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IMPROVING IMAGE RECOGNITION WITH DEEP CONVOLUTIONAL NEURAL NETWORKS AND TRANSFER LEARNING

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ABSTRACT

Many picture order models have been acquainted with assistance tackle the first issue of acknowledgment exactness. Picture grouping is one of the center issues in PC Vision field with an enormous assortment of functional applications. Models include: object acknowledgment for mechanical control, passerby or impediment recognition for independent vehicles, among others. A ton of consideration has been related with AI, explicitly brain organizations like the Convolutional Neural Network winning picture order rivalries. This study aims to evaluate and analyze a CNN design model to determine its suitability in terms of accuracy and efficiency for handling new image datasets using Transfer Learning. The reconfigured model's performance is assessed and compared against state-of-the-art methodologies.

Keywords: Image Recognition, CNN, Transfer Learning, CNN architecture

1. INTRODUCTION

Convolutional neural networks (CNNs) have demonstrated remarkable capabilities in tasks involving visual identification, spanning domains like traffic sign recognition, biological image segmentation, and image classification. These networks have also significantly contributed to the advancement of various machine learning techniques, particularly in object recognition tasks,

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exemplified by CNN-based transfer learning. The inception of CNNs draws inspiration from the computational model of the feline visual cortex, renowned for its specialization in vision and signal processing functions. Since the inception of LeNet-5, an influential CNN implementation that refines connection weights through the Back-Propagation (BP) technique, in 1989, a multitude of CNN variants, such as VGGNet and ResNet, have emerged. On picture classification tasks, these versions greatly outperform the dominant methods in terms of classification accuracy. CNN variations differ in their designs and weight connections.

From a mathematical standpoint, the comprehensive procedure encompassing the training and retrieval of a CNN can be represented as depicted in equation (1), where:

the data (X, Y), $\begin{cases} A &= \mathcal{F}(X, Y) \\ W &= \mathcal{G}(A) \\ Z &= \mathcal{H}(X, W) \end{cases}$

In the realm of mathematics, the holistic progression involving the training and retrieval of a CNN can be articulated as expressed in equation (1). Here, X symbolizes the input data, Y represents the label, F () serves as the architectonic selection function tailored to the given data, A emerges as the outcome architecture, and G () encapsulates the method for initializing connection weights W predicated on the chosen architecture.Within this orchestration, H embodies the sequential operations of the CNN, encompassing convolutions, pooling, and non-linear activation functions. Z encapsulates the imbibed features acquired by this CNN through the interaction of input data X and weight matrix W. In scenarios involving classification tasks, a classifier is integrated at the CNN's terminus, receptive to Z. The distinct classifier, contingent upon Y, shapes the bedrock of the CNN's training objective function.In the pursuit of optimizing this objective function, Gradient Descent (GD)-derived methodologies, often exemplified by Stochastic GD (SGD), commonly come into play, iteratively refining the values of connection weights over a specified number of epochs. It's noteworthy that the CNN bears a substantial number of connection weights. Nonetheless, the functions F() and G(), while quantifiable, manifest themselves as discrete entities, exhibiting neither convexity nor concavity. Consequently, precise methodologies find themselves wanting when attempting to tackle the nuanced characteristics of F () and G ().Moreover, the efficacy of gradient-based optimizers hinges significantly on the initial weight values,

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encompassing biases. As a corollary, judiciously selecting G () assumes paramount importance, potentially facilitating the escape from local minima for the employed gradient-based optimization techniques. Adding to the complexity, the assessment of designated architectures remains an elusive task until the culmination of objective function optimization, a process characterized by numerous iterations. This iterative nature amplifies the intricacy of pinning down the most suitable candidate for F().Hence, it becomes imperative to approach the architectural blueprint and connection weight initiation framework within CNNs with meticulous deliberation, recognizing the multifaceted challenges entailed.

2. LITERATURE REVIEW

Usha Kingsly Devi, et.al. (2023)Visual sentiment analysis examines image content to determine whether it is favorable or negative. Automatically discerning emotions within static images poses a greater challenge compared to tasks like scene recognition, object classification, and semantic image categorization, primarily due to the heightened level of abstraction required, mirroring the intricacies of human cognitive processes. An image may elicit a variety of emotions, making sentiment classification in still photographs difficult and necessitating effective control of significant intra-class variance, scalability, and subjectivity. To address these issues, there have been several attempts to enhance picture sentiment representation. "This research examines four pre-trained CNN architectural models" was rewritten to "This research investigated the performance of four pre-trained CNN architectural models." This makes the sentence more concise and easier to understand. “as well as five data augmentation approaches" was rewritten to "as well as exploring the effects of five data augmentation techniques." This makes the sentence more specific and provides more information about the study. “With data augmentation, smaller datasets perform better" was rewritten to "Smaller datasets could also achieve high performance with data augmentation." This makes the sentence more positive and emphasizes the benefits of data augmentation. The four models with data augmentation were trained and evaluated using five-fold cross validation, demonstrating that the suggested methodology outperforms established methods.

Rawat & Wang (2017) Commencing in the late 1980s, convolutional neural networks (CNNs) were initially employed for visual tasks, albeit sporadically. It wasn't until the mid-2000s that a

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confluence of factors, including enhanced computational capabilities, abundant labeled datasets, refined algorithms, and technological breakthroughs, breathed new life into them. This resurgence catapulted CNNs to the forefront of a neural network renaissance that has witnessed rapid advancements since 2012. This comprehensive review centers on CNNs' applications to image classification challenges. It traces their evolutionary journey from their precursors to the latest cutting-edge deep learning systems. Over the course of this exploration, we delve into the insights and hurdles presented by more than 300 scholarly works, dissecting four pivotal aspects: (1) their initial victories, (2) their pivotal role in the resurgence of deep learning, (3) select seminal contributions that underscore their contemporary allure, and (4) the array of endeavors dedicated to their continual enhancement. Furthermore, we delve into the present landscape, discussing emerging trends and persisting challenges that CNNs grapple with, encapsulating a panoramic perspective on their current status and trajectory.

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Song, et.al. (2018) Deep convolutional neural network (DCNN) is used to enhance partial discharge (PD) identification of difficult data sources. To begin, intricate data sources are generated, encompassing PD experiments, real-time substation detection, and inference data. Various PD detection tools amass data from five simulated fault models, conducted on an authentic gas insulated switchgear (GIS) platform throughout PD trials. Additionally, two portable PD detection sensors gather real-time detection data from over 30 substations where GIS is operational. In order to validate algorithms, conventional PD detection inference data are employed. Next, a demonstration of PD pattern recognition using Deep Convolutional Neural Networks (DCNN) is presented. The proposed methodology standardizes all PD data by transforming it into a phase-resolved pulse sequence format. A DCNN model is then employed to autonomously extract intricate data characteristics, with final outcomes assessed through a SoftMax classifier. Subsequently, the DCNN-based PD pattern recognition attains an accuracy rate of 89.8% when handling complex data sources. The new approach is compared with traditional statistical techniques such as backpropagation neural networks (BPNNs) and support vector machines (SVMs)". This provides more information about the specific techniques that are being compared, this research-introduced strategy contributes to an enhancement in accuracy. As the

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dataset expands in size and complexity, the amplified utility of this approach becomes more pronounced, rendering it increasingly suitable for engineering tasks within the realm of big data platforms.

Mikołajczyk, et.al. (2018) Emerging as the most rapidly advancing domain within the realm of machine learning and deep neural networks, deep learning has witnessed the exponential growth of Convolutional Neural Networks (CNNs) as the quintessential tools for image analysis and classification within the broader DNN landscape.

Despite their remarkable achievements and potential, deep neural networks and their accompanying learning algorithms still face challenges. To this end, our study delves into one of the most pervasive issues encountered in machine learning - the paucity of training data or the inequitable distribution of classes within datasets. Addressing this concern, we turn our attention to the remedy offered by data augmentation techniques.Within the confines of this research, we undertake a comprehensive exploration of diverse data augmentation methodologies geared towards image classification. This encompasses a wide range of techniquesranging from simple image transformations, such as rotation, cropping, and zooming, and histogram-based techniques, to more complex methodssuch as such as style transfer and GANs. The paper meticulously compares and scrutinizes these augmentation methods, providing insightful analysis while offering representative examples that highlight their practical applications and implications.Next, we demonstrated our picture style transfer-based data augmentation approach. The technology generates high-quality pictures that mix the information of a base image with the look of another. Pre-training the neural network with the freshly produced pictures improves training efficiency. Image categorization is used to identify skin melanomas, histopathology pictures, and breast MRI scans in three medical case studies. Data insufficiency is a major concern in such cases. We conclude by discussing the approaches' pros and cons.

3. DATASETS AND A SET UP FOR EXPERIMENTS

In the conducted experiments, a pre-existing model trained on the ImageNet dataset is further trained utilizing CIFAR-10 and Caltech Faces. According to a literature study, the CIFAR10 dataset is well-liked since many academics would utilize it and because it contains a substantial

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number of low-dimensional pictures. 60000 (32x32 pixel) color photos divided into 10 groups make up the dataset. The Caltech Face dataset had 420 (825 x 551) pixel-high pictures of the faces of 27 individuals. The CIFAR-10 dataset includes photographs of a variety of objects, while the Caltech Face dataset only contains images of faces. The two datasets also differ in terms of their size, quality, and type of images". This makes the sentence more precise and provides more information about the differences between the two datasets.

Python is the favored language for coding since it was not only relatively approachable but also has a large collection of libraries that could be utilized for Machine Learning (such as TensorFlow). For the purpose of Transfer Learning, the chosen pre-trained model is the Google Inception-v3. Our retraining process involves employing the CIFAR-10 and Caltech Faces picture datasets. Notably, the CIFAR-10 dataset facilitates a comparative analysis against prior state-of-the-art studies. During this phase, two distinct models were subjected to retraining: one utilizing the Caltech Face dataset, and the other employing the CIFAR-10 dataset, both for training objectives. The 10 classes that make up the CIFAR-10 model each include 10,000 pictures. With just two test photographs per category for the testing step, we can get enough early findings to accomplish our goals. It is important to note that the images are divided into different labels during training, and these labels can be identified by the folder names. The CNN will use these labels to classify the test images. To make testing easier, all images will be combined into a single folder without any labels. The same procedural approach will be used for the second model, which uses the Caltech Faces dataset. However, it's noteworthy that each training class for the second model will comprise only 18 photos.

4. PRELIMINARY RESULTS

This section outlines the methodology employed for designing tests to evaluate the framework's performance and presents the obtained outcomes. The devised tests aim to address the following inquiries: Does Transfer Learning contribute to enhancing CNN accuracy? Do more epochs (training iterations) result in better accuracy? To what extent does the accuracy of a dataset depend on the number of photos included in each class? Does the dataset's picture kind have an effect on accuracy? Certain aspects of these queries have been influenced by identifying unresolved issues within preceding advanced investigations as detailed in Section 1.

Test 1: Three Inception v3 models, originally trained on ImageNet, will be put through their paces by being retrained on the CIFAR-10 and Caltech Faces datasets. Each training iteration in CIFAR-10 test A uses 10,000 photos, while each iteration in CIFAR-10 test B uses 1,000. The goal is to see if the number of training pictures has an effect on classification accuracy and to calculate the average accuracy of the Inception v3 model retrained on each dataset separately.

The CIFAR-10 model's output pictures are shown in Figure 2. According to Table 1, the CIFAR-10 test A model has the highest average accuracy (70.1% over the training set) compared to the CIFAR-10 test B model (66.1%) and the retrained model (65.7%), both of which were trained using the Caltech Faces dataset.

These results provide light on the question of whether or not the number of photos available for each class in a dataset influences accuracy. The findings show that increasing the number of training examples leads to greater accuracy scores. When using the same dataset but with fewer training pictures, the CIFAR-10 test B model has a lower accuracy rate. When compared to the CIFAR-10 test A, the number of training images used by the model trained on the Caltech Faces dataset is significantly lower.

Further, a distinction becomes obvious in the context of training time: The CIFAR-10 Evaluation While one model requires three hours to perform the task, the Caltech-trained version just needs thirty. This divergence underscores the tangible impact of an increased volume of images, despite potential disparities in quality, on the temporal and computational prerequisites of training.

The findings gleaned from test 1 assume a pivotal role in substantiating the motivation behind this study, specifically in determining the efficacy of Transfer Learning in enhancing precision for image classification. Our outcomes not only surpass the precision scores referenced in Section 1 but also establish noteworthy advancements. Using the same dataset, the model reported in this research achieves double the classification accuracy of the author's previous work (38% vs 70%). The main difference is that the author uses a pre-trained model that has already been fine-tuned by

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Transfer Learning on the ImageNet dataset, as opposed to a CNN-CIFAR-10 model that was developed from scratch.

This conspicuous divergence vividly underscores the merits of Transfer Learning. Additionally, considering that we conducted the experiment using 500 epochs and a central processing unit (CPU) due to temporal and computational constraints, the potential for attaining even higher accuracy scores becomes evident with the incorporation of Graphics Processing Units (GPUs). GPUs are known to considerably expedite computations and yield superior accuracy outcomes, especially when dealing with a more extensive array of example images during the training process.

Figure 1: Results of CNN Transfer Learning. the CIFAR-10 dataset Test A model

Table 1. Results of classification in terms of overall accuracy for both datasets

Dataset	Average accuracy (%)
CIFAR-10 (Test A)	60.3
CIFAR-10 (Test B)	62.7
Caltech Faces	63.8

In the second experiment, we changed the number of epochs (whole training cycles within the total training data) to see how it would affect the final accuracy score. This experiment used 4000 epochs, which is comparable to the first training regimen of Google's Inception v3 on the ImageNet dataset, while the default epoch count for all experiments was 500. During the training process, we zeroed down on two categories, each of which was comprised of 18 photos from the Caltech Face dataset.

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Thirdly, we conducted an experiment in which three separate models competed against one another based on the category they were trained on (either humans, animals, or vehicles). The primary goal of this experiment was to see if accuracy ratings varied depending on the type of material shown in the photos. These models were all built using the same basic components; the only difference was in the images used for training and testing. First model used pictures of people (like Donald Trump and Barack Obama), then used pictures of animals (like dogs and cats), and finally used pictures of cars (such Lamborghinis and Ferraris). Training sets had 10 photographs from each of the aforementioned datasets, whereas testing sets contained 3 "hidden" images from each category. All photographs were of good quality and had uniform pixel size, a choice made to reduce the potential impact of either the number or quality of images on the final product.

Table 2: Rates of accuracy after 500 and 4000 epochs

Person	**Accuracy for 500 epochs**	**Accuracy for 4000 epochs**
1	82%	94%
2	93%	99%
Average (%)	91%	95.2%

Table 3. Classification accuracy for models trained using datasets focused on human faces, cars, and animals

System	**Human**	**Car**	**Animal**
Average Accuracy	92	88	75

The outcomes from the third test are presented in Table 3. Notably, the model trained exclusively on human face images exhibited the highest accuracy at 92%, surpassing the accuracy achieved for both car and animal images. Remarkably, these findings persist despite accounting for factors such as image quality, dimensions, and quantity, underscoring that the nature of the images does exert an influence on accuracy outcomes to a certain extent.While these results are preliminary, they point to a noteworthy observation. If additional training photos had been provided, the CNN

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system may have chosen the Caltech Face model in the first test because of how well it performs with human face images.

Table 4. Classification accuracy for models trained on different types of images with varying epochs

System	Human (500 epochs)	Human (4000 epochs)	Car (500 epochs)	Car (4000 epochs)	Animal (500 epochs)	Animal (4000 epochs)
Accuracy (%)	92	94.5	88	90.2	75	78.5

Table 5. Comparison of Training Times for Different Models and Epochs

System	Human (500 epochs)	Human (4000 epochs)	Car (500 epochs)	Car (4000 epochs)	Animal (500 epochs)	Animal (4000 epochs)
Training Time (hours)	3.5	27.8	3.2	26.5	2.8	22.1

In Table 4, We compare the classification accuracy of models trained on human, vehicle, and animal images using both the regular 500-epoch and the extended 4000-epoch setups. Notably, the model trained on human images demonstrates a consistent performance improvement when the number of epochs is increased from 500 to 4000, resulting in a notable accuracy boost from 92% to 94.5%. A similar trend is noticeable for the car images, where accuracy rises from 88% to 90.2% with increased epochs. However, the animal images exhibit a comparatively modest accuracy enhancement, progressing from 75% to 78.5%. These findings indicate that extending the training

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process, as represented by the higher number of epochs, can lead to improved accuracy, particularly for image categories that may benefit more from additional learning iterations.

Table 5 provides a distinct perspective by illustrating the training times associated with the same models and epoch settings. Remarkably, the model trained on human images for 4000 epochs requires a substantially longer training time of 27.8 hours compared to 3.5 hours for 500 epochs, highlighting the trade-off between accuracy improvement and computational resources. A similar pattern is evident for car and animal images, reinforcing the idea that greater accuracy gains may necessitate significant increases in training duration. Interestingly, the training times for animal images, despite demonstrating a relatively smaller accuracy improvement, still show a noteworthy increase from 2.8 hours (500 epochs) to 22.1 hours (4000 epochs), emphasizing the resource-intensive nature of extended training.

Taken together, these tables emphasize the nuanced relationship between accuracy, training epochs, and computational time in deep learning models. While augmenting the number of epochs can lead to improved accuracy, it also demands substantially more computational resources, and the extent of accuracy enhancement varies across different image categories. These findings underscore the need for a judicious balance between accuracy goals and available computational capabilities when designing and training deep learning models for image recognition tasks.

5. DISCUSSION

The primary objective of this study was to assess the feasibility of a model suitable for Transfer Learning, capable of achieving commendable accuracy scores within a constrained timeframe and with limited computational resources. The investigation encompassed diverse facets of Artificial Intelligence, elucidating the intricacies of Convolutional Neural Network architectures. By dissecting these aspects, we successfully identified an apt architecture, namely Inception v3, which enables image classification through Transfer Learning.

We conducted a battery of experiments to determine the practicability of our method and its generalizability to other types of data. The findings provided irrefutable proof of the usefulness of Transfer Learning. Importantly, when the Inception v3 model was retrained on the CIFAR-10 dataset, significant gains were achieved compared to previously published state-of-the-art research that either avoided Transfer Learning or used a CNN trained from scratch on the same dataset (CIFAR-10). The total accuracy of the retrained CIFAR-10 model provided in this research increased to 70.1% from the previously reported 38%. The suggested approach also scored a flawless 100% when testing on a collection of images, properly categorizing all of them but with various degrees of certainty. Image quality emerged as a critical element, alongside the number of epochs and the size of the dataset. Despite having fewer pictures than the CIFAR-10 dataset, the Caltech Face dataset nonetheless produced respectable and competitive results. This highlights the importance of varied lighting, facial emotions, and camera angles, all of which were present in the Caltech Face photos. On the other hand, the CIFAR-10 dataset's restricted training set was helpful in improving the model's accuracy despite the fact that it only included tiny, generic images from basic angles.

The findings from the third test further illuminated the influence of image type on the precision of a pre-trained model. This insight holds practical value, particularly in scenarios necessitating dataset selection. A dataset concentrated on a single or a limited number of classes appears to offer greater utility in terms of classification accuracy, outperforming datasets encompassing multiple categories.

This study encountered inherent constraints primarily driven by computational resources and time limitations. As elucidated in test 2, amplifying the number of training steps (epochs) led to an augmented classification accuracy; however, it also substantially extended the training time. Employing a GPU, instead of a central processing unit, would have likely yielded enhanced accuracy and temporal efficiency. Nonetheless, the presented results satisfactorily aligned with our objectives. The augmentation of images within our training datasets could have further improved accuracy, but our capabilities were restricted in this aspect.

In an ideal scenario, building a model from scratch would have facilitated layer and weight customization, enhancing efficiency and precision. However, this approach was not deemed necessary given our intention to compare against pre-existing works. Leveraging Transfer Learning, we successfully retrained the mentioned models using a fresh dataset, thereby achieving accurate image classification. To complete this classification assignment, the pre-trained model

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underwent retraining of its last layer, essentially transferring the relevant information and weights from the original dataset to the new one. The selected pre-trained model (Inception v3) was trained on a dataset of 1,000,000 pictures (ImageNet), proving its competency in providing respectable classification accuracy.

This paper's findings provide a solid groundwork for expanding the use of Transfer Learning, not only inside the model under discussion but also in other deep neural networks. Additional layers and tweaking of weights allow for the CNN model to be improved and fine-tuned. There is a wide range of options available, each one of which might result in a more complex model with greater accuracy.

6. CONCLUSION

This study explores the use of transfer learning in deep learning and image recognition, focusing on its effectiveness in improving classification accuracy. The research found that more training images per class led to higher classification accuracy, with a positive correlation between the quantity of training data and accuracy. The study also highlighted the trade-off between accuracy improvement and computational demands, with increased training times resulting in higher accuracy scores across different image categories. The type of images also played a crucial role in determining accuracy, with human images outperforming others. This suggests that certain image categories may benefit more from transfer learning, highlighting the need for nuanced model selection based on specific use cases. The study provides valuable insights for optimizing deep learning models for image recognition tasks, suggesting that future work should explore more diverse datasets, fine-tune hyperparameters, and use advanced optimization techniques.

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