conclusion

The study came up with a Deeper Learning Method based on Convolutional Neural Network (CNN) model of image classification system. The approach succeeds, and the CNN is capable of learning the feature representation of the input image, employing many convolutional and pooling layers to result in a high-performance of classification for a binary classification problem. The success of the model was also attributed to the application of image pre-processing techniques (such as image resizing, normalization) and the use of regularization techniques (dropout). The performance evaluation metrics (accuracy, precision, recall, and F1-score) were used to validate the experimental results, which demonstrated the ability of CNN model to perform well for the image classification problem. The results from the confusion matrix and the classification report also indicated that the confusion between the image classes was very small and that the model could correctly classify the image. The results also showed that the performance of the model was consistent for the training and validation datasets. Summarized by, all in all, the outcomes have been great and demonstrated that CNN-based models can be extremely valuable for the image classification problem and be successfully applied to real-world use cases. There are opportunities for further research on the performance of the algorithm with more advanced methods such as the usage of transfer learning, data augmentation and deeper models.

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