Machine & Reinforcement & Deep Learning, Neural Network Proposal

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I. Team Members Info

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II. Objective

The main objective of our project would be image classification: given an image and K categories, the task is to select one category label. We will develop algorithms for image classification using methods including machine learning, reinforcement learning, deep learning, and neural networks. Image classification is used in industries ranging from healthcare to the automobile industry. A misclassification could have dire consequences, thus it is important to understand and compare the performance of various machine learning implementations to ensure that a reliable algorithm is used.

III. Current state of art

Many cutting edge algorithms are designed using image classification methods. Image classification has been utilized to recognize objects on the side of the road for assisted driving systems [1]. The healthcare industry has also benefited from image classification, including glioma cancer prediction [2] and early oral cancer diagnosis [3]. Image classification has also been used to provide navigation assistance to people who are blind [4].

Lu and Weng conducted a survey analyzing different classification methods for machine learning based image classification algorithms [5]. There are many different approaches to image classification, including machine learning, transfer learning, reinforcement learning, deep learning, and neural networks.

A. Machine Learning

Machine learning methods for image classification can be supervised, using data in training samples, or unsupervised, using clustering algorithms [5]. These algorithms are trained on image data, which can be either labeled, or unlabeled. One machine learning approach to image classification used Adaboost and linear classifiers for image classification [1]. Lecun et al. analyzed image classification using Linear, K-Nearest Neighbors, and Support Vector Machine with Gaussian Kernals [6].

B. Transfer Learning

Gathering images belonging to a specific domain and training a classifier from scratch is very difficult and time-consuming. Researchers mostly use a pre-trained model and modify the last few layers so that they can categorize images according to their desirable classes. This allows them to obtain good results even with a small dataset, because in the pre-trained model, the basic image features have already been learned from a much larger dataset.

C. Reinforcement Learning

Reinforcement Learning (RL) algorithms is based on a simple idea that enable an agent to learn optimal behavior as it enables it to connect with an unspecified environment and learn from the rewards it earns [7]. Based on the literature, although RL can be applied to such computer vision tasks such as image processing, massive amount of data involved is known as a major obstacle in solving image based problems [8].

D. Deep Learning

Deep Learning instead of teaching the algorithm to process and learn from data, it is learning to train itself to process and learn from data. It is using Hidden Layers and Layers method to processing to analyze a dataset depending on how many neurons each of these hidden layers have. Wu et al. used a weakly supervised learning approach to build a framework that uses dual multi-instance assumption where it can be recognised as two instance of sets [9]. Perez and Wang proposed a method that improves classifiers by allowing neural net to learn augmentation [10]. Deep learning is effective on large unstructured datasets.

E. Neural Network

Neural Network is based on the human brain, it is on cluster and raw data. It can predict and label or cluster data with machine prediction. Convolutional Neural Networks (CNNs) is the most popular neural network model being used for image classification problem. Convolutional neural networks have been used for image classification in the Pascal VOC 2012 challenge [11]. Residual neural network (ResNets) is an artificial neural network (ANN) of a kind that builds on constructs known from pyramidal cells in the cerebral cortex.

Alom et al. proposed a new model, Inception Recurrent Residual Convolutional Neural Networks, which is an improvement to the residual neural network approach that improves image classification accuracy [12].

IV. Approach

We will develop an algorithm for image classification using machine learning, reinforcement learning, deep learning, and neural networks. We will then compare the performance of each algorithm to each other and to the performance of algorithms reported in related works. Our analysis will report standard metrics used in machine learning, including classification accuracy, area under the precision-recall curve, positive predictive value, specificity, sensitivity, and a confusion matrix showing incorrect classification probability across each category. Then we will identify the strengths and limitations of each implementation, and the affect of these features on the overall performance.

V. Dataset

Many datasets have been developed for image classification. Some popular datasets include CIFAR-10 [13], CIFAR-100 [13], Imagenet [14], STL-10 [15], Caltech-101 [16] and Pascal VOC datasets [17].

Ultimately, we chose to use the Pascal VOC 2012 dataset [17] which can be accessed at host.robots.ox.ac.uk/pascal/VOC/voc2012/index.html#devkit. The Pascal VOC 2012 dataset includes 11,530 jpeg images which are classified into 20 classes. It also contains 27,450 ROI annotated objects and 6,929 segmentation images. We selected this dataset as it was publicly downloadable, popular in related literature, and because of its reasonable size.

VI. Timeline, Roles, and Tasks

Grade	Task	Due date	Responsible
5%	Proposal submission	11-Oct	Team
	Proposal acceptance	16-Oct	Dr. Ma
	Data Preparation	25-Oct	Team
	Creating the Models	30-Oct	Team
	Training the Models	3-Nov	Team
	Model Evaluation	4-Nov	Team
10%	Progress report submission	8-Nov	Team
10%	Progress presentation	9-Nov	Team
	Progress report acceptance	12-Nov	Dr. Ma
	Modifying report	20-Nov	Team
	Finalizing Report	5-Dec	Team
35%	Final report submission	6-Dec	Team
40%	Final presentation	7-Dec	Team

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