**DEEP LEARNING USING BIG DATA: A CONVOLUTIONAL NEURAL NETWORK APPROACH FOR IMAGE CLASSIFICATION**

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**Abstract**

The paper is established to show the effectiveness of Convolutional Neural Networks (CNNs) in image classification tasks such as with big data. The critical analysis states that the CNN model has coherent capability for complex patterns from raw pixel data that makes the model volumetric for object detection and facial recognition tasks. The study shows some of the issues like overfitting and the requirement of large datasets with annotated data that can be solved using transfer learning and data augmentation. CNNs are also beneficial in medical image analysis but, at the same time, are computationally intensive. In conclusion, this thesis highlights the importance of big data in enhancing the performance of CNNs and presents potential ways of addressing their weaknesses.

**1. Introduction**

**1.1 Overview of the Topic**

The research paper is established on deep learning techniques using big data such as describing the ***“convolutional neural network”*** approach for classifying the images dataset. In order to support the topic the researcher also established a practical demonstration with the help of an ***“Intel image classification dataset”*** as well as used ***“deep learning techniques”*** such as developing a neural network CNN to predict the Intel images. Also, for big data processing, the researcher will use ***“TensorFlow libraries and Jupyter Notebook***” to execute the codes (This demonstration will be shown via screen casting). Advanced data analysis as well as big data processing will help to boost the efficiency of the research and accelerate the project outcomes. The background research states that in the current era, deep learning has become a novel subfield of machine learning and has provided large enhancements to many disciplines like image analysis, natural language comprehension and predictive analytics. The effectiveness of deep learning techniques has been enhanced with the help of big data that delivers huge amounts of labelled and unlabelled data which is very beneficial for coherently training critical models [1]. Deep learning and big data are innovation enshrines for current technical domains; making it possible for machines to accomplish tasks that were previously thought only fit for novel input. CNN is one of the most recognisable sub-sets of deep learning and become extremely popular for image classification because of its ability to learn features directly from the raw pixel data [2]. Convolutional Neural Networks (CNNs) are deep learning models, intended for working with data in a grid, for example, images. CNNs work by fashioning layers, in which it can easily identify such features as edges and texture making it suitable for image classification and recognition. Also, the big data role is very beneficial as the amount of samples increases, CNNs are capable of learning different patterns, which as a result enhances the models' accuracy and the model's ability to make accurate predictions.

**1.2 Objective Statement**

The main agenda of this paper is to understand how deep learning especially CNN can use big data for image classification. This research strives to establish the benefits of big data in optimizing the performance of CNNs in the aspects of accuracy, speed and efficiency.

**1.3 Research Question**

1. What kind of enhancements does the convolutional neural network (CNN) bring to image classification when dealing with large datasets?

**2. Presentation of State of the Art**

In this phase, the researcher will represent the state of the art to show the efficiency of deep learning models such as CNN in image classification to underscore the image pattern from the raw data. It is seen from the journals and background study that CNN have volumetric capability for computer vision tasks such as image classification, object detection and facial recognition. In concluding this statement, the use of CNN with big data has brought a great deal of contribution to the advancement of the field by enabling researchers to design and create better models that can deal with large complex visual data.

**2.1 Research Methodologies in Image Classification**

It is understood from the various kinds of articles that the author uses supervised learning such as CNN-based image classification. The labelled datasets have been mainly used to train the models. The numerous types of datasets such as “***ImageNet, CIFAR-10 and Intel Image Classification Dataset”*** are mostly used for research to evaluate CNNs' performance on big and mixed image collections. These datasets consist of millions of images of which each image belongs to a certain class making the CNN models to be trained with diverse samples. CNNs learn to classify images by passing them through multiple layers: The convolution, pooling and fully connected layer where the features such as edges, shapes and textures are extracted and learned for classification [3]. In modern research, the enhancement of the CNN performance is linked with the integration of big data. The application of large sets of data helps to make generalizations that are more accurate in various types of images, and therefore enables accurate classification of such images.

**2.2 Key Studies Reviewed**

In the below section, the researcher will outline the research papers such as the reviewed papers which will be critically analysis in the literature review section.

***(Ashraf et al., 2020)***

In this paper, the author uses a coherent image classification method such as using a pre-trained ***“deep convolutional neural network”*** as well as fine-tuning the last three layers. The main agenda of this research is to coherently classify the medical images of various body organs as well as boost the diagnosis accuracy and give support to radiologists [6]. Also, this paper cogently underscores the challenges of automatic medical image categorization.

***(Vinay et al., 2023)***

This paper presents CNNs and cybernetic methods used in image classification based on the CIFAR-10 dataset. By evaluating the data, researchers discovered that CNNs are more accurate, precise, recall, and F1-score than cybernetic methods although they have longer training time and resource demands to complete it, so further study is needed [7].

***(Soudy et al., 2022)***

In this study, the author uses a coherent machine learning model such as RepConv for scene classification. The literature shows that the model shows coherent performance on the Intel scenes dataset [11]. The study notes that the RepConv model surpassed four benchmark models by achieving high accuracy, such as 93.55% and 75.54% for training and validation.

**3. Literature review**

It can be seen from the aforementioned paper reviewed section that the researcher outlines some key papers which will be critically analysis in this section to underscore the effectiveness of the existing methodology as well as evaluate the gaps. The coherent analysis of the papers will help to boost the knowledge of the researcher as well as understanding their technical implementation can be helpful in the technical demonstration.

**3.1 Deep convolution neural network for big data medical image classification**

In this literature, the author REHAN ASHRAF has been describing the efficiency of deep CNN for classifying medical images. By critically analysis, the literature it is understood that deep learning techniques make coherent advancements in medical image classification such as using transfer learning and convolutional neural networks [4]. The literature analysis also states that transfer learning offers an effective way of performing fine-tuning of existing pre-trained networks, which is beneficial since fine-tuning deep networks entails a high computational expense. Different works show that this approach can improve classification accuracy as observed in the multi-class dataset with knee and cytopathology images. CNNs have been observed to be superior to traditional methods of image classification such as RBMs and SAEs and are now the most commonly used model for medical image classification. It remains that the literature highlights their capacity to model local and global contextual features, which is crucial for tasks such as lesion detection in imaging modalities including MRI and CT. A number of works exploring the improved contextual comprehension of videos have been attempted where different methods like integration of CNNs with Recurrent Neural Networks (RNNs) have been integrated in order to build multi-stream models [6]. However, there are some issues that still persist most of which are on how to manage the differences in image size and quality. There are various proposals about multi-level CNN architectures and even combinations of supervised and unsupervised learning, but the key to good performance is to have good feature extraction [5]. Furthermore, the majority of research papers show high accuracy, but there are problems such as overfitting and the mandatory use of big annotated datasets. In conclusion, despite significant advances in medical image classification with deep learning, it appears that more variety of data and benchmark metrics is still necessary. Future work should be directed to overcome these issues and further investigate the use of new technologies to improve the diagnostic performance in medical imaging.

**3.2 A Comparative Study of Convolutional Neural Networks and Cybernetic Approaches on CIFAR-10 Dataset**

In this study, the author S. B. Vinay coherently describes a comparative analysis of applications and performances of Convolutional Neural Networks (CNNs) and cybernetic approaches in machine learning. The CIFAR-10 dataset mainly operates in this scenario for developing the image classification task. The authors deliver a coherent explanation of the structure and training of CNNs, as well as the process of automatically learning features as a major factor that enhances performance indicators such as accuracy, precision, recall, and F1-score. The results show that CNNs have a superior performance to cybernetic approaches, with an accuracy of 85% against 82% respectively, which shows that CNNs are more effective for dealing with large datasets [7]. Also, cybernetic approaches that are based on control systems theory deliver a vast range of techniques such as Adaptive Resonance Theory, Fuzzy Logic, Reinforcement Learning and Genetic Algorithms. Despite these advantages, these methods have drawbacks such as most of them are sensitive to noise and require a manual extraction of features, which can significantly affect their performance. The literature presents the computational complexity of these approaches, noting that, although CNNs require much computation for training and data, cybernetic methods may be more appropriate for applications with low computational power [8]. Also, the study plays the role of reference comparative research to highlight the advantages and limitations of each strategy. The literature has accomplished a coherent assessment of dissecting the various performance evaluation metrics, giving a complete picture of the performance of models. However, it might be useful to look at the causes of performance differences more profoundly, especially in terms of why cybernetic approaches may be effective in changing environments. Finally, some potential research directions are indicated in order to open the way to the development of new methodologies that can fill the gaps in both CNNs and cybernetic approaches.

**3.3 RepConv: A novel architecture for image scene classification on Intel scenes dataset**

In this literature, the author Mohamed Soudy and their teammates develop a comparative analysis of deep learning architectures to make image classification with the use of an intel image scene dataset. Here the authors use coherent ResNet variants and the RepConv model which boosts the design of the CNN model [10]. The critical analysis states using residual blocks ResNet achieve deeper networks which has helped to train the model in a coherent manner. Using this volumetric approach the author makes the model volumetric for deep learning tasks. But still, there are some problems like network degradation and computational complexity that occur in the ResNet models like ResNet 101 which is capable of handling deeper networks. The four benchmark models: ResNet50, ResNet101, and SE ResNeXt101 achieved high performance but with high parameters and training time. The incorporation of SE blocks in ResNeXt101 shows that researchers have made further improvements to performance while incurring small additional computational costs [9]. However, the problem of compromise between depth and efficiency persists, and this is particularly important for the practical use of models in terms of faster inference and lower resource utilization. These limitations are rectified by the introduction of RepConv which offers an external depth and a reduced parameter count but comparable accuracy. With such a manner, the residual structure simplifies to five layers, which can provide almost the same effect [11]. These findings suggest that RepConv could be practically useful for binary and multi-class classification tasks where few epochs of training are possible due to the limitations of computational resources. However, the literature does not contain a comprehensive discussion of the possible drawbacks associated with the use of the algorithm such as overfitting, for instance, because the model converges faster on the training set than on the validation set. Furthermore, although the model is promising, its extension to various other datasets other than scene classification tasks has not been investigated. The model’s capacity and applicability in different datasets require further study for broader implementation.

**4. Critical evaluation**

In recent years, deep learning techniques such as CNNs for image classification have drawn much attention from researchers and numerous aspects have been discussed, including the structure of the model, efficiency of computation and size of the available dataset. All the studies bring important results but they also have implications and limitations that should receive a detailed analysis.

**4.1 Key Findings and Implications**

**4.1.1 CNNs in Medical Image Classification (Ashraf et al., 2020)**

Ashraf et al., discuss CNNs in consideration of medical image classification and classify transfer learning and fine-tuning as two methods that could improve the performance of the model. The first practical conclusion of this research is that CNNs, especially if they are trained on large datasets, can be accurate even in the most focused and specific areas like medical imaging [6]. This is a very important aspect since collecting a large amount of medical images is a challenge due to privacy issues or the kind of medical images that may be required by the model. The fact that CNNs are capable of outperforming previous image classification techniques such as the ***“Restricted Boltzmann Machines (RBMs) and Stacked Autoencoders (SAEs)”*** add to the strength of CNNs in medical applications. Nonetheless, as the author also notes, there are certain drawbacks to using CNNs for detecting medical anomalies The proposed method achieves high accuracy with regard to identifying medical anomalies [12]. There is still a problem of overfitting, which is a common problem of CNNs, especially those trained on large datasets, the model can perform well on new unseen data. The other weakness is the reliance on annotated datasets; labelled medical images are scarce, and manual labelling is expensive and time-consuming. In addition, while observing CNNs for local and global feature extraction, the study points out that, for medical imaging modalities such as MRI and CT scans, there are disparities in picture size and quality.

**Implication**

The research suggests that although great advantages are achieved with CNNs in the field of medical image classification, there is a need for more advanced approaches to deal with different kinds of sources and avoid overfitting and dependence on large annotated datasets. As a result, future works need to explore the use of methods such as data augmentation or synthetic data generation in order to increase the size of the datasets and make the models more coherent.

**4.1.2 Comparative Study of CNNs and Cybernetic Methods (Vinay et al., 2023)**

In this paper, Vinay et al., (2023), develop a coherent comparative analysis with CNNs and cybernetic methods to develop the image classification using the CIFAR-10 dataset. Critically understanding the findings it can be said that CNN coherently outperforms the cybernetic approaches in terms of accuracy, precision, recall and F1-score. This approach encapsulates that the CNN model has the ability to handle large datasets. The cybernetic methods may be general and powerful, but they are weak in environments that involve automatic feature extraction since they depend on the manual definition of features [7]. This discovery further reinforces the fact that CNNs are well suited to quickly process images when it comes to image classification where a lot of data processing is needed. However, the study also exposes severe constraints to CNNs, firstly their high computational load and secondly long training time. However, cybernetic methods, which are less accurate, are more effective when the amount of computations that can be performed is restricted. For example, in the cybernetic approaches Fuzzy Logic and Genetic Algorithms are capable of handling noise and environment changeability and so on they are valuable in applications where computational resources are limited.

**Implications**

The results show that CNNs are better when used in high-resource conditions equipped with the latest computing technologies, while cybernetic approaches may be more effective in low-resource environments [13]. This remains a constraint for CNNs in practical use, especially in areas or fields with restricted computational power. One possible research direction could include including attempts to use the feature learning abilities of CNNs with the flexibility of the cybernetic approaches that would enable efficient use of resources in image classification.

**4.1.3 RepConv for Scene Classification (Soudy et al., 2022)**

In this literature, the author uses RepConv architecture to eliminate the flaws in CNN models such as ResNet for scene classification. The key result is that the proposed RepConv method provides comparable performance to the ResNet models, with less computational load and less complex architecture [11]. Thus, RepConv is a more efficient solution for tasks with a limited number of resources due to a simple model structure, which has a coherent architecture with fewer parameters. For instance, it takes Intel Core i9 7900X with 13GB NVIDIA GPU and 200GB storage and 17 hours to train ResNet-101, whereas, RepConv has few parameters and only 5 layers and it performs well on numerous standards. The main drawback of RepConv is the relatively small range of problems that can be solved using it. This work is limited to scene classification only and thus does not raise further inquiries concerning the model’s applicability to other domains or other datasets.

**Implications**

As such, RepConv has a wide impact on industries or research areas that need efficient models but cannot afford high computational budgets such as mobile or embedded applications. Nonetheless, given that it is only used for scene classification, it is evident that more work has to be done to test its performance in other image classification problems [14]. The reason lies in the fact that the model converges faster with respect to the training data than with respect to the validation data, which may lead to overfitting; therefore there is a need to enhance the methods of regularization.

**4.2 Limitations and Contradictory Viewpoints**

The above studies also show certain limitations of CNNs, which we discuss below. One common problem in these papers is overfitting where a model provides high accuracy in the training data set but has low accuracy in other data sets. This is well illustrated in medical image classification (Ashraf et al. 2020) where, despite the fact that CNNs are accurate, they fail to generalize well because of the scarcity of labelled medical images. Of these, one disadvantage is that the training of CNNs is computationally intensive. Two of the works that we reviewed, Vinay et al. and Soudy et al., argue that CNNs consume a lot of resources in order to be trained on large datasets, meaning that their use might not be feasible in low-resource scenarios [15]. This is in contrast to the other more efficient in terms of computation cybernetic methods that though less accurate are more suitable for constrained environments. These two positions emphasize the trade-off between precision and speed. Another issue is a dependence on large annotated datasets. In both medical image classification and scene classification, CNNs rely on large datasets to be effective in their execution. However, the process of manually creating labels for datasets is time-consuming and quite costly especially when working with focused domains such as in healthcare. More research work should be done in areas like self-supervised learning where the reliance on labelled data can be greatly reduced without compromising the accuracy.

**4.3 Research Gaps**

In the paper, some of the gaps found in the literature are as follows: There is a significant research void as to how one can integrate CNNs with other machine learning methodologies like cybernetic paradigms. The combination of these approaches could lead to higher accuracy at lower computational cost, thus, the hybrid models could be promising. Another research gap is that the generalization of new architectures such as RepConv is not well explored [6]. Thus, although the author demonstrated RepConv for the case of scene classification, its performance on other datasets and domains has yet to be explored. To this end, more elaborate work should be conducted to determine whether the gains in efficiency identified with RepConv can be generalised to other image classification problems. Finally, overfitting is a problem in all studies, and few attempts have been made to address it [11]. Other techniques like dropout or data augmentation could help solve this problem but more work has to be done to understand which techniques work better on which datasets and domains.

**5. Conclusion**

In concluding this research paper we can state that ***“Convolutional Neural Networks”*** is coherent for image classification tasks as well especially when used with big data. CNNs outcompete other traditional methods as they can learn features from raw pixel data and are hence recommended for the identification and detection of objects, faces and scenes. Large datasets are helpful in CNNs since with them, a model learns more patterns and becomes better at generalizing over new data. There are some challenges sometimes encountered when using CNNs, these include overfitting and the fact that they require large amounts of annotated data, which can periodically be rather difficult to obtain. Transfer learning and data augmentation have been discussed as possible solutions to these problems based on the use of transfer learning and the creation of additional data samples for categorical datasets. Moreover, CNNs generate significant performance in specific application domains, including medical image classification, thus holding promise for broad applications in the diagnosis area. Although it does have high computational requirements the variation in image quality may affect the result. This research proves the potential of big data as a tool for the enhancement of CNN performance, and it leaves further studies regarding the specific issue of overfitting, the general enlargement of the range of datasets for CNN training and the improvement of computational efficiency for future investigations.

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