A diverse reinforcement learning based approach to identifying noisy images

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1 Background

Image processing has been one of the topics at the forefront of machine learning. Machine learning algorithms are capable of not only classifying images, but also performing more complex operations such as filtering and segmenting. While reinforcement learning has successfully solved many problems such as Atari and AlphaGo [3], it has rarely been applied to image processing. Typical methodologies in the image processing field of artificial intelligence centre around supervised learning.

One problem that arises during image processing that cannot be solved with supervised learning is the problem of noisy data. While the ideal dataset has clean, easily identifiable images and labels, this is almost never the case in the real world. Many datasets are filled with noisy images that are fuzzy, difficult to interpret, and have incorrect labels. In well-known datasets such as MNIST and CIFAR100, adding noise has been show to reduce testing accuracy by anywhere from 10-30% [1]. Because there are no labels indicating whether or not an image is noisy, this task is impossible for supervised learning to accomplish. However, reinforcement learning is capable of generating solutions to problems based only on environment input and reward from the environment, and thus should be able to solve the noisy image problem. The proposed research will train a reinforcement learning agent to learn noisy image data, and subsequently remove it from the dataset to allow for better image processing tasks. This is similar to how humans will remove noticeable error outliers from datasets when they process them.

2 Method

The proposed research will be conducted using the MNIST and CIFAR10 datasets, which are both widely available and commonly used image datasets for machine learning. These datasets will be altered to add noise to a small percentage of the images. A deep convolutional neural network will be implemented to classify these image datasets. In addition, a selection agent will be created and trained. The selection agent will take in an environment input of a batch of images, and the output action will be whether or not to keep each image - mapped to [1, 0], where 1 indicates keeping the image for training and 0 indicates discarding the image as it is potentially noisy. Thus, the agent will pull aside a subset of images from the training set, and the classifier would train based on the remaining samples. The reward for each episode will be the difference in training accuracy with and without the subset of samples that the agent removed. After each epoch, the selection agent will be trained based on the actions and rewards received during that epoch. As the episodes progress, the agent will eventually learn how to identify noisy samples. After the selection agent has been trained for a number of episodes, the performance of the CNN with and without the selection agent on the testing set will be compared.

3 Milestones

The first goal of the proposed research will be to implement the selection agent using both genetic algorithms and policy gradient. Policy gradient has been successfully used in the past to solve a similar problem of data evaluation [4]. In addition, genetic algorithms are able to generate a diverse variety of solutions, which allows it to better overcome local minima when compared to policy gradient. In the context of this research, local minima can be associated with identifying certain types of noise very well (ex: always correctly removing images with jumbled pixels around the center), but missing other types of noisy images. The performance of these two algorithms will be compared.

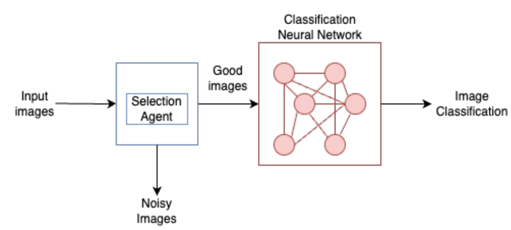

Figure 1: Proposed model architecture

The next goal of the proposed research will be to combine novelty search with the reinforcement learning algorithms mentioned above. Novelty search is known to successfully overcome local optima, even more so than genetic algorithms. The performance of the selection agent with novelty search will be compared to its performance without.

If the above goals are successfully achieved, an additional goal of the proposed research will be to adapt these methods to a medical ultrasound dataset. Specifically, the dataset contains 258 prostate biopsies collected from Vancouver General Hospital. However, these images often don't contain cancer-specific image signatures [2], and contain lots of noise generated from the modality. For machine learning methods such as CNNs to be applied successfully to this dataset, it is important that they know which images are important. Applying the proposed research to this dataset could help remove the noisy images.

References

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