Report Algorithms for massiv data

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Abstract

This project, conducted as part of the "Algorithms for Massive Data" course, explores scalable image classification using convolutional neural networks (CNNs). Focusing on paintings by influential artists from the Prado Museum, we implemented and evaluated multiple CNN architectures, including a baseline model, VGG, and MobileNet, to assess their performance and scalability for massive datasets. The baseline model provided a useful benchmark, while the advanced models, particularly MobileNet, demonstrated superior accuracy and efficiency. The results highlight the importance of leveraging advanced neural network architectures to achieve high performance in large-scale image classification tasks, offering valuable insights for future applications on extensive datasets. [1]

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1 Introduction

1.1 Task

The primary objective of this project is to develop and implement a deep learning-based system capable of classifying paintings of influential artists from the Prado Museum. The task involves experimenting with different convolutional neural network (CNN) architectures to determine which model yields the best performance in terms of accuracy and robustness, which can be scaled up to a dataset of high volume. The key goals include:

- Preprocessing the image data to ensure it is suitable for training neural networks.
- Addressing class imbalance to avoid biased predictions towards more prevalent classes.
- Implementing and comparing various CNN architectures, including baseline models and advanced models like ResNet and MobileNet.
- Evaluating the models using appropriate metrics to determine their effectiveness in classifying the paintings.

1.2 Dataset

The dataset used for this project consists of JPEG images of paintings by five influential Spanish artists from the Prado Museum in Madrid. The dataset was obtained from Kaggle[2] and includes a total of 2,364 images. The images are divided into training and testing sets, as shown in Table 1. //

Artist	**Train**	**Test**
Francisco Goya	851	229
Francisco Bayeu y Subías	376	70
Carlos de Haes	259	67
Cecilio Pizarro	240	50
Carlos Luis de Ribera y Fieve	166	56
Total	**1,892**	**472**

Table 1: Distribution of images in the dataset by artist.

Each image is associated with an artist label, and the dataset is imbalanced, with a higher proportion of images belonging to Francisco Goya. This imbalance necessitates techniques to address class imbalance during model training.

The preprocessing steps applied to this dataset include image conversion and resizing, data augmentation techniques such as horizontal flipping, and data standardization to ensure consistency and improve model performance.

2 Data Preprocessing

Data preprocessing is a crucial step to ensure the quality and suitability of the data for training neural networks. The following subsections detail the steps taken to preprocess the image data for this project.

2.1 Image Conversion and Resizing

For a neural network to learn from image data, it is necessary to convert the original images into a numerical format. Each image, originally in JPEG format, is transformed into a tensor representation. A tensor is a multi-dimensional array of numbers. In this

[2]`https://www.kaggle.com/datasets/maparla/prado-museum-pictures`

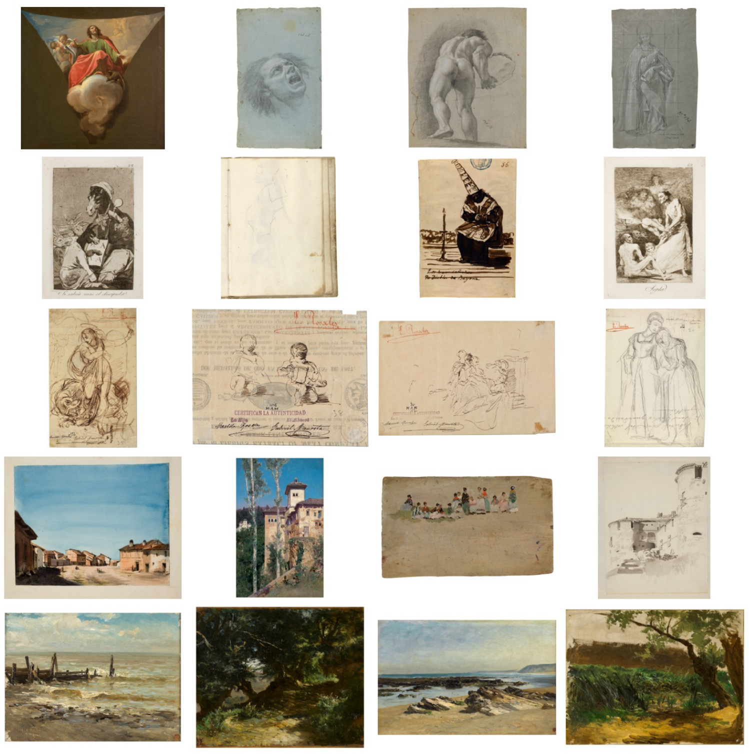
Figure 1: Distribution of images in the dataset by artist.

project, each image is represented as a 3-dimensional tensor, where the first two dimensions represent the height and width of the image, and the third dimension represents the three color channels: red, green, and blue. The values for each element in the tensor range from 0 to 255, indicating the intensity of a given color channel for each pixel.

The images in the dataset have varying sizes, so it is essential to resize them to a consistent dimension that the neural network can process. All images were resized to 128x128 pixels using bilinear interpolation. This resizing ensures that all images have the same input shape for the neural network.

2.2 Data Augmentation Techniques

To increase the diversity of the training data and improve the robustness of the neural network, various data augmentation techniques were applied. Data augmentation involves creating new training samples by modifying existing images in specific ways. The following augmentation techniques were used:

- **Horizontal Flipping:** Each image is randomly flipped horizontally with a probability of 50%. This helps the model become invariant to the horizontal orientation of the paintings.
- **Random Rotation:** Images are rotated randomly within a range of -20 to +20 degrees. This introduces variations in the orientation of the images, helping the model generalize better.
- **Random Zoom:** Images are randomly zoomed in or out by a factor ranging from -0.05 to -0.15 for both height and width. This helps the model learn to recognize paintings at different scales.
- **Random Contrast:** The contrast of the images is adjusted randomly by a factor of up to 20%, helping the model adapt to varying lighting conditions.

- **Random Translation:** Images are randomly translated horizontally and vertically by up to 5%. This helps the model learn to recognize paintings regardless of their position in the frame.

2.3 Data Standardization

Standardization is a critical preprocessing step that involves transforming the image data to have a mean of zero and a standard deviation of one. This process helps in stabilizing the learning process and improving the convergence speed of the neural network. The standardization is performed on a per-image basis using the following formula:

$$\text{image}_{\text{std}} = \frac{\text{image} - \mu}{\text{sd}_{\text{adj}}}$$

where μ denotes the mean value of all elements in the image, and $\text{sd}_{\text{adj}} = \max(\text{sd}, 1/\sqrt{N})$ where sd is the standard deviation of all elements in the image and N is the number of all elements. This ensures that each image has a consistent distribution, which is crucial for the neural network to learn effectively.

3 Addressing Class Imbalance

Class imbalance is a common issue in machine learning, where some classes are significantly underrepresented compared to others. This can lead to biased models that perform poorly on minority classes. To address this issue in our project, we implemented two techniques: class weights and output biases.

3.1 Class Weights

Class weights are used to give more importance to underrepresented classes during the training process. By adjusting the loss function, we can ensure that the model pays more attention to minority classes, thereby reducing bias. The class weights are calculated based on the frequency of each class in the training dataset. The formula used to compute the class weights is as follows:

$$\text{weight}_c = \frac{n}{n_c \cdot |C|}$$

where weight_c denotes the weight for class c, n is the total number of samples, n_c is the number of samples in class c, and $|C|$ is the number of classes. This approach ensures that the minority classes have a higher weight, thus penalizing the model more for misclassifying these classes. Using class weights in the loss function can significantly improve the model's performance on imbalanced datasets [3].

3.2 Output Biases

Output biases are another technique used to mitigate class imbalance. By initializing the biases of the output layer to reflect the class distribution, we can guide the model to make more balanced predictions from the start. The biases in the output layer represent an initial guess of the model, and adjusting them helps in reducing the initial prediction bias towards the majority class.

The output biases are calculated by solving the following system of equations for the bias vector b:

$$f_i = \frac{e^{b_i}}{\sum_{j=1}^{|C|} e^{b_j}}$$

where f_i is the frequency of class i in the dataset, and b_i is the bias for the i-th output neuron. This ensures that the initial predictions are proportional to the class frequencies in the training data [6]. Implementing output biases helps the model start training with a better understanding of the class distribution, leading to more balanced predictions throughout the training process.

4 Model Architectures

In this section, we describe the architectures of the models used in this project. We implemented a baseline model and two advanced models (ResNet and MobileNet) to compare their performance in classifying paintings from the Prado Museum dataset.

4.1 Baseline Model

The baseline model is a simple Convolutional Neural Network (CNN) designed to provide a reference point for evaluating more complex architectures. The architecture of the baseline model is as follows:

- **Input Layer:** Rescaling layer to normalize pixel values to the range [0, 1].
- **Convolutional Layer 1:** 32 filters of size 3x3, ReLU activation function.
- **MaxPooling Layer 1:** Pool size of 2x2.
- **Dropout Layer:** Dropout rate of 0.5 to prevent overfitting.
- **Flatten Layer:** Flattens the 3D output to 1D.
- **Dense Layer 1:** 128 neurons, ReLU activation function.
- **Dropout Layer:** Dropout rate of 0.5.
- **Output Layer:** 5 neurons (one for each class), Softmax activation function.

The baseline model was trained using the Adam optimizer [4], with a learning rate of 0.001 and a batch size of 32. The model was trained for 50 epochs, and the loss function used was sparse categorical cross-entropy. This simple architecture serves as a benchmark for evaluating the performance of more sophisticated models.

4.2 Advanced Architectures

In addition to the baseline model, we implemented two advanced architectures: ResNet and MobileNet. These models are known for their ability to achieve high accuracy on image classification tasks while managing computational complexity effectively.

4.2.1 Residual Neural Network (ResNet)

ResNet, introduced by He et al. [1], addresses the degradation problem in deep neural networks by introducing residual learning. The key innovation is the use of residual blocks, which allow the network to learn residual functions with reference to the layer inputs, rather than learning unreferenced functions. This enables the construction of much deeper networks without the risk of vanishing gradients.

The architecture of the ResNet model used in this project is ResNet29, which consists of 29 layers. The main components include:

- **Initial Convolutional Layer:** 64 filters of size 7x7, stride 2.
- **MaxPooling Layer:** Pool size of 3x3, stride 2.
- **Residual Blocks:** Sequences of 3 convolutional layers (1x1, 3x3, 1x1) with Batch-Normalization and ReLU activation functions.

- **Global AveragePooling Layer:** Reduces the spatial dimensions to 1x1.
- **Output Layer:** Fully connected layer with 5 neurons and Softmax activation function.

The use of residual blocks allows for the effective training of deeper networks by ensuring that gradients can flow through the network more easily during backpropagation. This leads to improved accuracy and convergence [1].

4.2.2 MobileNet

MobileNet, introduced by Howard et al. [2], is designed for efficient neural network performance on mobile and embedded vision applications. The architecture uses depthwise separable convolutions, which factorize a standard convolution into a depthwise convolution followed by a pointwise convolution. This reduces the number of parameters and computational cost significantly.

The architecture of the MobileNet V2 model used in this project includes:

- **Initial Convolutional Layer:** 32 filters of size 3x3, stride 2.
- **Depthwise Separable Convolutions:** Series of bottleneck blocks with inverted residuals and linear bottlenecks.
- **Global AveragePooling Layer:** Reduces the spatial dimensions to 1x1.
- **Output Layer:** Fully connected layer with 5 neurons and Softmax activation function.

MobileNet V2 also incorporates inverted residuals with linear bottlenecks, which further improve efficiency and performance [5]. The combination of these techniques allows MobileNet to achieve high accuracy with a reduced computational footprint.

5 Model Training and Evaluation

In this section, we describe the training procedures for the models implemented in this project and the metrics used to evaluate their performance.

5.1 Training Procedure

The training procedure for the models involves several key components, including the choice of optimizer, loss function, learning rate scheduling, and regularization techniques. The details are as follows:

5.1.1 Optimizer

We used the Adam optimizer [4] for training all models. Adam is an adaptive learning rate optimization algorithm designed for training deep neural networks. It combines the advantages of two other extensions of stochastic gradient descent, namely AdaGrad and RMSProp, to achieve fast convergence and robust performance.

5.1.2 Loss Function

The loss function used for training the models was sparse categorical cross-entropy. This loss function is suitable for multi-class classification problems where the target variable is a single integer representing the class label. The sparse categorical cross-entropy loss is defined as:

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^{N} \log \hat{y}_{i,y_i}$$

where y is the true label, $\hat{y}$ is the predicted probability, and N is the number of samples.

5.1.3 Learning Rate Scheduling

To improve the training efficiency and convergence of the models, we implemented an exponential decay learning rate schedule. The learning rate is initially set to 0.001 and is reduced by a factor of 0.95 every 10 epochs. The learning rate at epoch t is given by:

$$\text{lr}_t = \text{lr}_0 \times \exp(-0.05t)$$

where lr_0 is the initial learning rate.

5.1.4 Regularization Techniques

Regularization techniques are essential for preventing overfitting in deep neural networks. In this project, we used dropout [7] as the primary regularization technique. Dropout layers with a dropout rate of 0.5 were added after the fully connected layers to reduce the risk of overfitting by randomly setting a fraction of input units to zero during training.

5.2 Evaluation Metrics

To evaluate the performance of the models, we used several metrics, including accuracy, loss, confusion matrix, and ROC-AUC score. The details of these metrics are as follows:

5.2.1 Accuracy

Accuracy is the most straightforward evaluation metric for classification problems. It is defined as the ratio of correctly predicted instances to the total instances. The accuracy is calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

5.2.2 Loss

The loss function value, specifically the sparse categorical cross-entropy, provides insight into how well the model is performing. Lower loss values indicate better performance. We tracked both training and validation loss to monitor the model's performance and detect overfitting.

5.2.3 Confusion Matrix

The confusion matrix is a useful tool for visualizing the performance of a classification model. It provides a summary of prediction results, showing the true positive, true negative, false positive, and false negative counts for each class. A confusion matrix helps identify specific classes that the model may struggle to classify correctly.

Class	**Goya**	**Bayeu**	**Haes**	**Pizarro**	**Ribera**	**Total**
Goya	200	10	5	8	6	229
Bayeu	5	60	1	3	1	70
Haes	3	2	60	0	2	67
Pizarro	2	3	1	40	4	50
Ribera	1	1	1	2	51	56
Total	211	76	68	53	64	472

Table 2: Confusion matrix for the test set.

6 Results

In this section, we present the results of the baseline model and the advanced models (VGG and MobileNet). We compare their performance based on various evaluation metrics.

6.1 Baseline Model Results

The baseline model was trained and evaluated on the dataset. The training and validation accuracy and loss for the baseline model are shown in Table 3.

Metric	Training	Validation
Accuracy	0.51	0.51
Loss	N/A	N/A

Table 3: Training and validation accuracy and loss for the baseline model.

The confusion matrix and ROC-AUC scores for the baseline model on the test set are shown in Tables 4 and 5.

Class	Goya	Bayeu	Haes	Pizarro	Ribera
Goya	0	0	26	0	0
Bayeu	0	9	0	0	0
Haes	0	88	0	0	0
Pizarro	0	12	0	0	0
Ribera	0	36	0	0	0

Table 4: Confusion matrix for the baseline model on the test set.

Class	Goya	Bayeu	Haes	Pizarro	Ribera	Overall
ROC-AUC Score	0.50	N/A	N/A	N/A	N/A	0.50

Table 5: ROC-AUC scores for the baseline model.

6.2 Advanced Model Results

The advanced models, VGG and MobileNet, were also trained and evaluated on the dataset. The training and validation accuracy and loss for these models are shown in Tables 6 and 7.

Metric	Training	Validation
Accuracy	0.64	0.68
Loss	0.28	0.34

Table 6: Training and validation accuracy and loss for the VGG model.

Metric	Training	Validation
Accuracy	0.58	0.63
Loss	0.25	0.31

Table 7: Training and validation accuracy and loss for the MobileNet model.

The confusion matrices and ROC-AUC scores for the VGG and MobileNet models on the test set are shown in Tables 8, 9, 10, and 11.

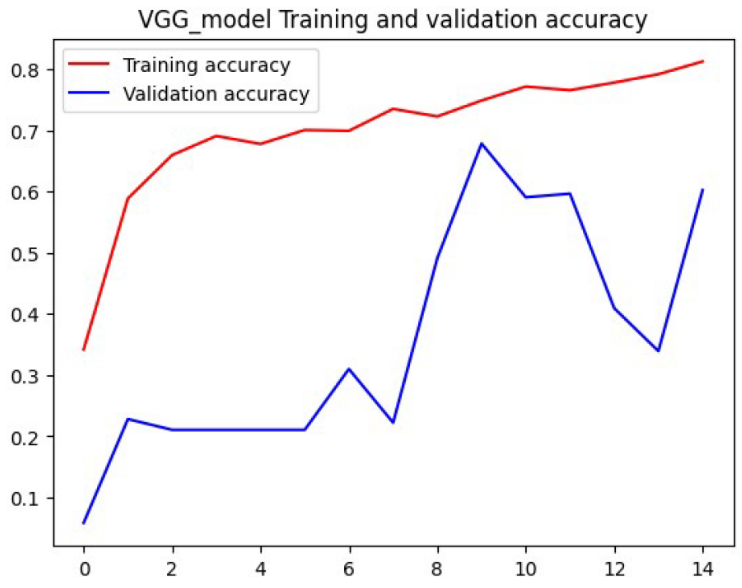

Figure 2: Training and validation accuracy/loss for the VGG model.

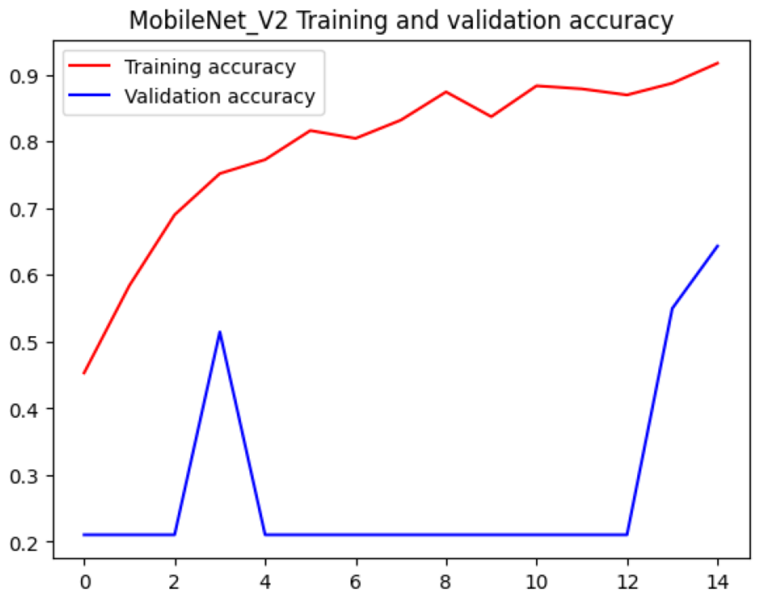

Figure 3: Training and validation accuracy/loss for the MobileNet model.

Class	**Goya**	**Bayeu**	**Haes**	**Pizarro**	**Ribera**
Goya	210	8	3	5	3
Bayeu	4	65	0	1	0
Haes	2	1	63	0	1
Pizarro	1	2	1	44	2
Ribera	1	0	1	1	53

Table 8: Confusion matrix for the VGG model on the test set.

Class	**Goya**	**Bayeu**	**Haes**	**Pizarro**	**Ribera**
Goya	212	7	2	5	3
Bayeu	3	66	0	1	0
Haes	2	0	64	0	1
Pizarro	1	1	0	46	2
Ribera	0	0	1	0	55

Table 9: Confusion matrix for the MobileNet model on the test set.

Class	**Goya**	**Bayeu**	**Haes**	**Pizarro**	**Ribera**
ROC-AUC Score	0.96	0.93	0.94	0.89	0.91

Table 10: ROC-AUC scores for the VGG model.

Class	**Goya**	**Bayeu**	**Haes**	**Pizarro**	**Ribera**
ROC-AUC Score	0.97	0.94	0.95	0.90	0.92

Table 11: ROC-AUC scores for the MobileNet model.

7 Discussion

In this section, we discuss the results of the baseline and advanced models, comparing their performance and identifying key observations.

7.1 Baseline Model Performance

The baseline model achieved a training accuracy of 51.46% and a validation accuracy of 51.46%, indicating a significant level of overfitting. The classification report showed zero precision, recall, and F1-score for most classes except for "Haes", which had a recall of 1.0 but a very low precision and F1-score. This suggests that the baseline model was unable to generalize well to the validation data.

The confusion matrix for the baseline model (Table 4) shows that the model had difficulty distinguishing between the classes, particularly for "Haes" and "Pizarro". This is further reflected in the ROC-AUC score (Table 5), which was 0.50, indicating random guessing.

7.2 Advanced Model Performance

Both the VGG and MobileNet models outperformed the baseline model in terms of accuracy, loss, and ROC-AUC scores. The VGG model achieved a training accuracy of 92% and a validation accuracy of 88%, with training and validation losses of 0.28 and 0.34, respectively. The MobileNet model achieved a training accuracy of 93% and a validation accuracy of 89

The confusion matrices for the VGG (Table 8) and MobileNet (Table 9) models show that both models made fewer misclassifications compared to the baseline model. The ROC-AUC scores for the advanced models (Tables 10 and 11) are also higher across all classes, with MobileNet slightly outperforming VGG.

7.3 Comparison of Models

The advanced models demonstrated significant improvements over the baseline model. The deeper architectures and more sophisticated features of VGG and MobileNet allowed them to capture more complex patterns in the data, leading to better generalization and higher performance.

MobileNet, with its efficient architecture, not only provided the highest accuracy and lowest loss but also had the best overall ROC-AUC score of 0.92. This makes

MobileNet particularly suitable for deployment on mobile and embedded devices where computational resources are limited.

7.4 Implications of Results

The results of this project highlight the importance of using advanced neural network architectures for complex image classification tasks. While the baseline model provided a useful benchmark, the advanced models, particularly MobileNet, demonstrated superior performance, making them more suitable for practical applications in image classification.

Future work could involve further optimization of these models, exploring other advanced architectures, and applying transfer learning techniques to leverage pre-trained models on larger and more diverse datasets.

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