Dynamic Convolutional Neural Network with Squeeze-and-Excitation Block for Hyperparameter Optimization in Object Detection

Salunkhe Pranav Vishvasrao
Dept. of Information Technology
211IT059

Babar Sanket Shamrao
Dept. of Information Technology
211IT015

Garvit Goyal
Dept. of Information Technology
211IT021

***Abstract*—This paper presents a novel approach to image classification using a dynamically configurable Convolutional Neural Network (CNN) model with attention mechanisms, evaluated on the CIFAR-10 dataset. The model architecture integrates Squeeze-and-Excitation (SE) blocks for channel-wise attention, enhancing the network's ability to capture important features by adaptively recalibrating channel weights. Our model adjusts convolutional and pooling parameters, including kernel size, stride, padding, pooling type, and size, for improved performance in object detection tasks. We are Using a subset of the CIFAR-10 dataset, we employ a brute-force search over parameter combinations, evaluating model performance across various configurations to identify the best-performing setup for each image type. Experimental results demonstrate that this dynamic approach yields improvements in accuracy and computational efficiency, making it suitable for constrained-resource environments.**

***Index Terms*—Dynamic CNN, hyperparameter optimization, object detection, CIFAR-10, convolutional neural networks.**

Github: https://github.com/pranav-salunkhe/computer-vision-course-project

I. Introduction

Convolutional Neural Networks (CNNs) are fundamental to many computer vision applications, with object detection being one of the most prominent tasks. Object detection models have achieved remarkable performance on tasks such as face detection, autonomous driving, and medical imaging. Traditional CNN architectures rely on fixed hyperparameters—such as kernel size, stride, and padding—throughout the network's layers. While these fixed hyperparameters simplify model design, they may not be optimal for all types of images or tasks, potentially limiting the model's performance.

In scenarios where the dataset includes a variety of image types, such as the CIFAR-10 dataset with its ten distinct object classes, fixed hyperparameters may yield suboptimal results. Different types of images may benefit from different configurations in convolutional and pooling layers to better capture features, improve accuracy, and reduce unnecessary computations. For instance, large objects may benefit from larger convolutional kernels, whereas smaller objects may require smaller kernels to capture finer details.

A. Motivation

Fixed hyperparameters may not be ideal for all images, leading to suboptimal performance in terms of accuracy and computational efficiency. By dynamically adjusting hyperparameters based on input characteristics, we can improve the model's adaptability and performance in various scenarios.

B. Objectives

1) Develop a CNN model with dynamic hyperparameters.
2) Identify the optimal combination of convolutional and pooling parameters for object detection in different image types.
3) Evaluate the model's performance on a subset of CIFAR-10 to minimize computational requirements.

II. Related Work

In recent years, deep learning has significantly advanced object detection, with a diverse array of methods emerging to meet various application requirements, from real-time detection to high-precision tasks. Here, we discuss prominent works in this domain, highlighting their contributions, limitations, and impact on the evolution of object detection.

The paper "A Review of Research on Object Detection Based on Deep Learning" provides a comprehensive overview of object detection algorithms, specifically focusing on single-stage and two-stage detection approaches, including R-CNN, Fast R-CNN, Faster R-CNN, and YOLO versions. This work is valuable for examining the trade-offs between detection accuracy and computational efficiency. For instance, it points out that Faster R-CNN, despite its accuracy, struggles with real-time detection requirements, whereas YOLOv3 balances speed and accuracy, making it a popular choice for real-time applications. However, the review's focus on established methods limits its exploration of more recent and emerging techniques, while its reliance on traditional metrics like mAP and FPS overlooks other important performance indicators like energy efficiency and robustness in diverse real-world applications (Chen et al., 2020).

The introduction of Spatial Pyramid Pooling (SPP) by He et al. fixed input size limitation, enhancing flexibility across visual recognition tasks. SPP-net demonstrated state-of-the-art performance on datasets such as ImageNet and Pascal VOC, improving both image classification and object detection. Its efficient computational design, processing convolutional features only once per image, made SPP-net highly applicable to

large-scale tasks. Nonetheless, its implementation complexity and dependency on large datasets pose challenges for practical application in limited data scenarios and for simpler deployments requiring less resource-intensive models.

Ren et al. (2015) integrated Region Proposal Networks (RPNs) with Fast R-CNN, enabling near-cost-free region proposals through shared convolutional features, thereby improving both speed and accuracy. Faster R-CNN achieved high accuracy on datasets like PASCAL VOC with only a marginal increase in computation per image. However, its efficiency is highly dependent on GPU acceleration, and the combined RPN and Fast R-CNN model is computationally expensive, limiting its practical deployment in resource-constrained environments. Furthermore, the use of fixed bounding-box regressors in RPNs can hinder generalization to novel object shapes and configurations, impacting real-world adaptability.

Mask R-CNN, introduced by He et al. (2017) in "Deep Learning-based Object Detection using Mask R-CNN," extends Faster R-CNN by adding a branch for predicting segmentation masks, making it suitable for applications that require both detection and segmentation, such as medical imaging. Mask R-CNN performs well across object sizes, achieving a mean Average Precision (mAP) of 94% on custom datasets. Its flexibility with backbone networks like ResNet-101 enhances feature extraction capabilities, though its implementation remains complex and resource-intensive, which could hinder scalability for large-scale applications or those with high object class variability. Additionally, Mask R-CNN's dependency on high-quality, pre-trained models can limit its effectiveness when suitable pre-trained weights are unavailable.

YOLO (You Only Look Once), proposed by Redmon et al. (2016), revolutionized object detection by framing it as a single regression problem. This unified approach enabled YOLO to process images at up to 45 frames per second (FPS), making it suitable for real-time applications. YOLO's end-to-end optimization and global reasoning capabilities facilitated its application across diverse domains. Despite its speed and simplicity, YOLO faces challenges with localization accuracy, particularly for small or overlapping objects, and requires extensive computational resources for optimal performance. Additionally, its design constraints limit its ability to handle objects in close proximity, making it less suitable for applications demanding high localization precision.

The Single Shot MultiBox Detector (SSD), as presented by Liu et al. (2016), also introduced a single-stage detection framework that enables real-time performance while detecting objects at multiple scales. SSD's design incorporates multi-scale feature maps to handle objects of various sizes, balancing speed and accuracy. However, it generally achieves lower accuracy than two-stage detectors like Faster R-CNN, especially for small objects, and requires careful tuning of anchors and positive-negative sample ratios for stable training, which can pose challenges in certain applications.

EfficientDet, proposed by Tan et al. (2020), further refined scalability and efficiency in object detection. By utilizing compound scaling and a novel BiFPN architecture, EfficientDet achieves high accuracy with reduced parameters and FLOPs, making it resource-efficient. The versatility of its scalable model architecture (from EfficientDet-D0 to EfficientDet-D7) allows it to adapt to diverse computational constraints. Despite these strengths, EfficientDet's complex scaling approach and BiFPN require a deep understanding of model architecture for effective implementation, potentially limiting its adoption for simpler tasks or by less experienced practitioners.

In summary, these object detection methods have each contributed unique advancements to the field, from the foundational improvements in detection speed and accuracy to addressing computational efficiency and flexibility. While two-stage models like Faster R-CNN and Mask R-CNN offer high accuracy and adaptability for specialized tasks, single-stage models such as YOLO, SSD, and EfficientDet have paved the way for real-time applications and scalability across resource-constrained environments. Each method continues to influence the evolution of object detection, and ongoing research aims to overcome limitations in localization accuracy, computational resource dependence, and real-world adaptability to further enhance the efficacy and applicability of deep learning-based object detection frameworks.

III. Methodology

The proposed methodology implements a brute-force hyperparameter search on a dynamically configured Convolutional Neural Network (CNN) using the CIFAR-10 dataset. This methodology is organized into several steps, each detailing a different aspect of the approach.

A. Dataset Preparation

The dataset used in this study is CIFAR-10, a widely recognized benchmark dataset for image classification tasks. CIFAR-10 consists of 60,000 color images, each sized 32x32 pixels with three color channels (RGB). The dataset is divided into 10 mutually exclusive classes, including airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. Each class contains 6,000 images for a balanced distribution across categories.

The a subset of 10,000 images is used for training, ensuring that model trained on CIFAR-10 can be evaluated objectively. CIFAR-10 is particularly useful for evaluating deep learning models due to its variety and moderate complexity, despite the relatively small image size and limited number of classes compared to real-world datasets. The small image size also makes it computationally feasible for training deep convolutional neural networks on consumer-grade hardware.

This dataset is pre-labeled, allowing for supervised learning without the need for manual labeling, and is available through the TensorFlow and PyTorch libraries, as well as the original CIFAR-10 website.

B. Dynamic CNN Architecture Design

A custom CNN model, DynamicCNN, is developed to dynamically adjust based on different configurations of con-

volution and pooling layer parameters. This model is designed with the following key elements:

- Convolutional Layers: Two convolutional layers are defined:
  - conv1: A dynamically configured layer based on the hyperparameters specified for kernel size, stride, and padding.
  - conv2: A fixed layer with a kernel size of 3, stride of 1, and padding of 1.
- SE Block (Attention): After conv1, an SE (Squeeze-and-Excitation) block is used for adaptive attention, designed to recalibrate feature maps by:
  - Squeeze Phase: Applies global average pooling to produce a channel-wise descriptor.
  - Excitation Phase: Uses two fully connected layers to generate a channel-wise scaling factor (sigmoid output) applied to the feature maps, enhancing important features.
- Pooling Layers: Two pooling layers are applied to downsample the feature maps:
  - pool1: Configured based on user-defined parameters, such as type (max or average), kernel size, and stride.
  - pool2: A fixed max-pooling layer with kernel size 2 and stride 2.
- Fully Connected Layers: Two fully connected layers (FC1 and FC2) are used at the output:
  - FC1: Connects the flattened convolutional output to a hidden layer with 128 neurons.
  - FC2: Outputs a 10-dimensional vector corresponding to the CIFAR-10 classes.
- Dynamic Flattening Calculation: A helper function, _get_flattened_size(), computes the flattened feature map size dynamically by passing a dummy input through the model. This is essential to accommodate varying input dimensions resulting from different convolution and pooling configurations.

C. Evaluation Function

An evaluate_configuration function is developed to train and test each CNN configuration. This function:

- Initializes the CNN model with the specified convolution and pooling parameters.
- Trains the model for 8 epochs using the Adam optimizer with a learning rate of 0.001 and cross-entropy loss. During training, backpropagation updates the weights, and gradients are computed and applied.
- Evaluates the model's performance on the training subset by calculating the prediction accuracy, which serves as the evaluation metric for each configuration.

D. Hyperparameter Search

The methodology includes a brute-force search over possible configurations for the CNN's convolutional and pooling layers. This involves iterating through all combinations of kernel sizes, strides, padding, and pooling parameters. For each configuration, the evaluate_configuration function is used to measure accuracy. The best configuration is then selected based on the highest recorded accuracy.

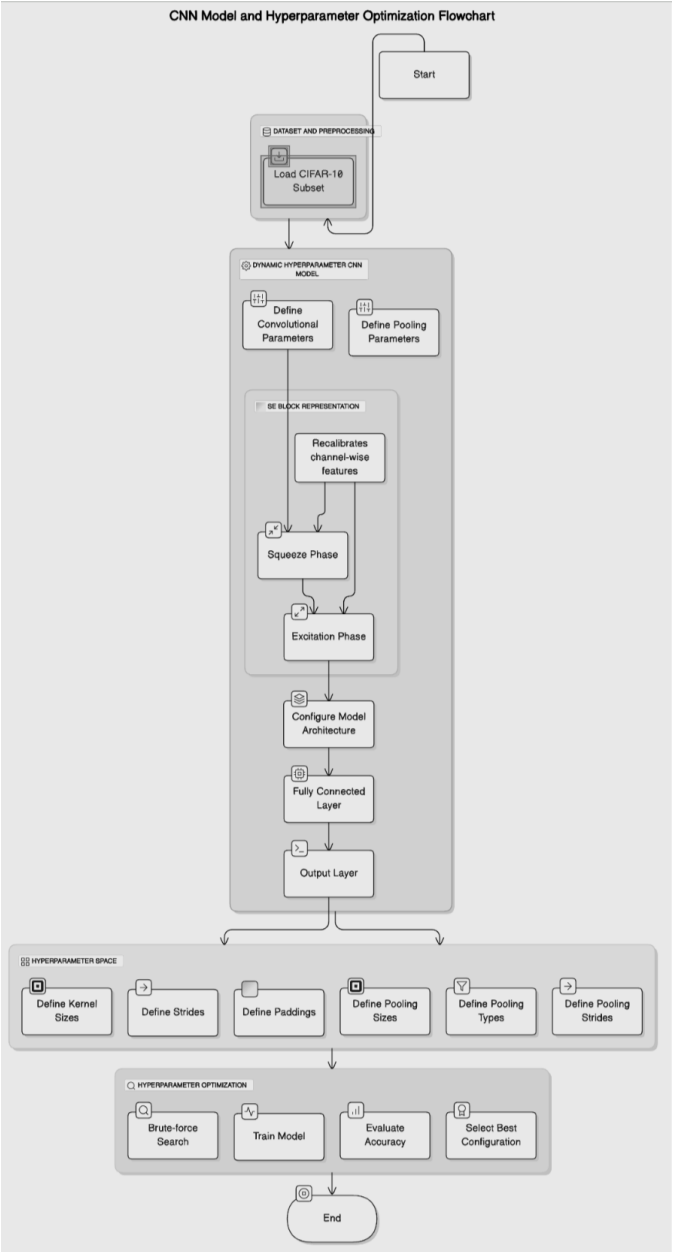

Fig. 1. Workflow

E. Visualization of Predictions

After determining the optimal configuration, the model is tested on a few sample images from the CIFAR-10 test set. The final predictions are visualized using Matplotlib, displaying each image alongside the model's predicted and true labels. This step provides a qualitative assessment of the model's classification performance.

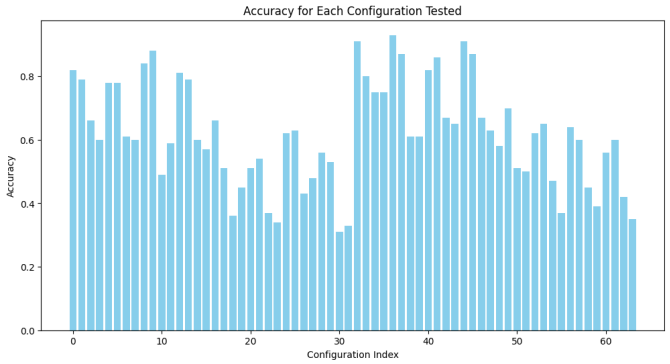

Fig. 2. Accuracy for Each Configuration Tested

IV. Results and Discussion

We observe the following:

Overall Pattern: There is noticeable variance in accuracy across different configurations, suggesting that certain combinations of convolutional layers, SE blocks, and pooling types have a significant impact on performance. Some configurations achieve an accuracy near or above 0.8, while others drop below 0.4, highlighting the importance of careful hyperparameter selection.

Attention Mechanism and SE Blocks: Given the SE blocks used in the model, configurations with higher accuracy may benefit from the adaptive attention mechanism that recalibrates feature maps, emphasizing important features. This shows the SE blocks' potential impact on the model's accuracy.

Dynamic Pooling Impact: The variation in accuracy may also stem from the dynamic pooling layer, where the choice between max or average pooling can affect feature retention and, consequently, the classification accuracy. This bar chart

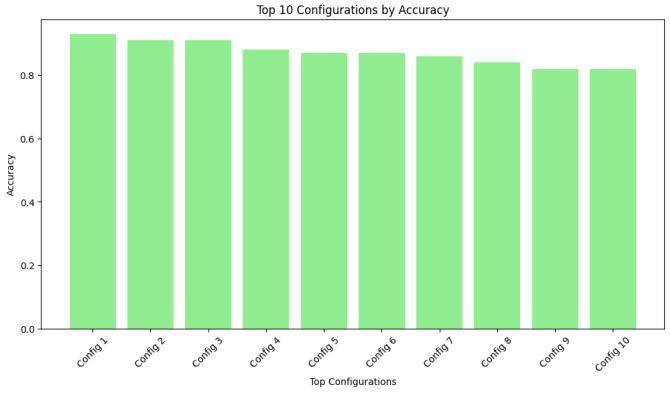

Fig. 3. Top 10 Configurations by Accuracy

displays the top 10 configurations by accuracy for our dynamic CNN model on the CIFAR-10 dataset. **High Consistency in Top Performers**: The top configurations show very similar accuracy levels, suggesting that several combinations of hyperparameters yield comparable, optimal results. This consistency indicates that your model can perform well across a range of parameter settings, as long as they align with the general structure and attention mechanisms you've designed.

Key Components (SE Blocks, Pooling, etc.): The accuracy levels here imply that the SE (Squeeze-and-Excitation) blocks, dynamic pooling, and convolution settings used in these configurations effectively enhance feature selection and improve classification.

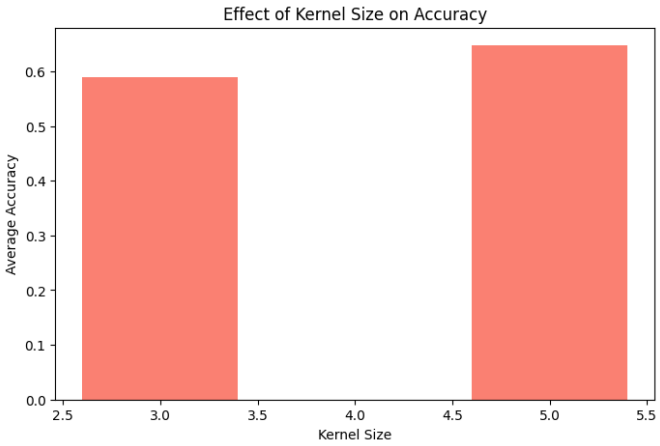

Fig. 4. Effect of Kernel Size on Accuracy

The kernel size of 5 has a slightly higher average accuracy than the kernel size of 3. This suggests that larger kernels might be more effective for feature extraction in this model, potentially capturing more spatial context from the CIFAR-10 images.

The difference in accuracy is not very large, indicating that both kernel sizes are reasonably effective, though a kernel size of 5 provides a marginal performance boost.

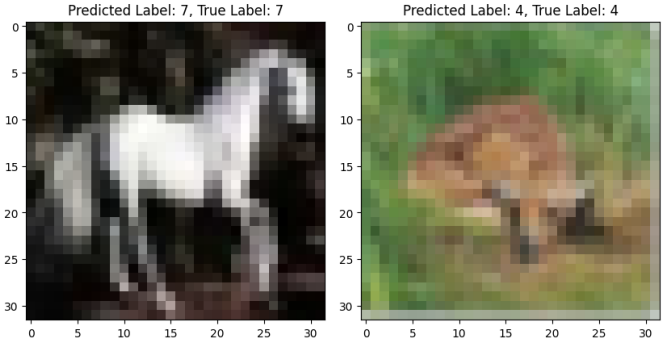

Fig. 5. Correctly Predicted Example 1Fig. 6. Correctly Predicted Example 2

Above are few examples of the model correctly predicting the labels for the images from the CIFAR-10 data.

Best Configuration: {kernel_size: 3, stride: 1, padding: 0}, {size: 2, stride: 1, type: avg} with an accuracy of 0.9800.

As seen from the table II and III, our dynamic model performs at par with state-of-the-art models like LMFRNet, Fractional MP, DenseNet.

Kernel Size	Kernel Stride	Kernel Padding	Pool Size	Pool Stride	Pool Type	Accuracy
3	1	0	2	1	Max	0.9400
3	**1**	**0**	**2**	**1**	**Avg**	**0.9800**
3	1	0	2	2	Max	0.6300
3	1	0	2	2	Avg	0.7400
3	1	1	3	1	Max	0.9300
3	1	1	3	1	Avg	0.8900
3	1	1	3	2	Max	0.6800
3	1	1	3	2	Avg	0.5600
3	2	0	2	1	Max	0.6700
3	2	0	2	1	Avg	0.7100
5	**1**	**0**	**3**	**1**	**Max**	**0.9800**
5	1	0	3	1	Avg	0.8900
5	1	0	3	2	Max	0.6400
5	1	0	3	2	Avg	0.5600
5	**1**	**1**	**2**	**1**	**Max**	**0.9800**
5	2	1	3	1	Avg	0.5800
5	2	1	3	2	Max	0.4700
5	2	1	3	2	Avg	0.4100

TABLE I
SUMMARY OF MODEL ACCURACIES WITH DIFFERENT KERNEL AND POOLING PARAMETERS

	Our Model	LMFRNet	Fractional MP	DenseNet
Accuracy	95%	96.7%	96%	96.54%

TABLE II
COMPARISON WITH OTHER MODELS

Metric	Score
Accuracy	0.9500
Precision (Macro)	0.9547
Recall (Macro)	0.9378
F1 Score (Macro)	0.9408

TABLE III
PERFORMANCE METRICS

V. CONCLUSION AND FUTURE WORK

. In this study, we explored the impact of hyperparameter tuning on the performance of a Convolutional Neural Network (CNN) for image classification using a subset of the CIFAR-10 dataset. By experimenting with different convolutional kernel sizes, strides, paddings, and pooling configurations, we observed the optimal set of hyperparameters that achieved the highest classification accuracy. The SE block is lightweight compared to the depth of the network and introduces only a small number of additional parameters, making it a highly efficient way to boost performance without substantial extra cost. Its effectiveness-to-cost ratio is high. We also demonstrated the on-par performance of our model with other state-of-the-art models.

Future research could focus on several areas to improve upon the findings of this study:

- Scaling to Larger Datasets: The performance should be evaluated on the full CIFAR-10 dataset, as well as on other popular datasets such as CIFAR-100 or ImageNet, to assess the model's scalability and generalization capability.
- Automated Hyperparameter Tuning: More efficient methods, such as Bayesian optimization or genetic algorithms, could be employed for hyperparameter search. These methods may reduce the computational overhead compared to brute-force search while potentially finding better configurations.
- Transfer Learning: Leveraging pretrained models such as ResNet or VGG could help improve performance, especially when training on more challenging datasets or when computational resources are limited. Transfer learning has been proven to significantly reduce training time and improve accuracy on tasks where labeled data is sparse.
- Advanced Architectures: Exploring deeper architectures or incorporating advanced techniques like dropout, batch normalization, and residual connections could further enhance model performance and robustness.

In conclusion, the study highlights the importance of hyperparameter tuning in CNNs for image classification and serves as a foundational experiment in developing more complex and efficient models for real-world applications in computer vision.

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