Using CNNs to classify and localize ionized particles from cosmic rays

Galactic cosmic rays are a mixture of high-energy photons and subatomic particles formed by supernova explosions and other cosmic events. As cosmic rays enter Earth's atmosphere, they interact mainly with oxygen and nitrogen molecules. This phenomenon, known as an air shower, results in secondary radiation including x-rays, protons (p), alpha particles (α), pions (π), muons ($\mu-$), electrons ($e-$), neutrinos (ν), and neutrons (n). Currently, accurately tracking and quantifying cosmic rays is difficult; direct detection methods--including particle detectors housed in the ISS, satellites, or high-altitude balloons-- require a considerable amount of time to develop the readings. Indirect detection methods, specifically extensive air shower arrays, require large areas of land and highly specialized, expensive equipment. Historically, the Wilson cloud chamber was used as an indirect detection method; this cheap and widely available method is widely disregarded in the scientific community as it requires careful manual tracking which can only be detected the instant particles pass through the chamber. Substituting the manual work required for tracking and classifying particles passing through the cloud chamber by using an artificial neural network (ResNet), detection using object detection resulted in a mean average precision of $\geq$89%.

Introduction

Galactic cosmic rays are a mixture of high-energy photons and atomic nuclei formed by supernova explosions and other cosmic events. As cosmic rays enter Earth's atmosphere, they interact mainly with oxygen and nitrogen molecules. This phenomenon, known as an air shower, results in the creation of secondary radiation including x-rays, protons (p), alpha particles (α), pions (π), muons (μ−), electrons (e−), neutrinos (ν), and neutrons (n). As the cosmic rays pass through the atmosphere, these newly formed ionizing particles rain down through the atmosphere [1][2][3].

Currently, accurately tracking and quantifying cosmic rays is difficult. There are two types of detection: direct and indirect. Direct detection requires complex particle detectors that live on the ISS, in satellites, or in high-altitude balloons [4]. These detectors require lots of human intervention to classify and quantify the data. Existing indirect detection methods are far less economical since most methods utilize extensive air shower arrays made of particle detectors, which require lots of land and expensive equipment [5].

The Wilson cloud chamber is a sealed environment containing a supersaturated vapor of water and alcohol used to visualize the passage of ionizing radiation. The Wilson cloud chamber is an indirect particle detector created in the 1920s which shows the passage of particles that have ionizing radiation as cloud-like trails which dissipate 2-3 seconds after particle interaction. The cloud chamber works by creating a supersaturated environment using hot water, alcohol, and dry ice (or a substitute such as a frozen plate) [6].

VERITAS (Very Energetic Radiation Imaging Telescope Array System) array is an indirect detection method, which is estimated to have cost $20.7 million and require an additional $1.5 million yearly to maintain [7][8]. When compared to a cloud chamber, which is often neglected due to direct detection methods or other indirect detection methods that don't require human supervision, it can be competitive by using artificial intelligence in lieu of humans removing the possibility for error.

This research aims to detect secondary cosmic rays within Earth's atmosphere easier and cheaper by using a convolutional neural network—the most commonly used neural network for vision models—to classify, localize, and quantify these particles emitted within a cloud chamber [9].

Materials and Methods

One of the most important factors when training a neural network is the expansivity dataset—entailing both lots of examples in diverse forms. I downloaded a video [10] approximately 3 minutes in length of high-quality slow-motion footage from inside of a cloud chamber similar to the one I possess. I wrote code to convert the video into images for every frame, and selected every 10th frame which provided me with the 17 pictures I used to build my dataset.

Using reference images from a CERN guide for students building their own cloud chambers [11], I created the ground truth for my dataset. The ground truth is the labels that I generated by drawing bounding boxes—boxes depicting the region in which an object is located as well as the classification for the object—around every instance of an ionized particle trail in the dataset.

After labeling the dataset, I added preprocessing steps to the dataset (cropping and resizing) and augmentation steps (flip, rotate, and shearing). These steps increase the size of the dataset - my dataset increased from 17 images to 35 images - as well as increase the complexity of the training which generally results in enhanced prediction accuracy.

After developing the dataset, I wrote code that utilized TensorFlow's (a Python library for creating neural networks) object detection API to train the network.

Results

Part I: Comparison of augmentation and pre-processing in CNN: No pre-training

When training the dataset without any augmentation or preprocessing on the dataset, without pretraining—when the model weights are initiated from an existing setting rather than from scratch—a mean average precision (mAP) of 80.4% percent was achieved. This mean average precision represents how often it accurately predicts the type of particle given that it has successfully located a particle. When training with augmentation and preprocessing, without pretraining, the mAP increases to 84.0% mAP.

Part II: Comparison of augmentation and pre-proprocessign in CNN: Pre-training

Pretraining the dataset without augmentation or preprocessing, mAP increased from 80.4% trained from scratch to 85.8% utilizing pretraining. mAP increases even further when pretraining and applying augmentation and preprocessing; adding pre-training brings the mAP from 84.0% to 89.5%.

Discussion

Data augmentation and preprocessing provided significant improvements to model accuracy as it expanded the dataset's size as well as complexity. Furthermore pretraining decreases time to train and improves quality as it requires less images to generate the weights.

Despite the accuracy, this work is significant in its innate ability to lower the "barrier-to-entry" of detecting ionizing radiation. Existing research [12] suggests a link between cosmic rays and climate change. By providing the global community with the tools needed to detect cosmic rays, it would expand the amount of data available on regional cosmic ray activity which may be combined with regional climate data to help draw conclusions.

The portability of the cloud chamber and the lower price could pave the way for an increase in research regarding the effects of cosmic rays in many different fields. While existing research suggests that there isn't enough data to support that cosmic rays worsen the effects of climate change, additional data could be used to validate this link.

Future Work and Conclusion

The results presented indicate that artificial intelligence has the ability to be competitive with existing detection methods while being easier to manage by removing the need for extensive human labor while also being portable.

Continuing my research, I would like to increase the size of my dataset. The standard minimum size for a dataset is recommended to be anywhere between 100-200 images when retraining. Since curating significant amounts of high-quality footage of a cloud chamber is difficult, producing my own cloud chamber and recording my own footage would be a needed and useful step to drastically improve the mAP of my model.

Furthermore, measuring performance using other models will allow me to better gauge where the boundaries between model accuracy and model performance are slim, so that I can find a model both efficient on low-powered compute devices while maintaining high accuracy.

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