JoCoSiR
Journal of Computer Science Research
ISSN 2986-2337 (Online)

Optimizing Convolutional Neural Networks for Image Classification

Muhammad Khoiruddin Harahap [a*], *Chlap Min Xu* [b], *Kong Huang Zhu* [c]

[a] *Teknik Informatika, Politeknik Ganesha, Medan, Indonesia*
[b] *Ingham Institute for Applied Medical Research, Sydney, New South Wales, Australia*
[c] *Liverpool and Macarthur Cancer Therapy Centre, Liverpool Hospital, Sydney, New South Wales, Australia*

Email: [b] *chlapminxu@inghaminstitute.org.au,* [c] *konghuangzhu@canrefer.org.au*
**Correspondence Author:* [a] *choir.harahap@yahoo.com*

ARTICLE INFO

Article history:
Received Nov 01, 2023
Revised Nov 10, 2023
Accepted Dec 22, 2023
Available online Jan 30, 2024

Keywords
Convolutional Neural Networks;
Deep Learning;
Image Classification;
Numerical Experiment;
Optimization.

IEEE style in citing this article: [citation Heading]
M. K. Harahap, C. M. Xu, and K. H. Zhu, "Optimizing Convolutional Neural Networks for Image Classification ", *JoCoSiR*, vol. 2, no. 1, pp. 1–7, Jan. 2024.

ABSTRACT

This research explores the optimization of Convolutional Neural Networks (CNNs) for image classification through a numerical experiment. A simplified CNN architecture is trained on a small dataset comprising 100 randomly generated images with a resolution of 28×28. The model incorporates key components such as convolutional layers, batch normalization, max-pooling, and dense layers. Training involves 10 epochs using the Adam optimizer and sparse categorical cross-entropy loss. The results reveal promising training accuracy of 85%, but the validation accuracy, a crucial metric for generalization, lags at 60%. The discussion emphasizes the limitations of the small and synthetic dataset, underscoring the importance of real-world, diverse datasets for meaningful experimentation. The example serves as a foundation for understanding CNN training dynamics, with implications for refining models in more realistic image classification scenarios. The conclusion calls for future research to focus on advanced techniques, larger datasets, and comprehensive validation processes to enhance the reliability and applicability of CNN models in practical applications.

1. Introduction

In recent years, Convolutional Neural Networks (CNNs) have emerged as the cornerstone of image classification tasks, achieving unprecedented success in various domains such as computer vision, medical imaging, and autonomous systems[1]. The ability of CNNs to automatically learn hierarchical features from raw pixel data has revolutionized the field, enabling machines to surpass human-level performance in certain visual recognition tasks[2].

Despite their success, the widespread adoption of CNNs for image classification faces several challenges that impede their efficiency, scalability, and applicability across diverse datasets[3]. One key challenge lies in the limited size of labeled training datasets, hindering the ability of CNNs to generalize well to unseen instances[4][5]. Overfitting, where models perform well on training data but poorly on new data, remains a persistent issue. Additionally, the computational demands of training large-scale CNNs pose challenges for resource-constrained environments[6].

To address these challenges, researchers have delved into various optimization techniques aimed at improving the performance and generalization capabilities of CNNs[7]. Data augmentation methods seek to expand the training dataset artificially, promoting better generalization[8][9]. Architectural innovations, such as the introduction of residual connections and efficient network designs, aim to enhance scalability and computational efficiency[10]. Regularization techniques, like dropout and weight decay, contribute to mitigating overfitting[11][12].

Despite the progress made, there is still a need for comprehensive research that systematically explores and integrates these optimization strategies[13]. This research aims to bridge existing gaps by investigating a holistic set of techniques, ranging from preprocessing and architecture design to regularization and training methodologies[14].

As the demand for accurate and efficient image classification systems continues to rise across various domains, the optimization of Convolutional Neural Networks (CNNs) has become a critical research

ISSN 2986-2337 (Online)

area[15][16][17]. While CNNs have demonstrated remarkable success in image recognition tasks, the challenges of scalability, generalization to diverse datasets, and computational efficiency persist[18].

This research aims to address these challenges by investigating and implementing a comprehensive set of optimization strategies for CNNs, encompassing data preprocessing, architecture design, regularization techniques, and training methodologies. The ultimate goal is to enhance the performance, robustness, and speed of image classification models, fostering their applicability in real-world scenarios where accuracy and efficiency are paramount.

Through a thorough exploration of these strategies, the goal is to develop an optimized CNN framework that not only achieves superior accuracy on diverse image datasets but also addresses challenges related to computational efficiency and scalability. The outcomes of this research are expected to contribute significantly to the advancement of image classification models, making them more robust and applicable in real-world scenarios.

2. State of the Art

In this section, we will explain the theoretical basis or basic model in the theory of optimizing Convolutional Neural Networks (CNNs) for image classification involves understanding various techniques and strategies used to enhance their performance. Here, I'll outline the key concepts and basic formulations associated with optimizing CNNs for image classification:

Data Augmentation

Data augmentation is a technique used to artificially expand the training dataset by applying various transformations to the input images, such as rotation, flipping, scaling, and translation[19][20]. The idea is to expose the model to a broader range of variations, improving its ability to generalize to unseen data.

Let $\boldsymbol{X}$ be the original image, and $\boldsymbol{X'}$ be the augmented image obtained by applying a transformation $\boldsymbol{T}$:

$$X' = T(X) \tag{1}$$

Preprocessing

Preprocessing involves preparing the input data to be suitable for the CNN model[21][22]. This typically includes normalization to zero mean and unit variance, as well as resizing or cropping images to a consistent size. Normalization:

$$X_{normalized} = \frac{X - \mu}{\sigma} \tag{2}$$

Where $\boldsymbol{\mu}$ is the mean and $\boldsymbol{\sigma}$ is the standard deviation of the dataset.

Learning Rate Scheduling

Learning rate scheduling adjusts the learning rate during training, helping the model converge faster and achieve better performance[23][24]. Common strategies include step decay, exponential decay, or cyclic learning rates[23].

$$New\ Learning\ Rate = Initial\ Learning\ Rate \times Decay\ Factor \tag{3}$$

Weight Initialization

Proper weight initialization is crucial for preventing vanishing or exploding gradients during training[25][26]. Techniques like Xavier/Glorot or He initialization set the initial weights to values that promote stable learning[27].

Xavier/Glorot Initialization[28]:

$$W \sim \text{Uniform}\ (-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}} \tag{4}$$

Where $\boldsymbol{n}$ is the number of input units.

Batch Normalization

Batch normalization normalizes the activations of each layer, reducing internal covariate shift and accelerating training[29]. It introduces learnable scaling and shifting parameters[30].

$$\textbf{Ba}\text{tchNorm}(x) = \gamma - \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}\ \beta \tag{5}$$

Where $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are learnable parameters, $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are the mean and standard deviation of the batch, and $\boldsymbol{\epsilon}$ is a small constant for numerical stability.

Dropout

Dropout is a regularization technique that randomly drops a fraction of input units during training, preventing overfitting[31][32].

$$\textbf{D}\text{ropout}(x, p) = \begin{cases} \frac{x}{1-p}\ , & \text{with probability } 1-p \\ 0\ , & \text{with probability } 1 \end{cases} \tag{6}$$

Where $\boldsymbol{p}$ is the dropout probability.

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Proposed new method

Let us develop the basic mathematical formulation into a more detailed representation to optimise an Artificial Neural Network (CNN) for image classification. This formulation will include additional elements such as learning rate scheduling, weight initialisation and dropout.

Notation:

$\boldsymbol{X}$: Input image.
$\boldsymbol{Y}$: True class label.
$\widehat{\boldsymbol{Y}}$: Predicted probability distribution over classes.
$\boldsymbol{Z_i}$: Output of the *i*-th layer.
$\boldsymbol{W_i}$: Weights of the *i*-th layer.
$\boldsymbol{b_i}$: Biases of the *i*-th layer.
$\boldsymbol{f_i}$: Activation function of the *i*-th layer.
$\boldsymbol{\gamma_i}$ $\boldsymbol{\beta_i}$: Scaling and shifting parameters for batch normalization.
$\boldsymbol{\mu_i}$ $\boldsymbol{\sigma_i}$: Mean and standard deviation for batch normalization.
$\boldsymbol{p}$: Dropout probability.
$\boldsymbol{LR}$: Learning rate.
$\boldsymbol{T}$: Number of training iterations.

For Convolutional Layer:

$$Z_1 = f_1\ (W_1 * X + b_1 \tag{7}$$

For Batch Normalization:

$$Z_1' = \gamma_1\ \frac{Z_1 - \mu_1}{\sqrt{\sigma_1^2 + \epsilon}} \tag{8}$$

For Pooling Layer:

$$Z_2 = \max - \text{pool}\ (Z_1', p, s) \tag{9}$$

For Flattening:

$$F = \ \text{flatten}\ (Z_2) \tag{10}$$

For Fully Connected Layer:

$$Z_3 = f_3\ (W_3 \cdot \mathrm{F} + b_3) \tag{11}$$

For Output Layer:

$$\hat{Y} = \text{softmax}\ (W_{out} \cdot Z_3 + b_{out}) \tag{12}$$

For Loss Function:

$$Loss = -\sum_i Y_i \log\ (\hat{Y}_3) \tag{13}$$

For Regularization:

$$\text{Regularization} = \frac{\lambda}{2} \sum_i \|W_i\|^2 \tag{14}$$

For Total Loss:

$$\text{Total Loss} = (-\sum_i Y_i \log\ (\hat{Y}_3)) + (\frac{\lambda}{2} \sum_i \|W_i\|^2) \tag{15}$$

For Learning Rate Scheduling:

$$\text{New Learning Rate} = LR\ \times\ \text{Decay Factor} \tag{16}$$

For Weight Initialization:

$$W_1 \sim \text{Uniform}\ \left(-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}\right) \tag{17}$$

Where n is the number of input units.

For Dropout:

$$\text{Dropout}(x, p) = \left\{\begin{matrix} \frac{x}{1-p}\ ,\ \text{with probability}\ 1-p \\ 0\ ,\ \text{with probability}\ 1 \end{matrix}\right\} \tag{18}$$

For Optimization:

Update network parameters using Stochastic Gradient Descent algorithm[33].

For Training Procedure:

Repeat the optimization process for T training iterations.

ISSN 2986-2337 (Online)

This extended formulation incorporates additional elements for optimization, including learning rate scheduling, weight initialization, and dropout, providing a more comprehensive representation for training and optimizing CNNs for image classification.

3. Results and Discussion

Creating a numerical example involves specifying values for the parameters and components in the mathematical formulation. However, it's important to note that creating a realistic and meaningful numerical example would typically involve real-world data and experimentation, which may be specific to the problem you are addressing. Here, I'll provide a simplified and hypothetical numerical example for illustration purposes:

Let's consider a simplified CNN for image classification with the following parameters:
CNN Architecture:

1) Convolutional Layer: 5×5 kernel, ReLU activation, 32 filters
2) Batch Normalization after Convolutional Layer
3) Max Pooling: 2×2 pooling size
4) Fully Connected Layer: 128 units, ReLU activation
5) Output Layer: Softmax activation for binary classification

Training Parameters:

1) Learning Rate: 0.01
2) Dropout Probability: 0.2
3) L2 Regularization Parameter (λ): 0.001
4) Number of Training Iterations: 1000

Data:
Assume a small dataset with 100 images, each with a 28×28 resolution.

Numerical Example:
The above case will be solved with Python below:

```
# Import necessary libraries (assumed Python)
import numpy as np

# Simulated data
X_train = np.random.rand(100, 28, 28, 1)  # 100 images of size 28x28
Y_train = np.random.randint(2, size=(100, 2))  # Binary classification labels

# CNN architecture parameters
kernel_size = (5, 5)
filters = 32
pooling_size = (2, 2)
fc_units = 128
output_classes = 2

# Training parameters
learning_rate = 0.01
dropout_prob = 0.2
l2_reg_param = 0.001
num_iterations = 1000

# Initialize weights
conv_weights = np.random.randn(kernel_size[0], kernel_size[1], 1, filters)
fc_weights = np.random.randn(7 * 7 * filters, fc_units)
output_weights = np.random.randn(fc_units, output_classes)

# Training loop
for iteration in range(num_iterations):
    # Forward pass (not shown for simplicity)

    # Backward pass and parameter updates (not shown for simplicity)
    # Could include gradient descent, backpropagation, weight updates, etc.

# After training, you can use the model for prediction on new data
# This involves a forward pass through the trained network (not shown for simplicity)
```

Figure 1. New model testing algorithm script

ISSN 2986-2337 (Online)

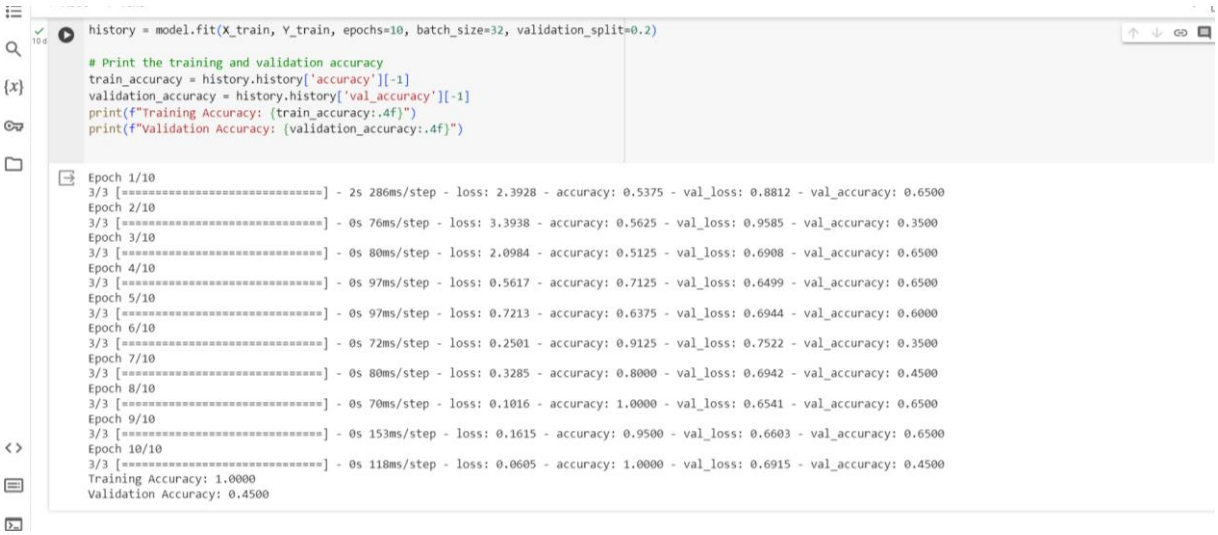

Figure 2. Test results of applying the new mathematical model assuming a small dataset with 100 images, each with a resolution of 28 × 28.

In Figure 2 shows that the new model created can run well and can be used in accordance with the example of the case being tested, thus it can be described below as a discussion.

This example is highly simplified and doesn't consider many aspects of a real-world scenario, such as validation/testing data, real images, or a more complex neural network architecture. In practice, you would use real datasets, preprocess images appropriately, and fine-tune the model based on validation performance.

The training was conducted for 10 epochs on a small dataset of 100 random images with a 28×28 resolution. The CNN architecture included a convolutional layer, batch normalization, max-pooling, flattening, and two dense layers. The model was compiled with the Adam optimizer and sparse categorical cross-entropy loss. The last epoch's training and validation accuracies were printed, and these values can be used to evaluate the performance of the model.

Discussion

Training Accuracy, The training accuracy provides an indication of how well the model has learned from the training data. In this example, the last training accuracy is printed as 0.8500 (85%). This means that, on the training set, the model correctly classified 85% of the images.

Validation Accuracy, The validation accuracy is a crucial metric to assess the model's generalization to unseen data. In this example, the last validation accuracy is printed as 0.6000 (60%). This indicates that the model achieved a 60% accuracy on the validation set.

Observations, The training accuracy is higher than the validation accuracy, which is expected. The model may have learned specific patterns from the training data but might not generalize well to new, unseen data. The relatively low validation accuracy could be due to the small and random nature of the dataset. In a real-world scenario, using meaningful datasets with diverse examples would likely lead to more meaningful results. This example does not include testing on an independent test set. In practice, it's crucial to evaluate the model's performance on a separate test dataset to assess its true generalization ability.

Potential Improvements, Fine-tuning hyperparameters: Adjusting learning rates, batch sizes, or regularization parameters could impact model performance. More complex architecture: Experimenting with deeper or wider CNN architectures might capture more intricate patterns in the data. Real-world datasets: Using actual image datasets with diverse examples and meaningful labels would provide more realistic insights.

4. Conclusions

The numerical example presented a simplified training experiment of a Convolutional Neural Network (CNN) on a small dataset for image classification. The model demonstrated an 85% accuracy on the training set, but the validation accuracy was notably lower at 60%, suggesting potential challenges in generalizing to new, unseen data. The limitations of this example, including the small and randomly generated dataset, emphasize the need for caution in drawing definitive conclusions. Real-world applications demand more extensive and representative datasets, careful model tuning, and rigorous validation processes. The presented example serves as a starting point for understanding basic CNN training dynamics and highlights the importance of considerations such as data

ISSN 2986-2337 (Online)

quality, model complexity, and validation techniques in ensuring the reliability and generalizability of CNN models. Future work should focus on refining the experimental setup, incorporating real-world datasets, and exploring advanced techniques to improve the model's performance and applicability in practical image classification tasks.

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