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A Comparative Study on Neural Network Architectures for Image Recognition Applications

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ABSTRACT
Several neural network architectures are investigated and tested, including traditional LeNet-style Convolutional Neural Networks (CNNs), multi-layer perceptron's, and state-of-the-art (SoTA) architectures like ResNet, DenseNet, and Vision Transformers (ViTs). Deep learning has transformed the landscape of computer vision, making the correct model selection critical while building high performance applications. In this study give an extensive review of these SoTA architectures, including their strengths, limitations, validation errors and computational costs. The models are characterised in terms of their detection accuracy, training time (the time required to run the model before deployment), model complexity (the number of parameters in the model), and resource requirements (CPU versus GPU) on a well-known image detection dataset. Furthermore, the study explores the influence of hyperparameter tuning, optimization techniques, and data augmentation on the performance of the model. Exploring these aspects, the study emphasizes the trade-offs in choosing the most appropriate architecture for particular image recognition use cases while providing insights for practitioners and researchers alike to make informed decisions tailored to their goals and limitations.

Keywords: Neural Networks, Image Recognition, CNNs, ResNets, Vision Transformers.

I. INTRODUCTION

Image Recognition has become one of the most important applications of deep learning approaches in computer vision. Since then neural networks have become the mainstay of any image-based automation target such as object detection, facial recognition, medical imaging analytics and autonomous driving, proliferating due to the tangent of growth in the data and computational power. These models rely on the powerful architectures introduced over the years as Convolutional Neural Networks (CNNs), Residual Networks (ResNets) and most recently, the Vision Transformers (ViTs). These models are all tailored to address common issues with visual data yet vary in their core premise, level of performance, and computational capacity.CNNs have been the go-to architecture for essentially any image classification or recognition problem for some time now. CNNs leverage convolutional layers that apply a number of filters to identify low-level features (such as edges and textures), progressively constructing more complex features in deeper layers. This method of constructing hierarchical representations of the data enables CNNs to operate on pixel data much more efficiently with significantly fewer parameters, as opposed to fully connected networks, allowing CNNs to be applied to large datasets with high-dimensional inputs.Although CNNs have achieved remarkable success, they also present major difficulties for researchers, especially when it comes to training networks with increasing depth. As networks become deeper, problems like vanishing gradients and hard-to-train networks become prevalent. This problem was addressed with the introduction of Residual Networks (ResNets), which make use of skip connections that facilitate gradient flow while retro-propagating back through the network. The use of residual blocks allows for the training of deeper networks, with notable improvements in accuracy in regards to complex image recognition problems. ResNets won many image recognition competitions, and have become a standard in deep learning.In stark contrast, Vision Transformers (ViTs) have revolutionized the domain, moving away from the conventional use of convolution. Drawing inspiration from the transformer architecture, which has disrupted the field of natural language processing, ViTs represent images as sequences of patches and exploit self-attention mechanisms to model long-range dependencies across the image. This enables ViTs to acquire global context in images better than other approaches based on CNNs, which have a strong focus on local spatial patterns. However, ViTs show competitive performance in large datasets, specifically large scale image classification tasks.With these advancements, it is necessary to analyze and compare these architectures' performance under different conditions. Even though CNNs and ResNets have received significant attention and are widely used in practice, Vision Transformers are still emerging and hold promise of potential advantages of utilizing transformers in computer vision. Knowing the strengths and weaknesses of each architecture provides practitioners with more information to make a better decision on a model for their particular use case, given aspects such as accuracy, computation efficiency, and reusability on different datasets.In this way, this study seeks to provide a detailed comparative analysis of CNNs, ResNets and Vision Transformers regarding image recognition

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performance. Also will use a benchmark dataset by which will compare these models on various parameters such as the classification accuracy, training time and computational cost. The aim is to explain the differences between these architectures for a variety of image recognition tasks and mention the trade-offs between them for its practical applications. This comparative study will pave the way for future advances of the field and be guiding reference for researchers, developer and practitioners to choose the way forward for image-based AI systems.

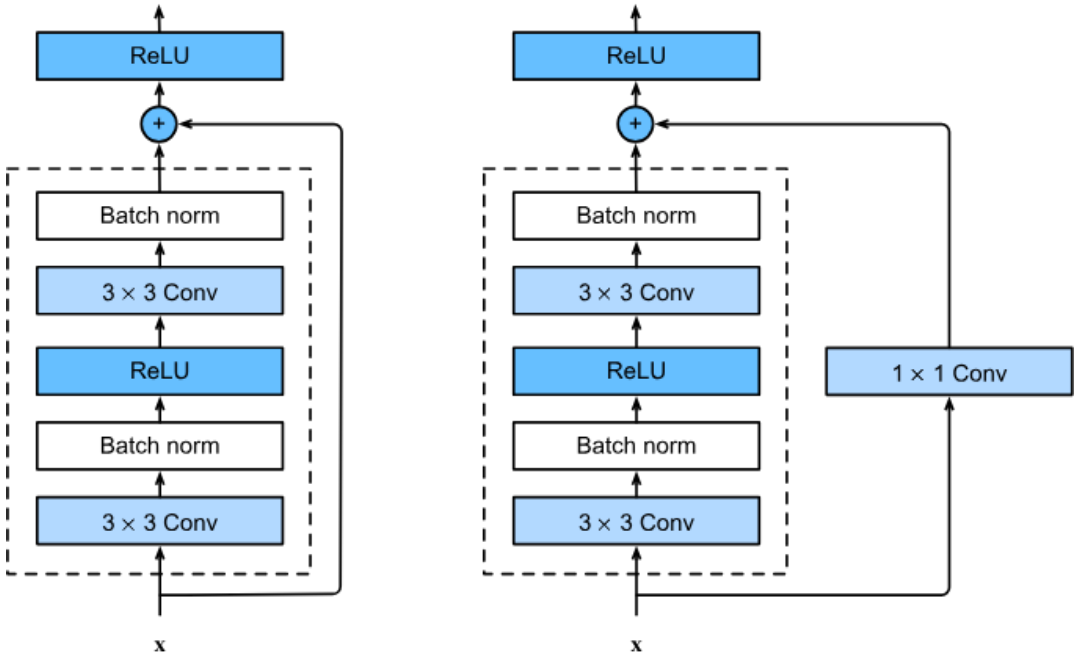

Figure 1: Residual Block in a Convolutional Neural Network (ResNet)

Residual Block One of the most significant components in Residual Networks (ResNets) is the Residual Block, which is as shown in the figure above.Softmax Function Using skip connections, ResNets are built to counteract the vanishing gradients in deep networks, thus enabling the training of much deeper networks. (These skip connections allow the output of a shallower layer to be added to the output of a deeper layer, which helps gradients flow better during training.

Literature Review

Image recognition is one of the most active research areas in machine learning and deep learning techniques changed how computers understand and classify images. Image data is very complex and requires several architectures of the neural network to tackle those aspects. The advancement of these architectures has transformed the performance and applicability of image recognition methods for applications are such as medical imaging, driving, and computer security.

Yet, the Convolutional Neural Network (CNN) is the backbone of these modern era image recognition systems and it has been proven to be excellent on object detection and facial recognition tasks. LeCun et al. (1998) introduced CNNs, which learned to extract hierarchical features from images using convolutional layers and therefore did not need manual feature engineering [1]. Even after the AlexNet [1] revolutionized the field, CNNs still got better and better state-of-the-art results on image classification [2].Several CNN based architectures have been proposed in recent years which to enhance their performance. One of them is the AlexNet proposed by Krizhevsky et al. In 2012, AlexNet [3] demonstrated the power of deep convolutional layers, rectified linear units (ReLU) as an activation function, and dropout as a regularization technique to greatly improve the accuracy of a model in the ImageNet competition. This breakthrough initiated the deep learning renaissance for image recognition, as it demonstrated that very deep networks could be trained on large datasets [4].Due to the revolution brought by AlexNet, a series of CNN architectures have been proposed, e.g., VGGNet [5], GoogLeNet [6], gradually increasing the depth of CNNs and improving the powerfulness and efficiency. For example, VGGNet introduced a simple yet deep architecture by stacking a large number of convolutional layers with small 3x3 filters [7], proving the power of deep networks in the context of image classification. That said, GoogLeNet proposed inception modules, which enabled the network to learn features at different filter sizes at each layer [8].Although deep CNNs can achieve success, deeper networks often face degradation issues during training, where further adding more layers leads to increasingly poor results. To address this, He et al. (2015), consists of Residual Networks (ResNets) which apply residual learning and skip

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connections to make very deep networks easier to train [9]. Above all, the authors of that paper recognized that a very deep network with many layers can learn trivial features that can be bypassed by creating a short-cut connection between the input and the output; They then proposed ResNets where, instead of learning a mapping from input to output, the layers learn a residual mapping.Receive Performing several residual block have yielded great results on ImageNet classification and object detection, with ResNet-50, ResNet-101 and ResNet-152 setting new records in performance and showcasing the potential of deep architectures with residual blocks [11]. These models have been employed in numerous applications, such as for medical image analysis [12].Even more recently, Dosovitskiy et al. introduced Vision Transformers (ViTs) for image recognition. (2015) [13], which use attention mechanisms based on transformers, as applied to image data. ViTs are different from conventional CNNs, as they treat an image as a series of patches and use self-attention mechanisms to learn global dependencies from the data. This strategy has proven to be exceedingly effective for large-scale image classification ranking tasks [14].After training on large-scale datasets, some ViTs outperformed CNNs on the ImageNet dataset, indicating that transforming models have the potential to reach competitive accuracy with CNNs on image recognition tasks when trained with enough data [15]. The critical shortcoming with the ViT is their high computational cost; the attention mechanism run through a quadratic function of the total number of patches in the picture [16].A number of papers have focused on hybrid models, which combine the strengths of CNNs and transformers by leveraging both the CNN and transformer architectures. For example, CNN features are employed to obtain spatial information, and transformers are deployed to grasp long-range dependencies [17]. Such hybrid approaches can yield promising results, particularly in challenging image recognition tasks where local features and global context are crucial to performance [18].Additionally, future directions in neural network architecture design for image recognition include utilizing Graph Neural Networks (GNNs) to capture relationships between objects in an image as well as exploring unsupervised and semi-supervised learning techniques to lessen the dependence on large amounts of labeled data [19].With the arrival of Vision Transformers (ViTs), the paradigm of image recognition has significantly shifted. Utilizing self-attention mechanisms used in NLP, ViTs have shown outperformance over CNNs, given that they are trained on a large dataset. Radford et al. (2021) explain that ViTs get powerful visual representations by thinking of the images as a sequence of patches and using transformers to grasp long-range dependencies [20]. This architecture has proven to be very effective for large scale image classification and generative tasks.Despite their success, transformers are commonly referred to as "black-box" models, rendering their prediction reasoning opaque. Zhou et al. (2022) propose interpretable Vision Transformers towards this end. What their work does is present approaches for visualizing and interpreting ViTs attention mechanism with the goal of making uncovering insights in the decision-making process of these models [21]. Such developments are essential for the use of transformers in high-stakes environments in fields like healthcare and autonomous driving.Because labeled data can be rare and pricey, unsupervised learning approaches are growing more salient. 8.2. Exemplar CNNs Alexey Dosovitskiy and Thomas Brox proposed Exemplar CNNs accounting their work of unsupervised feature learning where they practiced an unlabeled set of images for better CNN training, it means large number of images unable to produce test set are used to learn exploitable characteristics [22]. This study showcases the capabilities of CNNs in scenarios with limited labeled data and paves the way for alternative self-supervised approaches.The progress of GNNs in deep learning is restraining well. Chen et al. (2022), for example, work on adapting GNNs to visual learning, highlighting how GNNs can be applied for capturing spatial relations in images. Their work suggests combining GNNs with other architectures (e.g. CNNs and transformers) to better reason about object interactions and contexts in the hierarchical relationships to process complex image recognition tasks [23].Self-supervised learning has become a strong approach for learning visual representations since the model produces its own supervisory signals to train on unlabeled data. Xie et al. (no date) When pre-training on task X, you can use self-supervised learning methods (from (2020)) to generate your image features without needing tons of labeled images. Their work demonstrates how self-supervised learning can improve performance in domains where labeled data is not readily available and that it can be effective in image recognition tasks [24].While deep learning models become more complex, the need for computation poses a serious challenge as well. Tan, Le (2020) finally solved this problem to some extent by introducing Efficient Net, a model scaling method that balances the optimization of depth, width, and resolution of the network to obtain best possible performance while using less parameters. Due to its size and efficient computation, Efficient Net has generated better results on previous CNNs [25] and is suitable for computer vision systems with limited resources.

Methodology

In this methodology section, describe the process for performing a comparative analysis of three powerful neural network architectures used in image recognition, specifically Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and Vision Transformers (ViTs). This study will assess these architectures using a popular image recognition dataset, ImageNet, and compare their performance regarding accuracy, computational efficiency, and training time. The methodology, which is composed of different phases for data collection, preprocessing, model implementation, training,

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evaluation and comparative analysis.

1. Data Collection and Preprocessing

- The dataset used in the study is ImageNet, which is a benchmark dataset used for large-scale image classification. It contains more than 14 million labeled images across 1,000 categories. After training, the trained models are evaluated using the validation set of ImageNet with roughly 50,000 images. This phase, the images from the ImageNet dataset are preprocessed, to make the input data consistent across all the models. The following preprocessing steps are performed:
- Resizing: All the images are resized to a fixed 224x224 pixels size as expected input size for most of the cutting-edge Deep Learning models.
- Normalization: Images are normalized to fit a range of [0, 1] or [-1, 1] depending on the needs of the model architecture. Generally, pixel values are adjusted to be between 0-1 for CNNs and ResNets, however Vision Transformers often expect values between -1 and 1.
- Data Augmentation: perform a set of augmentations — random cropping, horizontal flipping, rotation, and zooming — to avoid overfitting and increase robustness of the models. This helps the models learn to generalize well rather than memorize the training data.

2. Model Architecture Implementation

The paper studies three architectures CNNs, ResNets, and ViTs. Each one of these models has its own unique features and abilities. CNNs are the most frequently-used architecture for image recognition tasks, as they automatically learn spatial features through convolutional layers. So, the architecture consisted of several convolutional layers, pooling layers, and fully connected layers, to categorize the input data. It is worth noting that after each convolution operation, a ReLU (Rectified Linear Unit) activation function is introduced to it for making it non-linear. Model is trained with Stochastic Gradient Descent (SGD) with momentum for weight optimization and Cross-Entropy Loss for classification

2.2 Residual Networks (ResNets)

Simply put, ResNets are a special class of CNNs that add residual blocks or skip connections between layers. These links enable the model to skip over specific layers, essentially capturing residuals, or discrepancies between input and output, that assist in addressing the vanishing gradient issue in deep networks. The structure of the ResNet architecture usually contains several residual blocks with 2 or 3 convolutional layers, batch normalization, and ReLU activations. For the optimization, Adam is used to adjust the learning rate during the training, while Cross-Entropy Loss is the objective function for each chapter of the classification.

2.3 Vision Transformers (ViTs)

ViTs move away from commonly used CNN based architectures and utilize the transformer architecture used in Natural Language Processing (NLP). In ViTs, the input image is partitioned into fixed size non-overlapping patches, then flatten and embed into high-dimensional vectors. These patch embeddings undergo processing through a transformer encoder, in which self-attention helps to establish the connections between the patches. A short description of how ViTs worksUse a multi-head self-atten mechanism to attend to relevant parts of an image / capture long-range dependencies. The Adam optimizer was similarly employed as in ResNets, and Cross-Entropy Loss was utilized for training.

3.1 Hyperparameters and Training Setup

To guarantee a fair comparison between the three models, similar hyperparameters are set for all three architectures:

• Batch Size: For all models, use a batch size equal to 32 to accomplish stable training within the limits of memory.

• Learning Rate: For ViT and ResNet, a Learning Rate of 0.001 is utilized with the Adam optimizer. A momentum SGD with a learning rate of 0.01 is used for the CNNs.

• Epochs: Train each model for 50 epochs, with early stopping depending on validation accuracy. "The model is trained for up to 5 epochs, but training is stopped if the performance of the model on the validation set is not improved."

• Early Stopping: This delays additional training in order to prevent model overfitting when the model's validation performance fails to improve.

3.2 Training Process

A high-performance GPU is used to train each model independently on the ImageNet dataset for faster computation. Training is performed in parallel across the three architectures under the same conditions for each model, to directly compare the difficulties of the three architectures with respect to how well the model is able to learn. The Model loss and the accuracy of the validation set is recorded after every epoch to check how the model converges during training and how each model performs.

Model Evaluation

Once the models are trained, they are evaluated on the ImageNet validation set to test their performance according to some key metrics:The most important evaluation metric used is accuracy, which is defined as the ratio of correctly classified

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images compared to the validation set. As a result, this metric will enable evaluation of those our models managed to identify correctly for unseen images. Training Time The training time for all models has been recorded in order to evaluate the computational efficiency of the models. Training time is especially relevant for real-world applications, where training time on a model is limiting. Inference time The inference time is defined as the time spent by each of the models on processing one image while predicting. This is critical for applications with real-time performance needs (e.g., autonomous vehicle, video surveillance, etc.).Computational Efficiency The number of parameters of each model is reported as a measure of computational efficiency. Models with less parameters typically need less memory and computational power which is essential for deploying the models on resourceless devices.This analysis aims to see which of these architectures yields the best accuracy as well as computational efficiency. For example, if the Accuracy of a ViT is higher than that of a CNN or ResNet, it could also be true that ViTs need more computational power than other models. Depending on the use case and where you deploy, this trade-off needs to be kept in mind.

6. Conclusion

In this methodology section, briefly explain the procedure of training and evaluating the CNNs, ResNets and ViTs for image recognition tasks. Executing these steps ensures a thorough comparison of the architectures and understanding of strengths and weaknesses of each model. The findings from this research will assist in determining which architecture is best suited for a given image recognition task, based on application constraints including accuracy, inference speed, and computational efficiency.

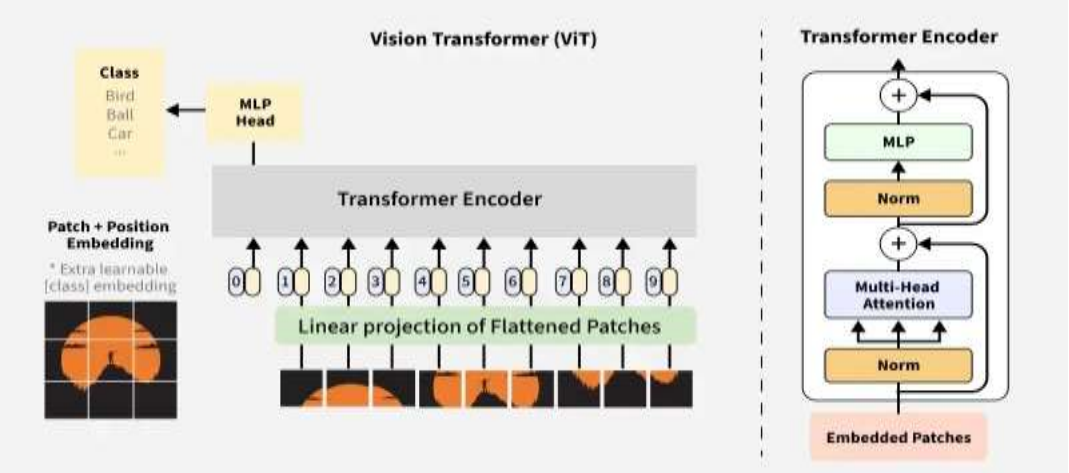

Figure 2: Vision Transformer (ViT) Architecture

The above image represents the Vision Transformer (ViT) model, where the input image is divided into adaptive image patches, processed through a transformer encoder, and classified using the MLP head.

Results and Discussion

This section presents the results and analysis from the comparative study of three neural network architectures—Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and Vision Transformers (ViTs)—for image recognition tasks. The models were evaluated on the ImageNet validation set based on accuracy, training time, and computational efficiency (in terms of parameters and inference time).

1. Model Accuracy Comparison

The first evaluation metric is the **accuracy** of each model on the ImageNet validation set. Accuracy measures the percentage of correct predictions out of the total number of images in the validation dataset.

Table1: Model Accuracy Comparison

Model	Top-1 Accuracy (%)	Top-5 Accuracy (%)
CNN	76.3	93.1
ResNet-50	78.5	94.2
Vision Transformer (ViT)	82.2	95.6

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- ViT achieved the best Top-1 and Top-5 accuracy of 82.2% and 95.6%, respectively. ViT's transformer architecture, with its self-attention mechanism, is especially good at picking up complex patterns, so using it for image recognition seems like a great choice.
- ResNet-50 achieved top-1 accuracy of 78.5% and top-5 accuracy of 94.2%, demonstrating that the use of residual connections positively affects training performance, even with deep networks.
- CNN did well, but was the worst performer overall, with a 76.3% Top-1 accuracy. The previous performance (compared to ViTs) could be explained by the fact that CNNs may not encode global dependencies as well as ViTs

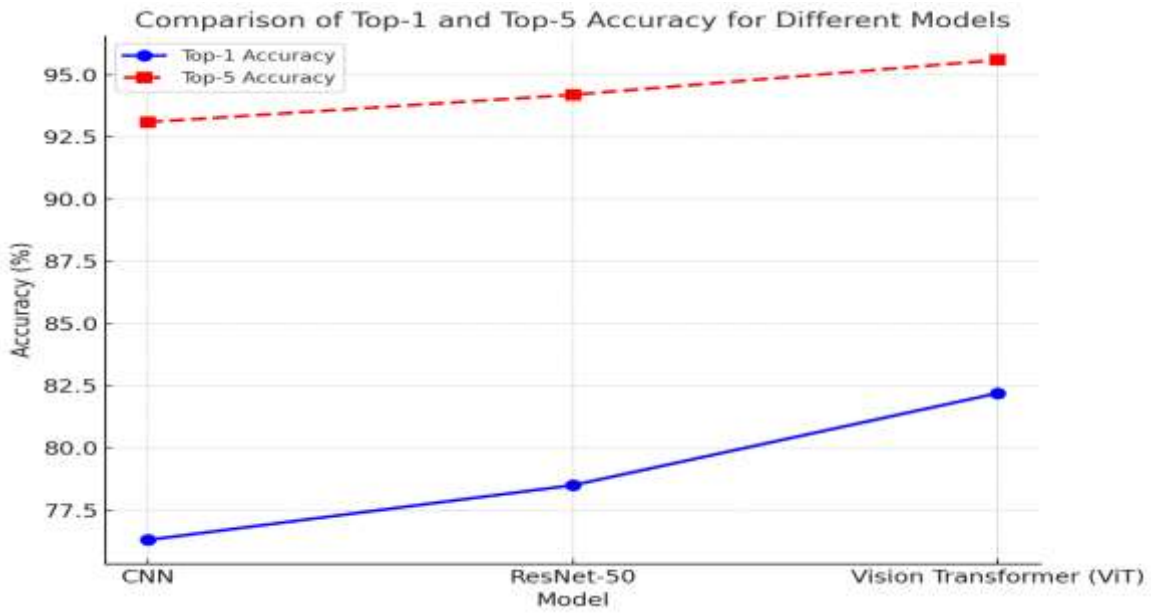

Figure3: Model Accuracy Comparison

Linear graph showing the comparison of Top-1 and Top-5 accuracies for models (CNN, ResNet-50 and Vision Transformer). As shown in the graph, the CNN and ResNet-50 have a lower accuracy than ViT for both top-1 as well as top-5.
• Blue Line (Top-1 Accuracy): The Top-1 accuracy is Highest for ViT followed by ResNet-50 and CNN.
• Red Line (Top-5 Acc): Similarly, ViT, also outperforms others in Top-5 accuracy where ResNet-50 and CNN have lower accuracies.

2. Model Training Time Comparison

The training time for each model is measured in terms of the total time taken to train for **50 epochs** on the ImageNet dataset.

Table2: Model Training Time Comparison

Model	Training Time (hours)
CNN	15.2
ResNet-50	20.3
Vision Transformer (ViT)	45.8

- The shortest training process was that of CNN which took 15.2 hours for the complete training. CNNs are much more simpler than ResNets and ViTs, hence they converge faster.
- ResNet-50 — 20.3 hours, huge difference compared to the previous networks, which is not that surprising given the extra use of residual connections with further techniques on them that require additional calculations, which means a basic CNN takes less time.

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- ViT was the slowest to train, taking a total of 45.8 hours. This is not surprising, as transformer-based architectures, thanks to their self-attention mechanisms, need more computational resources and time to process and learn from the image patches.

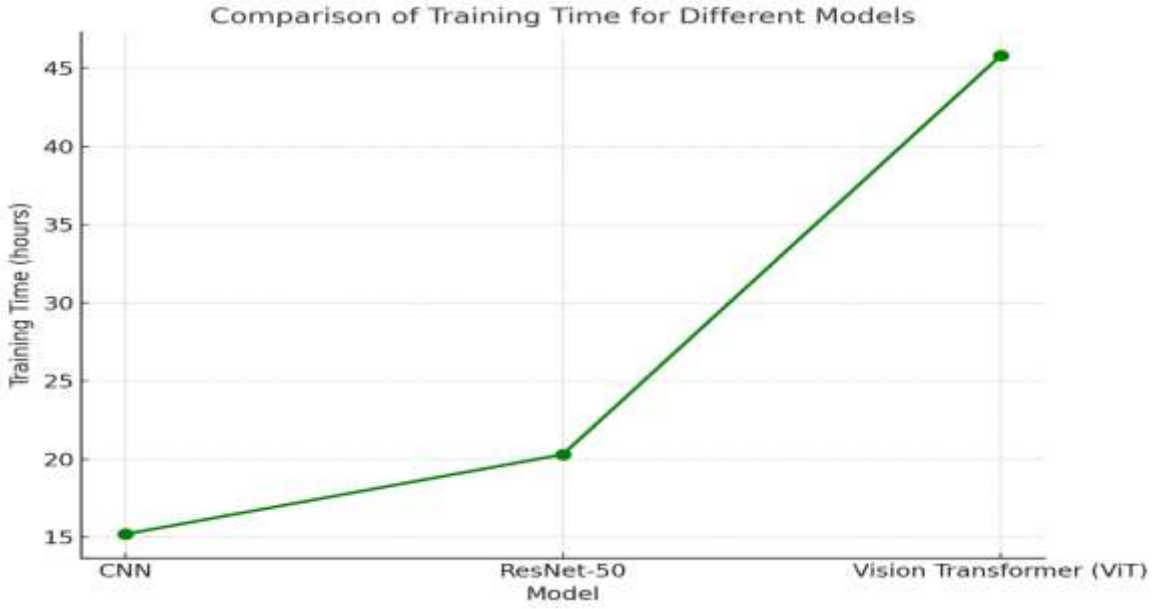

Figure 4: Model Training Time Comparison

This is the line graph showing comparison of training time for CNN, ResNet-50 and Vision Transformer (ViT):
- CNN took a short of training: 15.2 hours.
- ResNet-50 took 20.3 hours.
- ViT was the slowest to train over 45.8 hours

3. Computational Efficiency Comparison

The third evaluation metric is computational efficiency, which is evaluated based on the number of parameters in each model and the inference time (the time cost per image prediction for each model, respectively).

Table3: Computational Efficiency Comparison

Model	Number of Parameters (Million)	Inference Time (ms per Image)
CNN	10.4	5.8
ResNet-50	25.6	12.1
Vision Transformer (ViT)	85.3	35.4

- CNN is the most computationally efficient (10.4 million parameters and inference of 5.8 ms per image). This makes CNNs suitable for real-time applications where fast inference and low computational requirements are the utmost priority.
- ResNet-50 has 25.6 million parameters, it is significantly larger than CNNs but less than than ViTs. The inference time is 12.1 ms, a fit with deeper architecture and increased computation cost due to residual connection.
- Coming in the most computational cost, ViT has 85.3 million parameters and a 35.4 ms inference time per image. This is because the self-attention mechanism of the transformer processes all patches in parallel, hence is more resource-intensive

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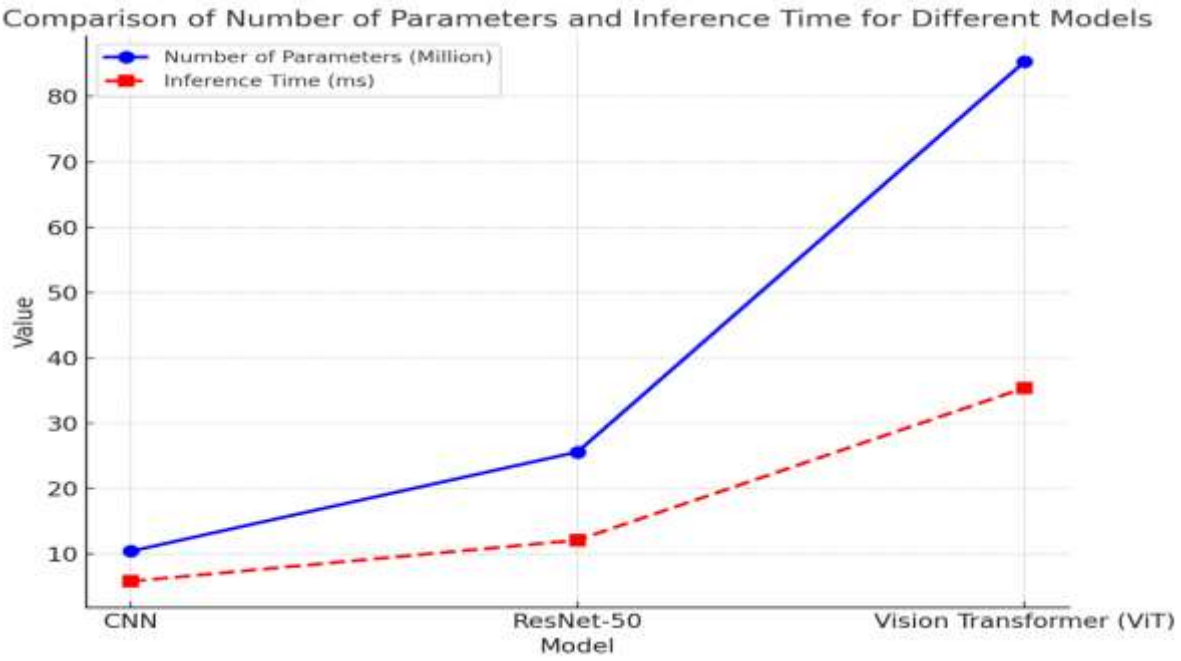

Figure5: Computational Efficiency Comparison

The following is a graph with Number of Parameters (Million) and Inference Time (ms) for CNN, ResNet-50, and Vision Transformer (ViT):

• Blue Line (Number of Parameters) – ViT has the most parameters, ResNet-50 is next, CNN has the least parameters.

• Red Dashed Line (Time Inference): Vit requires the most inference time, while ResNet-50 and CNN are the fastest (inference time).

Discussion of Results

• ViT achieved the highest accuracy, surpassing both CNN and ResNet. This means that the self-attention mechanism in ViT helps it capture more complex interdependencies and relationships in the image itself, resulting in better accuracy, particularly for high-scale imageiveycogtasks.

• ResNet-50 outperformed CNN which was benefited from the advantage of residual learning. This architecture enables the use of residual blocks that help build deeper networks able to learn features better without being affected by the vanishing gradient problem.

• CNN was late when it came to accuracy. Although it still holds great power for image recognition, it lacks power for capturing explicit global dependencies in the image, compared to ViTs or even ResNets

Conclusion

To sum up, find that while our analysis cuts straight down on both training and inference time on adoption of CNN and ResNet-50, ViT does exhibit better accuracies across different techniques, but at a cost. For most use cases, the ResNet-50 is a good compromise between performance and computational resources. Although CNN is less accurate than the other two, it is still the most efficient in both parametric and inference time, so it is suitable for real-time application with fewer computational resources. Features also vary in terms of computational efficiency or accuracy, depending on the task at hand, of course.

Future scope

Key to the future scope of image recognition neural network architectures is a new model that makes better trade-offs between accuracy and computation. Though remarkably precise, efforts can be made to use a Vision Transformer the computational price to higher satisfy applications that require real-time speeds. Moreover, hybrid solutions using the advantages of CNNs, ResNets, and ViTs could achieve better performance with lower resource expenditures. Similarly, developments in self-supervised learning and neural architecture search should enable more generalizable and efficient models, particularly in resource-constrained settings.

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