Interpretable Image Classification with CNN, Transfer Learning, GAN and Grad-CAM

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I. Abstract

Different species of birds have very different appearances. We apply data augmentation with GAN, train a few neural networks including CNN, VGG19 and Xception to identify bird species given the image, present the prediction evaluation metrics (accuracy and confusion matrices), and explain the model prediction through a few model explainers including LIME, SHAP, and Grad-CAM.

I. Introduction

Image classification or computer vision is one of the hottest topics in deep learning lately. It is useful in a wide variety of fields, including healthcare, e-commerce, forensics, manufacturing, etc. For example, computer vision models could performa classification tasks on CT scans for cancer diagnosis, recommend products for online shopping websites, flag spam pictures, and detect defects for manufactured products. Computer vision models' importance, flexibility and robustness have been proven in numerous use cases over the past decade, so we decide to focus on computer vision for this project.

Instead of training an image classification model and being done with it, we are interested in the entire data processing pipeline: data augmentation, model training/evaluation, and prediction explanation.

Data augmentation is shown to be very important when there is insufficient training data.

Model explainability is gaining popularity because there is increasing demand for building explainable AI from legal and business points of views. Explainable AI is important in "users, laws & regulations, explanations and algorithms". (Ras et al 1)

II. Related Work

Due to the time and hardware requirements to train good computer vision models, lots of work in this field has been dedicated to transfer learning. Some famous pre-trained computer vision models include VGG19, ResNet, Inception, Xception, etc. These models are largely trained on ImageNet with millions of parameters fine-tuned.

For data augmentation, there has been plenty of research around geometric transformations, color augmentations, kernel filters, image mixtures, random erasing, as well as adversarial training. One of the complex methods is training Generative Adversarial Networks (GANs) for image augmentation.

For model explainability, some relatively simple methods include LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations), which build simple, explainable surrogate models to replicate model results. Other more DNN-specific methods include Activation Maximization (AM), Layer-wise relevance propagation (LRP), Knowledge Graphs (KG), tree-based hierarchical methods, and many more. (Daniels et al 3 , Marino et al 1)

III. Dataset

Our project takes the bird species dataset from Kaggle. This dataset originally only contains images of 100 birds, but more species and images for each species have been added later on and so far there are 230 species collected, and each species has on average 140 images. Due to hardware and time limitations, we are only taking the top 10 species as our training dataset, performing data augmentation, and subsampling 500 images for each bird.

The images are already preprocessed to 224 * 224 pixels with 3 RGB channels. Each image contains one bird and the background. Most of the backgrounds are relatively neutral, without too many distracting items, but some images have messy backgrounds and the bird might seem to blend into the background at first glance.

Each of these birds have some distinctive features, including their colors, shape, beak, and habitat. Unfortunately, due to image preprocessing, the size information is lost and all species are cropped and fitted into the image such that the bird is placed in the center of the image and takes up most of the space.

Figure 1. Sample images from 10 species

IV. METHODS

We are applying two methods for data augmentation: regular image stretching, reshaping, and transformations as well as image augmentation with GANs. This network is most commonly used for image generation such as generating people's faces (DeepFake) and famous oil paintings (GANGogh). In this case, we are using GANs to generate more bird images from the original training data to achieve a better modeling result.

GANs have two main parts: discriminator and generator. They work hand-in-hand to improve each other's capabilities. They both start from random guesses -- the generator will create random noises and the discriminator has no knowledge of the difference between the true images and random noises. However, over the course of many iterations, the generator becomes better at generating fake images, and the discriminator becomes better at distinguishing the real and the fake.

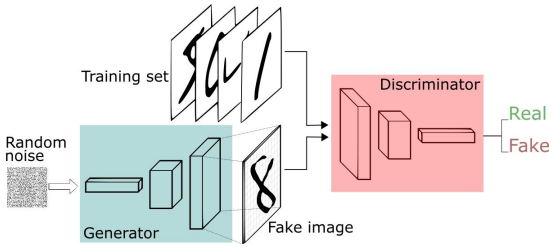


Figure 3. Illustration of GAN

We compare this result with the model without any augmentation and present the performance increase. Because the dataset is relatively balanced and the problem is multi-class classification, we are utilizing accuracy and confusion matrices as our performance metrics.

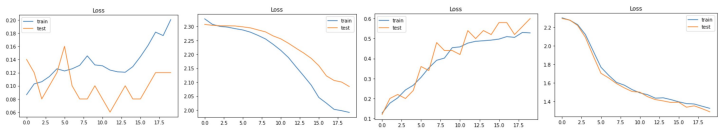
For model training, we train a simple CNN for benchmarking, but also apply a few pretrained models such as Xception and VGG19. Xception was inspired by the Inception model, but different from Inception, Xception takes better use of the parameters with an architecture that has a depthwise convolution followed by a pointwise convolution.

Finally, we explain the 'black-box' models with some model explainers including LIME , SHAP, and a computer-vision specific approach with Grad-CAM (Gradient-weighted Class Activation Mapping). LIME first generates random perturbed instances of the original image, then makes predictions for each perturbation and assigns weights to each area. Finally, it fits a simple, explainable linear model to recreate the actual model's predictions. SHAP takes a game theory approach, where the "players" are the features and the "game" is reproducing the outcome of the model. SHAP quantifies the contribution that each player brings to the game by their marginal contributions. Grad-CAM uses the gradient information in each convolutional layer, especially the last one, to understand the neuron's decision paths.

V. RESULTS

DATA AUGMENTATION

The first data augmentation method is applied on a simple CNN model. This model contains 3 convolutional layers followed by max pooling and 20% dropout. Without any data augmentation, the model is hardly learning anything. It tends to classify everything as Alexandrine Parakeet, Albatross and American Avocet. From the training loss, we see that the training and validation loss starts to diverge quickly after a few epochs, and we see that the accuracy keeps changing up and down but does not go above 30%. However, after some basic data augmentation procedures, including upto 40% rotation, 0.2 width and height shift, up to 20% zooming as well as horizontal flipping, the model is learning a lot better and is capable of making correct predictions on most of the classes.



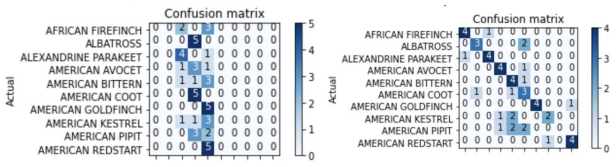


Figure 2. Training and validation losses and accuracy (top) and confusion matrices before and after data augmentation on the test data.

GAN

In our case, 5 Conv2DTranspose and 6 LeakyReLU layers were added into the generator and similar structures in discriminator.We used the african crowned crane as the training set and did 20,000 iterations which is about 9,000 epochs. However, since the image size is far larger than datasets like mnist, the result is not perfect enough, where only the basic color and structure is close to the real image.

Model Training

We trained three classification models and their performances are shown below. We see that Xception performs the best with 98% accuracy on the test dataset.

Model	Test Accuracy
CNN	0.76
VGG19	0.91
Xception	0.98

Table 1. Classification Model Comparison

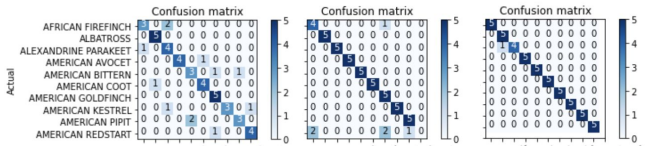


Figure 5. Test confusion matrices for CNN (left), VGG19 (mid) and Xception (right)

1. CNN

We first trained a CNN model. This model contains 3 convolutional 2d layers, each followed by a max pooling layer and a dropout layer to avoid overfitting. This model utilizes the Adam optimizer and was trained through 50 iterations. It was only able to achieve 76% classification accuracy on the test data.

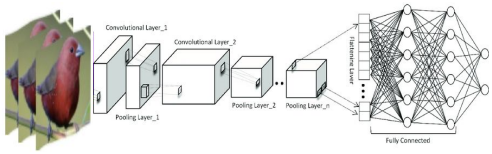


Figure 5. Illustration of the CNN model

2. VGG19

Besides CNN, we also tried the pre-trained model, VGG19, on our data. The VGG19 model contains 19 conv layers and 3 fully connected layers. This network on our dataset out-performed the CNN model and reached a 94% accuracy on the test data.

3. Xception

Xception has been trained on 350 million images with over 17,000 classes. This network on our dataset out-performed the CNN model and reached a 98% accuracy on the test data.

Model Explainability

1. LIME

From the illustration below, we see that LIME is not doing a great job of identifying the characteristics for the bird. The highlighted areas in the end are not distinguishing features for this type of bird.

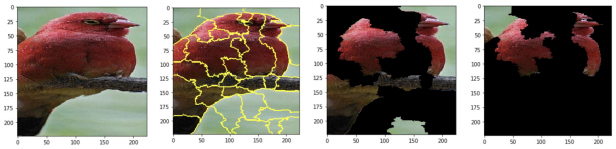


Figure 6, LIME explanation on the American Firefinch

2. SHAP

In our example, SHAP highlights the portrait outline, the red color block, and some backgrounds. SHAP correctly identifies the highest probability for the actual predicted class (top left), and it highlights the contour of the bird's head and the red color block. However, this explanation is still not very satisfactory because we are expecting the explainer to "see" what we see as the unique characteristics of the bird, which would be centered around the body of the bird in this case.

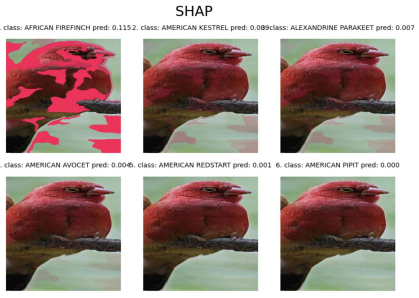


Figure 7. SHAP explanation of the American Firefinch

3. Grad-CAM

Grad-CAM is developed from CAM. The CAM model is able to generate a heat map of the essential part in a

picture. However, it has many restraints. To apply CAM on our model, we need to replace fully connected layers with global average pooling. The Grad-CAM overcomes this problem. The Grad-CAM could produce multiple essential content layers without global average pooling. Therefore, we do not need to rebuild our model and get essential content heat maps directly.

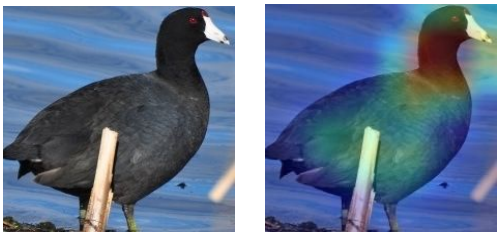


Figure 8,Grad-CAM explanation on the American Coot

VI. Discussion of Results

For data augmentation with standard methods, the results are as expected, but with GAN, the accuracy and the loss of the model didn't converge to a stable level. Obviously more training is required and the structure of the model required also. However, since the time and cost limit, those improvements haven't been done and would be finished in future.

Figure 9. Image generated by the GAN model (left)

For model training, Xception is the best performing model. Unsurprisingly, it is performing much better than the simple CNN, but interestingly, it is also doing better than VGG19. We suspect that this is because of Xception's efficient use of parameter sets.

For model explainability, Grad-CAM is doing better compared to traditional methods, which is probably because it is designed specifically for computer vision and localizes important features through multiple CNN layers, rather than adopting a simple linear model like LIME does.

VII. Conclusions

In this project, we compared the performance of CNN models with and without data augmentation.

For data augmentation, we tried CNN Image Data Generator and GAN data augmentation. The first method only applies simple rotation, distortion, and flip to original pictures, while GAN adds noise data to original pictures. Due to the time limits, GAN only produced vague images. We would apply more training time to this process in the future.

For model performance, we found simple data augmentation dramatically boosts the model performance from 12% to 60%. Besides the CNN model, we also applied two pretrained models (VGG19 and Xception). In the end, we get 91% for VGG, and 98% for Xception.

In the model explainability section, we tried LIME, SHAP, and Grad-CAM methods. LIME and SHAP explain the model by determining each part of the picture, while the Grad-CAM only focuses on one essential part of the picture.

In the future, we might explore more model explainability methods for computer vision, and include more classes for training.

VIII. References

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