Image-Classification of Elementary particles using Convolutional Neural Networks

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1 MOTIVATION

With advancements in technology, the High Energy Physics problems are now being addressed with greater precision and computation. But greater the accuracy of mining data, greater is the challenge posed to the community to write algorithms to solve them. Using modern machine learning techniques, it has been shown that many of the Particle Physics problems can be solved with great accuracy [1]. The field of High Energy Physics (HEP) is one of the most computationally costly. Tons of data is needed to be processed and stored for further analysis. Thus it has become very important to come up with smart solutions for the mentioned tasks.

The use of convolutional neural networks in particular (for image processing or image classification) has been seen as one of the first direct application of deep learning in this field. In this mini-project, a simple approach to image-classification problem has been discussed using the Convolutional Neural Networks. The raw data is processed, by up-scaling the pixel values and then used for training the network. Often a times, the small details in an image are not detected to our eyes but a highly trained neural network can learn subtle features in any image and given us the best results.

2 GOAL

In the presence of high intensity magnetic fields B, a charge particle q undergoes a circular motion with a fixed radius r and frequency f (also called as cyclotron frequency) given by the following equations:

$$r = \frac{mv}{Bq} \tag{2.1}$$

and

$$f = \frac{qb}{2\pi m} \tag{2.2}$$

where m is the mass of the particle and v is its velocity.

Each particle carries it own intrinsic mass and charge and thus the parameter $\frac{q}{m}$ play an important role in determining the formation of new fundamental particles. Since every collision involves billions of particles colliding against each other, it becomes tedious to manually label the collisions.

Using machine learning algorithm, i.e. a Convolutional Neural Network, a robust model can be designed and implemented to perform image classification of elementary particles. This computer vision problem can then further be extended in generating new simulated images for better understanding of physics.

3 Approach

In this work, a study of proton beam collision is discussed. The first approach was a very straight-forward technique. The raw data was converted into a RGB image (.jpg) and made available for training on the network. The network comprised of layers of Convolutional layer, Max-Pooling and drop-out functions. The resultant image was then flattened and applied to a dense network with the final-layer activation as soft-max function to obtain one-hot encoded output.

The second approach addressed the problems encountered in the first approach. A sorting algorithm was put to use to identify all the labelled Pions and reduce its numbers to minimize the bias in the training data. The second modification was to introduce a pixel up-scaling function as given below.

$$f(x) = 250(1 - e^{\frac{-x}{3}}) \tag{3.1}$$

As can be seen from the raw data, each pixel carries a very small amount of information. If we were to convert the raw data directly into a RGB image (each pixel in RGB image takes in a value from 0 to 255, where 0 is the darkest pixel and 255 is the brightest pixel), one can notice that all of our information lies pretty close to dark pixels. This was pressurizing our neural network to learn subtle details too precisely which was turning out to be too computationally costly. Max-Pooling layer was also undesirable here since the data we were working on was too sensitive and any image compression technique was destructive. The final modification was made by trying to optimize the confusion matrix along with accuracy and loss functions in order to obtain the best results.

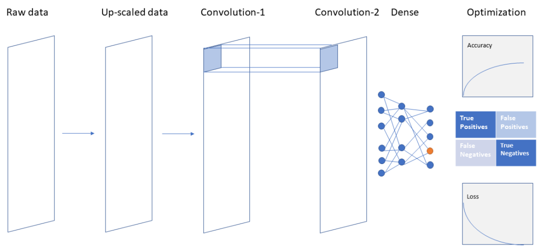


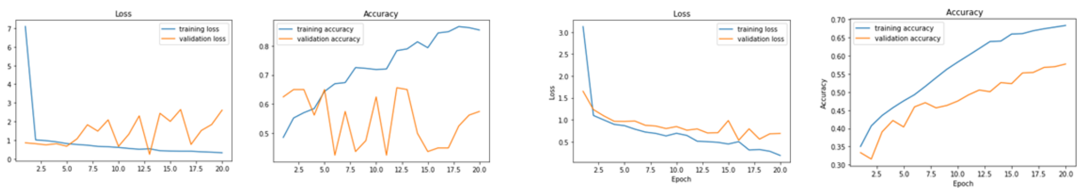
Figure 3.1: A schematic diagram of the workflow

The data in this problem was a part of The TrackML challenge 2018 [2]. The model was trained on Google collabratory's TPU [3]. Here Adam optimization, with a learning rate of 0.001 was used along with categorical cross-entropy as loss function with 20 epochs.

$$\text{Loss} = -\sum_{i=1}^{\substack{\text{output}\\\text{size}}} y_i \cdot \log \hat{y}_i \tag{3.2}$$

where $\hat{y}_i$ is the i-th scalar value in the model output, y_i is the target value, and output size is the number of output neurons in the model output. A confusion matrix of 3 most abundantly found particles in the experiment, namely Pions, Kaons and Protons was plotted along with loss and accuracy plots to get the results.

4 Result



Approach 1 Approach 2

Figure 4.1: Accuracy and Loss plots for Approach 1 and 2

The first model (Approach 1) was not up to the expectation. Validation training and loss plots showed poor results. However, the second approach displayed somewhat promising results. Also when the model from approach 2 was tested on unseen images, the testing accuracy reached 53%.

Future scope of this mini-project includes the use of auto-encoders for compressing the images to achieve easy and efficient training. Also PCA can be incorporated to understand even more subtle details by reducing the dimensions of data.

References

[1] arXiv:1912.08245v1

[2] David Rousseau, Sabrina Amrouche, Paolo Calafiura, Victor Estrade, Steven Farrell, et al.. The TrackML challenge. NIPS 2018 - 32nd Annual Conference on Neural Information Processing Systems,

[3] Bisong E. (2019) Google Colaboratory. In: Building Machine Learning and Deep Learning Models on Google Cloud Platform. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4842-4470-8-7