Sport Detection In ResNet50 And Video Processing In PyTorch

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Abstract

The goal of this project is to develop a powerful implementation for detecting sports in videos using the ResNet50 algorithm. Our approach uses a stochastic gradient descent (SGD) optimization algorithm to train the model on a large set of images. The goal is to create a robust and efficient sports detection model capable of accurately identifying different sports activities in a real-time video stream.

The ResNet50 algorithm, known for its depth and excellent feature extraction ability, serves as the backbone of the sports detection model. The models are trained using the SGD optimization algorithm, which can handle large data sets and efficiently minimize the loss function using huge image sets.

Once trained, the models are used to process video sequences in real time to detect and classify various sports activities. The proposed application has great potential for various applications such as sports analysis, automatic content labeling and real-time event recognition.

Through rigorous testing and fine-tuning, we hope to achieve state-of-the-art performance in sports activity detection and ensure the accuracy and effectiveness of the model in practical scenarios. This project is an important step toward the implementation of AI-based sports activity detection solutions that can be seamlessly integrated into various video systems and applications.

1 Introduction

This paper presents a comprehensive validation of a sport classification model trained with Torch. Our goal is to develop a state-of-the-art system that can accurately identify different sports activities in videos. With the growing popularity of sports content and the increasing need for automated analysis, such models are highly valuable for various applications.

Our model is based on the ResNet50 architecture, a deep convolutional neural network known for its excellent performance in image recognition tasks. Our model uses pre-trained ResNet50 weights from a wide variety of image datasets to access and build upon learned features for sport-specific recognition. By enhancing the model with our extended sports image dataset, you can specialize in discriminating different sports activities.

Our sports image dataset is an important part of this research, covering a wide range of sports, from team sports such as football, basketball and baseball to individual sports such as tennis, swimming and athletics. Thanks to the diversity of the data set, the model achieves high accuracy and is effectively generalised across different sports.

To optimize the performance of the model, a stochastic gradient descent (SGD) algorithm is used in the training process; SGD's ability to handle large datasets and update model parameters efficiently ensures that the sport classification model converges to an optimal solution for accurate detection. This is guaranteed.

Our model implementation is publicly available on GitHub : Source-code, providing researchers and practitioners with a valuable resource for reproducibility and new advances in sport detection. We also hope to facilitate research collaboration and encourage the use of our model in other relevant applications.

In this paper, we describe in detail the steps of data preprocessing, model architecture and hyperparameter tuning. We also present detailed experimental results and performance analyses to demonstrate the effectiveness of our sports classification model in real-world situations.

Our contribution to this study is multifaceted. First, we propose a robust and accurate sports detection model that can enhance various video-based applications such as sports analysis and content indexing. Second, we believe that the release of a large database of sports images can facilitate research and progress in sports recognition. Finally, we aim to create a collaborative environment for the advancement of sports recognition techniques and enable the wider research community to publish our applications.

In the following sections, we present a comprehensive validation of our methods, experiments and results to further confirm the potential power of our sport classification model. We believe our research is an important step towards effective real-time sports recognition and offers exciting opportunities for sports fans, broadcasters and content producers.

2 Data Cleaning

Our data is a bunch of images, our first problem is to transform the data from **pixels** to **tensors** in order to simplify the processing.

2.1 Filtering Images

The image is a 3D images (matrix of shape like $(x, y, 3)$) , first we need to extract the data from the dataset using **openCv** package, we need first to convert the image from BGR which is extracted by **openCv** to RGB , after we need to normalize all the shapes of images, from $(x, y, 3)$ to $(244, 244, 3)$.

Algorithm 1 Load and Preprocess Images

```
Initialize Sport_Labels as the set {boxing, swimming, table_tennis}
datapath ← '../data'
pathToImages ← ListPaths(datapath)
Initialize an empty list data
Initialize an empty list labels
for each image_path in pathToImages do
    label ← Split(image_path, os.path.sep)[-2]
    if label not in Sport_Labels then
        Continue to the next iteration
    end if
    image ← ReadImage(image_path)
    image ← ConvertToRGB(image)
    image ← ResizeImage(image, 244, 244)
    Append image to the list data
    Append label to the list labels
end for
End For
```

2.2 Converting The Result To Ndarray and Tensors

After getting the **images matrixes**, we need to convert them into **Ndarray** for example **NumPy** in python, for two main reasons :

1. **NumPy** arrays are so soft, easy, and simple to manipulate.
2. We will convert **NumPy** arrays into **Torch tensors** easily.

Algorithm 2 Data Processing

```
data ← np.array(data)
labels ← np.array(labels)
lb ← label_binarize(labels, classes=list(Sport_Labels))
class_labels ← list(Sport_Labels)                    ▷ Store the class labels separately
labels ← torch.tensor(lb, dtype=torch.float32)       ▷ Convert the labels to float
```

In the final result, we need to have two **data structures** : a list of images tensors and a list o labels of each bunch of images. By the end we have a **tensors variables**, so we can use **Torch** framework.

2.3 Splitting The Data For Training And Testing

In this step, we will split the data into **train set** and **test set**, we will use 25% of the **data** as **test set** and 75% of **data** as **train set**.

Algorithm 3 Train-Test Split

$X\_train, X\_test, Y\_train, Y\_test \leftarrow$ train_test_split(data, labels, test_size=0.25, stratify=labels, random_state=42)

3 Normalizing The Data

3.1 Data transformations

Data transformations are essential for improving the performance and robustness of machine learning models. By applying various random augmentations to the training data, the model learns to be more invariant to certain changes and generalizes better to unseen data. This reduces overfitting and helps the model achieve better accuracy on the test data. Using the **transforms** module in PyTorch makes it easy to create and apply these transformations efficiently during the data loading process. and we will use the same thing for the **test set**.

Algorithm 4 Train Transformation Pipeline

```
train_transform ← Compose([
    ToPILImage(),
    RandomRotation(30),
    RandomHorizontalFlip(),
    RandomVerticalFlip(),
    ToTensor(),
    Normalize(mean=[123.68/255.0, 116.779/255.0, 103.939/255.0], std=[1, 1, 1]),
    ])
```

3.2 Custom Dataset class

The Custom Dataset class is designed to create a custom dataset that can be used with PyTorch's Data Loader, which is an essential utility for efficient data loading during training or evaluation of machine learning models. By implementing the **len** and **getitem** methods, the class becomes iterable, allowing PyTorch's data loaders to access individual samples and process them on-the-fly as needed.

The class takes in two main inputs: images and labels. The images parameter represents the input data, typically a collection of images, while the labels parameter contains the corresponding target labels or classes for each image.

Additionally, the class has an optional transform parameter that allows you to pass a data transformation pipeline. This pipeline applies various image transformations or preprocessing steps to the input images before returning them during data loading. These transformations can include resizing, data augmentation (e.g., rotation, flipping), normalization, and more.

- Implementing **len()** and **getitem()**:

The **len** method is implemented to return the length of the dataset, which corresponds to the total number of samples in the dataset. This enables the use of Python's built-in **len()** function to retrieve the number of samples.

The **getitem** method allows accessing individual samples in the dataset by providing an index idx. It retrieves the image and its corresponding label at the specified index. If a data transformation pipeline (self.transform) is provided, it applies the transformations to the image before returning it along with the label. This ensures that the data is processed on-the-fly during data loading, avoiding the need to preprocess the entire dataset before training.

- Integration with PyTorch DataLoader:

Once the CustomDataset class is defined, you can use it with PyTorch's DataLoader to efficiently load and process the data during training. The DataLoader handles batch creation, shuffling, and parallel data loading, which are crucial for training deep learning models effectively.

Algorithm 5 CustomDataset Class

```
class CustomDataset(Dataset):
    def __init__(self, images, labels, transform=None):
        self.images ← images
        self.labels ← labels
        self.transform ← transform

    def __len__(self):
        return len(self.images)

    def __getitem__(self, idx):
        image ← self.images[idx]
        label ← self.labels[idx]
        if self.transform:
            image ← self.transform(image)
        return image, label
```

4 Creation Of The Convolutional Neural Network

4.1 Creation Of Deep Learning Model

The **ResNetModel** is a custom neural network architecture designed for image classification tasks. It is built upon the popular ResNet-50 model, a deep convolutional neural network known for its effectiveness in computer vision tasks. The custom model leverages the pre-trained weights of the ResNet-50 to extract powerful image features and then adapts it for the specific classification task.

4.2 Model Architecture

- **Forward Pass :** During the forward pass, an input image is fed into the **ResNetModel**. The image then passes through the base **ResNet-50** model to extract image features. The output of the base model contains high-level feature representations of the input image.
- **Custom Classification Head:** The extracted image features are then fed into the custom classification head, consisting of three layers:
  - A **fully connected layer** reduces the feature dimensions to 512, which acts as a bottleneck layer.
  - A **ReLU activation function** introduces non-linearity, allowing the model to learn complex relationships between features.
  - A **dropout layer** with a dropout rate of 0.5 randomly sets half of the neuron outputs to zero during training. This technique helps prevent overfitting by introducing robustness in the model's predictions.
- **Final Output:** The output of the custom classification head is a 1D tensor representing the predicted class probabilities for each input image. The tensor has a size of **numClasses**, where **numClasses** corresponds to the number of output classes required for the specific image classification task.

Algorithm 6 ResNetModel: Custom ResNet-Based Neural Network

```
class ResNetModel(nn.Module):
    def __init__(self, num_classes):    super(ResNetModel, self).__init__()
        self.base_model ← resnet50(pretrained=True)
        in_features ← self.base_model.fc.in_features
        self.base_model.fc ← nn.Identity()
        self.fc ← nn.Sequential(
            nn.Linear(in_features, 512),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(512, num_classes)
            )

    def forward(self, x):
        features ← self.base_model(x)
        out ← self.fc(features)
        return out
```

4.3 Approach Of Training

4.4 Optimizer

In this step, we will proceed to the function that will help us to train our neural network model. in our case, we will use **stochastic gradient descend**. The **SGD** optimizer is a widely used optimization algorithm for training machine learning models. The update step for each parameter is computed using the following formula:

$$\theta_{new} = \theta_{old} - (\alpha \times \nabla\mathcal{L}(x, C) - (\text{momentum} \times \text{previousUpdate}) - (\text{weightDecay} \times \theta_{old})) \tag{1}$$

with θ_{new} represents the updated value of the parameter after the update process, θ_{old} corresponds to the current value of the parameter before the update. α is a learning rate hyperparameter that controls the step size during updates. It determines how big or small the updates to the parameter will be. $\nabla\mathcal{L}(x, C)$ denotes the gradient of the loss function with respect to the parameter. The gradient indicates the direction and magnitude of the steepest increase of the loss, helping the algorithm find the optimal parameter values. momentum is hyperparameter introduces momentum into the update process. It smooths the updates by taking into account previous updates, which can help accelerate convergence, especially in cases where the loss landscape is rugged or noisy. previousUpdate represents the accumulated previous update for the parameter. The previous update is used in conjunction with momentum to influence the current update. weightDecay is the weight decay hyperparameter, which applies L2 regularization to the parameter. It helps prevent overfitting by penalizing large values of the parameter and encouraging smaller ones.

4.5 Loss Function

have somehow generated a model that predicts the probability of y given x. We denote this model by $f(x, \theta)$, where θ represents the parameters of the model. Let us again use the idea behind maximum likelihood, which is to find a θ that maximizes $P(D|\theta)$. Assuming a multinomial distribution, and given that each example $\{(x1, y1), (x2, y2), \ldots (xn, yn)\}$ is independent, we have the following expression:

$$P(\theta) = -\sum_{i=1}^{n} y_i \cdot log(x_i, \theta) \tag{2}$$

4.6 Training Loop

In PyTorch we need to define the Training loop, in order to train our neural network. the train loop function implements the training process for a neural network model using the provided data

Algorithm 7 Training the Model

```
function TRAIN(model, train_loader, criterion, optimizer, num_epochs)
    MODEL.TRAIN
    for epoch in [1, 2, ..., num_epochs] do
        running_loss ← 0.0
        for inputs, labels in train_loader do
            OPTIMIZER.ZERO_GRAD
            outputs ← MODEL(inputs)
            loss ← criterion outputs, torch.argmaxlabels, dim=1
            LOSS.BACKWARD
            OPTIMIZER.STEP
            running_loss ← running_loss + LOSS.ITEM
        end for
        print“Epoch [” + (epoch + 1) + “/” + num_epochs + “] Loss: ” + (running_loss /
lentrain_loader)
    end for
end function
```

loader, loss function, and optimizer. The function iterates over the training dataset multiple times (epochs) and updates the model's parameters to minimize the loss, ultimately improving the model's performance on the task at hand.

4.7 Conclusion

This approach is found to be highly effective in achieving accurate and robust image classification results. By leveraging the power of the ResNet-50 model and combining it with a custom classification head, we have successfully developed a deep learning architecture tailored for our specific task. The use of transfer learning and pretrained weights from the **ResNet-50** model significantly reduced the training time and data requirements, making it feasible to achieve exceptional performance even with limited labeled samples.

The training process, as implemented in the **train** function, demonstrates the capability of the model to learn from the training data and adapt to the target classes efficiently. The nested loops for epochs and batches ensure that the model iteratively updates its parameters to minimize the loss function and improve its predictive capabilities.

Moreover, the integration of PyTorch's DataLoader and CustomDataset classes allows seamless data loading, processing, and transformation, further streamlining the training pipeline. The ability to implement custom data transformations using **transforms.Compose** provides flexibility and convenience in data preprocessing and augmentation, contributing to the overall success of the project.

In conclusion, the presented approach not only achieves remarkable accuracy in image classification but also offers flexibility, efficiency, and scalability, making it a valuable solution for a wide range of computer vision tasks. As deep learning continues to advance, this architecture can serve as a foundation for building more complex and sophisticated models for various real-world applications.

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