AN EDGE-AND-CLOUD BASED WILDTRACK SOLUTION FOR IN THE FIELD FOOTPRINT IDENTIFICATION

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PROBLEM STATEMENT

WildTrack aims to monitor wildlife as non-invasively as possible. Traditional methods of footprint identification have relied on indigenous trackers or even animal capture. Drawbacks of these methods include possible negative impacts on fertility as well as cost and scale.

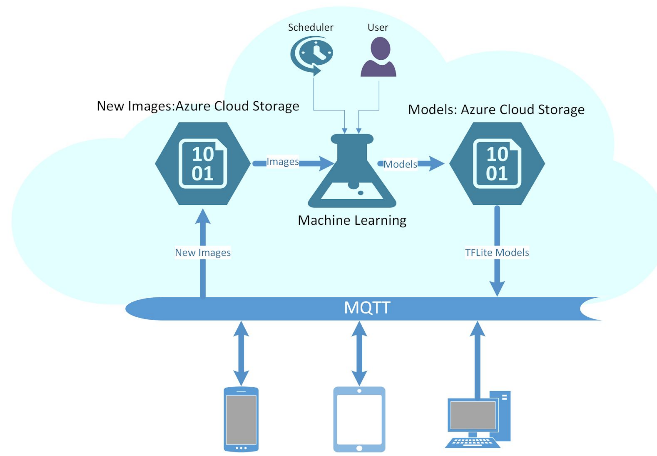
To address these drawbacks, teams of UC Berkeley students through the MIDS program have endeavored to construct and deploy computer vision methods to classify animal footprints. Past teams have developed and trained deep-learning models to classify images. Coupled with a database that is ever-expanding and a website to engage the public by permitting photo-uploads, the infrastructure has proven itself as an excellent and effective tool to extend the models and engage users. An expansion of the dataset is crucial because existing datasets have been limited in size.

The core WildTrack team had recently issued a call for improvements expressing interest in a possible smartphone app that can perform inference to engage citizen scientists as well as allow researchers to conduct such classification in the field with or without internet connectivity. As part of the W251 final project, our group has designed and implemented an Android based app for image collection in the field, inference as well as communicating this information to the cloud when internet connectivity is available. Furthermore, exceeding expectations, and meeting the challenges of small datasets, we have also adapted Generative Adversarial Networks (GANs) and GAN neural-style transfer methods to create synthetic data to augment the existing dataset as well balance classes for species with limited numbers footprints. Finally, to improve the overall model performance, we rebuilt and trained classification models whose performance has surpassed that of existing models currently deployed by WildTrack.

Architecture Design

Multiple Footprint classification is a multi-class classification problem. The models are trained in the cloud where GPU and storage resources are available while a streamed version of the model is loaded onto a smartphone app for in the field inference. Anyone with such an app can not only collect more footprint samples for uploading to the cloud when connectivity is available, but can also use the inference module to get a class prediction.

For a complete end-to-end solution that allows users to download the trained models and upload captured images as well as their input, MQTT(Message Queuing Telemetry Transport) queues are used for data transfer between edge and cloud. A retrain process has been implemented to train previous models with new images allowing models to remain up-to-date.

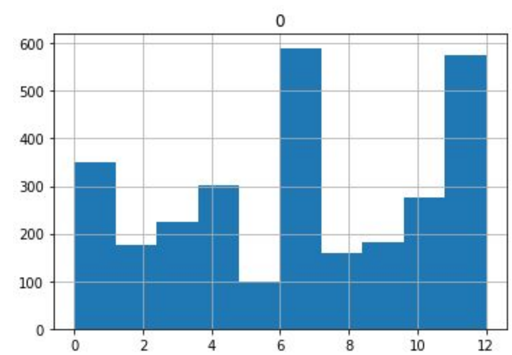


This design also provides an practical solution for following challenges:

1. Forgotten images - images stored on mobile phones that never make it to the image repo
2. Model Retrain - keep model updated with data changes
3. Pushing the most recent models to edge devices

MODELS

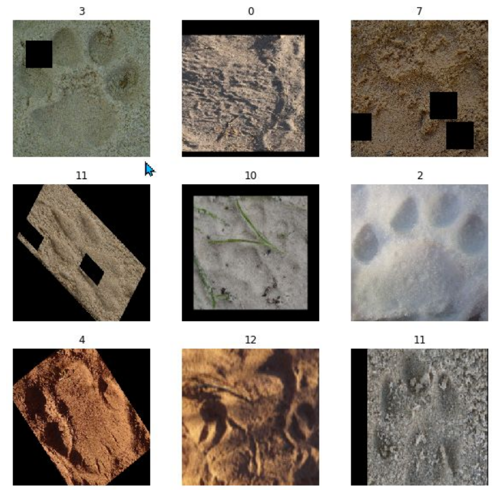
EDA



The training and validation images are provided. We have 2931 training images and 361 validation images belonging to 12 classes. The number of images for each class are uneven and we expected this could negatively affect the model performance. The histogram at right shows counts of the 12 classes :
0: 'African elephant',1: 'African lion',2: 'Amur Tiger',3: 'Bengal Tiger',4: 'Black Rhino',5: 'Bongo',6: 'Cheetah',7: 'Jaguar',8: 'Leopard',9: 'Lowland Tapir', 10: 'Otter',11: 'Puma',12: 'White Rhino'.

Data Engineering

The images have been processed to simplify the solution - there is one footprint on each image and all images have been labelled accordingly.



Model augmentation

Training process involves simple image augmentations like rotation and flipping relying mostly on more sophisticated augmentation techniques based on GANs and neural transfer techniques as discussed in the relevant sections below.

Model Training

Given we only have a few thousand images, we decided to use transfer learning for this task. Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task.

It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in skill that they provide on related problems.

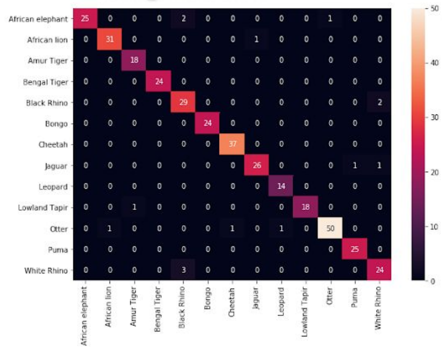
We chose to use 3 high performing models from Keras library judging from ImageNet result - Xception, Inception and NASNet.

To use pre-trained models, we first attached an inference layer with 12 class predictors, then froze the pre-trained layers and trained the last layer. Finally we trained the entire network.

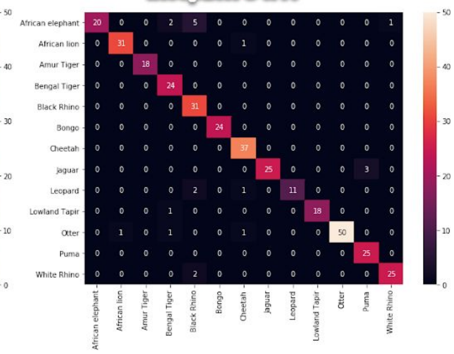
For 3 models, the 2 smaller models Xception and Inception took 5 hours and the largest model NASNet took 10 hours to finish.

Base models confusion matrices:

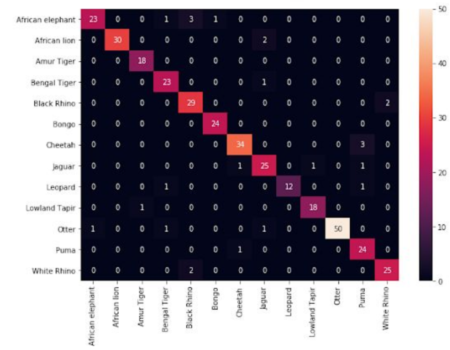
Xception 94.72



Inception 94.17



NASNet - 95.22%



Best Tensorflow Model with GAN images:

Model Name	Parameters	Size	Validation Accuracy
Xception	22,910,480	88MB	96.39%
InceptionResNetV2	55,873,736	215MB	96.94%
NASNetLarge	88,949,818	343MB	97.22%

Confusion matrices for the models with GAN augmented images:

xception: 96.39

```
[[25  0  0  0  3  0  0  0  0  0  0  0  0]
 [ 0 31  0  0  0  0  0  1  0  0  0  0  0]
 [ 0  0 18  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 23  0  0  0  0  1  0  0  0  0]
 [ 0  0  0  0 30  0  0  0  0  0  0  0  1]
 [ 0  0  0  0  0 24  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 28  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 14  0  0  0  0]
 [ 0  0  1  0  0  0  0  0  0 17  1  0  0]
 [ 1  0  1  1  0  0  1  0  0  0 49  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0 25  0]
 [ 0  0  0  0  1  0  0  0  0  0  0  0 26]]
```

Inception: 96.94

```
[[24  0  0  1  3  0  0  0  0  0  0  0  0]
 [ 0 32  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 18  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 24  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 29  0  0  0  0  0  0  0  2]
 [ 0  0  0  0  0 24  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 27  0  0  1  0  0]
 [ 0  0  0  0  0  0  0  0 14  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0 18  0  0  0]
 [ 0  0  0  0  0  0  1  0  0  0 52  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0 25  0]
 [ 0  0  0  0  2  0  0  0  0  0  0  0 25]]
```

Nasnet: 97.22

```
[[27  0  0  0  0  0  0  0  0  0  0  0  1]
 [ 0 32  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 18  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 24  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 30  0  0  0  0  0  0  0  1]
 [ 0  0  0  0  0 24  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 27  0  1  0  0  0]
 [ 0  0  0  0  0  0  0  0 14  0  0  0  0]
 [ 0  0  1  0  0  0  0  0  0 18  0  0  0]
 [ 1  0  1  0  0  0  2  0  0  0 49  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0 25  0]
 [ 0  0  0  0  2  0  0  0  0  0  0  0 25]]
```

Confusion matrix for the final models:

Xception:96.39

```
[[26  0  0  0  2  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  1  0  0  1  0  0]
 [ 0  0 18  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 23  0  0  0  0  1  0  0  0  0]
 [ 0  0  0  0 30  0  0  0  0  0  0  0  1]
 [ 0  0  0  0  0 24  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 28  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 14  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 18  1  0  0]
 [ 1  0  0  1  0  0  1  0  0  0 50  0  0]
 [ 0  0  0  0  0  0  1  0  0  0  0 24  0]
 [ 0  0  0  0  2  0  0  0  0  0  0  0 25]]
```

Inception:96.39

```
[[28  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 32  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  0 17  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 24  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 30  0  0  0  0  0  0  0  1]
 [ 0  0  0  0  0 24  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 27  0  0  1  0  0]
 [ 0  0  0  0  2  0  1  0 11  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0 18  0  0  0]
 [ 1  0  0  0  0  0  1  0  0  0 51  0  0]
 [ 0  0  0  1  0  0  0  0  0  0  0 24  0]
 [ 0  0  0  0  3  0  0  0  0  0  0  0 24]]
```

NASNet:98.61

```
[[28  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 32  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 18  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 24  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 31  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0 24  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 37  0  0  0  0  0  0]
 [ 0  0  0  0  1  0  0 27  0  0  0  0  0]
 [ 0  0  0  0  0  0  1  0 13  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 19  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0 52  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0 25  0]
 [ 0  0  0  0  2  0  0  0  0  0  0  0 25]]
```

We note that the previous UC Berkeley MIDS/Capstone group had validation accuracy of 95.22%; in contrast our model offers validation accuracy of 96.39% with NasNet the best at 98.61%.

Retraining

A cloud-based retraining process has been implemented to load all images including the most recent models and all images (including new uploaded images) and retrain the model for improved performance. This process can be run manually or automatically to prevent model drift. Each retrain will create a time stamped folder and store all 3 models in the folder.

This retraining process will also convert Tensorflow models to TFLite models for mobile inference purposes. Below are the accuracy and confusion matrices for TFLite models. Xception TFLite model and InceptionResNetV2 TFLite models have fairly similar validation accuracy as that of the Tensorflow models. NASNETLarge TFlite model has the largest drop in validation accuracy compared to the Tensorflow model: from 95.22% to 46.11%. It remains to be investigated exactly why the TFLite models perform poorly compared to the regular models, but we suspect the lower model sizes are related.

Connection between Edge and Cloud

MQTT queue is a lightweight queue service and is used to connect edge devices and cloud. It’s used for 2 purposes:

1. Upload mobile images to the cloud for further processing. Each image is time stamped and stored in the time stamped folder. Label is also provided (more details in the Cell Phone section).
2. Download TFLite models for local inference without internet connection.

Generative Adversarial Networks (GANs):

A key challenge in this work is the availability of enough training samples to enable deep learning. In addition, some of the species tracks are easier to obtain than others leading to significant class imbalances.

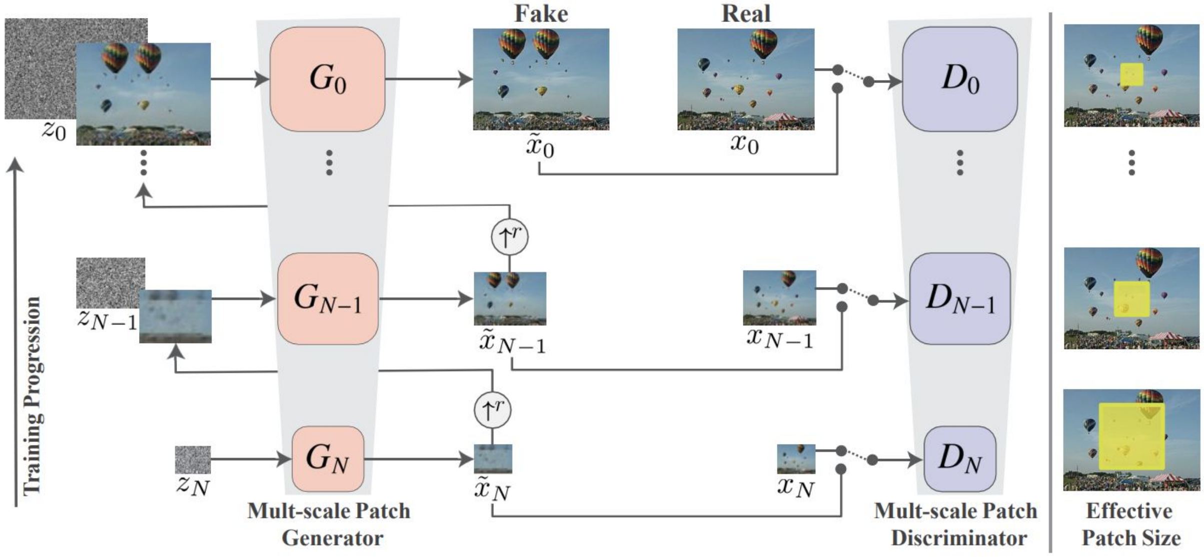
GANs are a type of generative networks that can produce realistic images from a latent vector or distribution. Typically, a GAN consists of two networks: generator (G) whose purpose is to map latent code to images and a discriminator (D) whose task is to evaluate if an image comes from the original dataset (real image) or if it was generated by the other network (fake image). Playing against the discriminator, the generator tries to fool it, generating new images from the latent vector so that the discriminator believes that they are real images. In this work, we used a special type of network called a SinGAN.

Generative adversarial networks have proved useful in recreating unlimited copies of images once the generator is trained. In this work, we attempted to address the issue of creating sufficient training samples per species as well as the generating of high resolution images from their low resolution conterpants. GANs typically require lots of images to train the generator. More recently, an unconditional generative model that can be learned from a single natural image by using versions of the same image at different scaling levels. The network is called Single GAN (“SinGAN”). The SinGAN model is trained to capture the internal distribution of patches within the image, and is then able to generate high quality, diverse samples that carry the same visual content as the image as shown in the architecture below.

SinGAN architecture consists of a multi-scale pipeline, in which a pair of generators and discriminator are present, learning representations at different scales. They can be trained in a coarse-to-fine fashion, where generator and discriminator at the lowest scale learn coarse features like background and stuff, whereas at high scales, they learn very fine details like edges and corners.

The source image is downsampled to the respective sizes and fed into the discriminator along with the generator’s output. And the generator is fed with the random noise along with the generated image from the generator below them (except for last, which is fed with random noise only). As we are dealing with only one source image, we consider a set of patches from the downsampled source images as our real image dataset. “You can think of patch as a sliding window which hovers over the image and samples are collected”. Usually, the patch area remained the same for all sizes, but the effective patch size decreases as the image is getting bigger and bigger for higher networks.

If we took a closer look at the generator, random noise vectors along with the generated image (upsampled to noise shape) from below are concatenated together and fed into 5 subsequent convolution layers, and the output of convolution layers is again concatenated with the generated image from below. This will output a new image further sent to a discriminator along with a real image (downsampled) for evaluation.



This task is conceptually similar to the conventional GAN setting, except that here the training samples are patches of a single image at different resolution scales , rather than whole image samples. Some of the sample GAN generated images for track augmentations of the various wildlife species are shown below:

Footprint samples from SinGAN. They are practically indistinguishable from the original samples. The trained generator is capable of reproducing unlimited variations of these samples from sampled noise data.

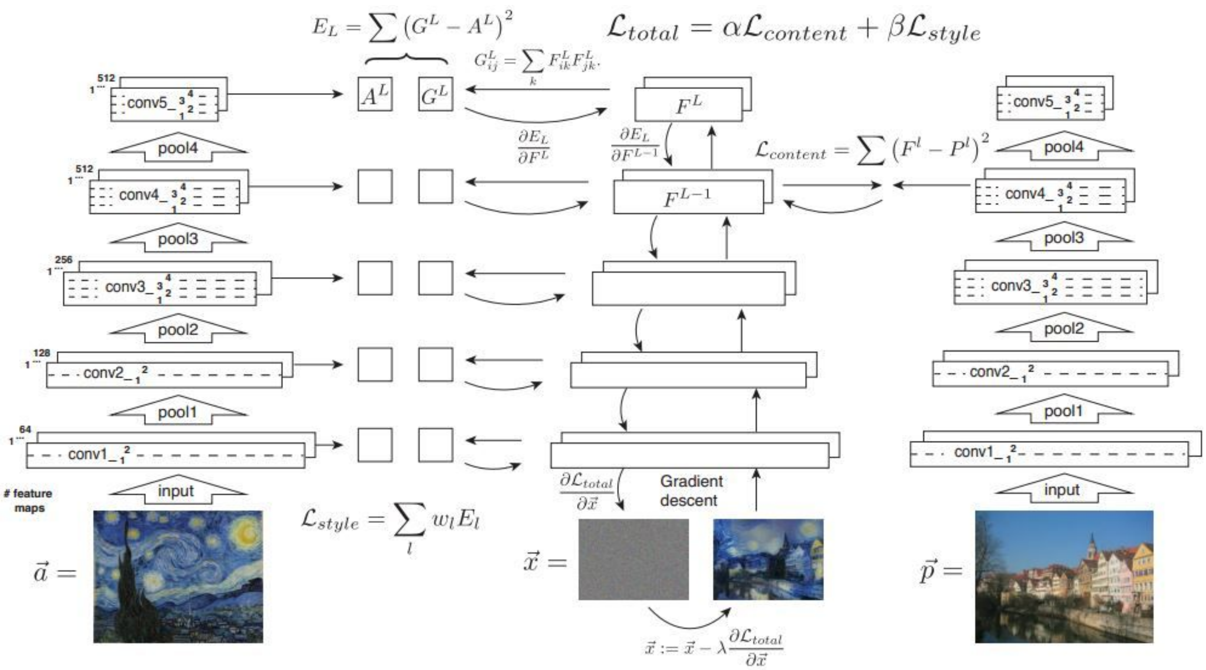
The benefit of this type of GAN is the ability to generate high resolution images. The stakeholders at wildtrack were very interested in converting low resolution track images into high resolution copies. Here is an example of such with a lion footprint:

An example of generation of high resolution images from a single low resolution example. Here is depicted high resolution generated copies of a lion footprints.

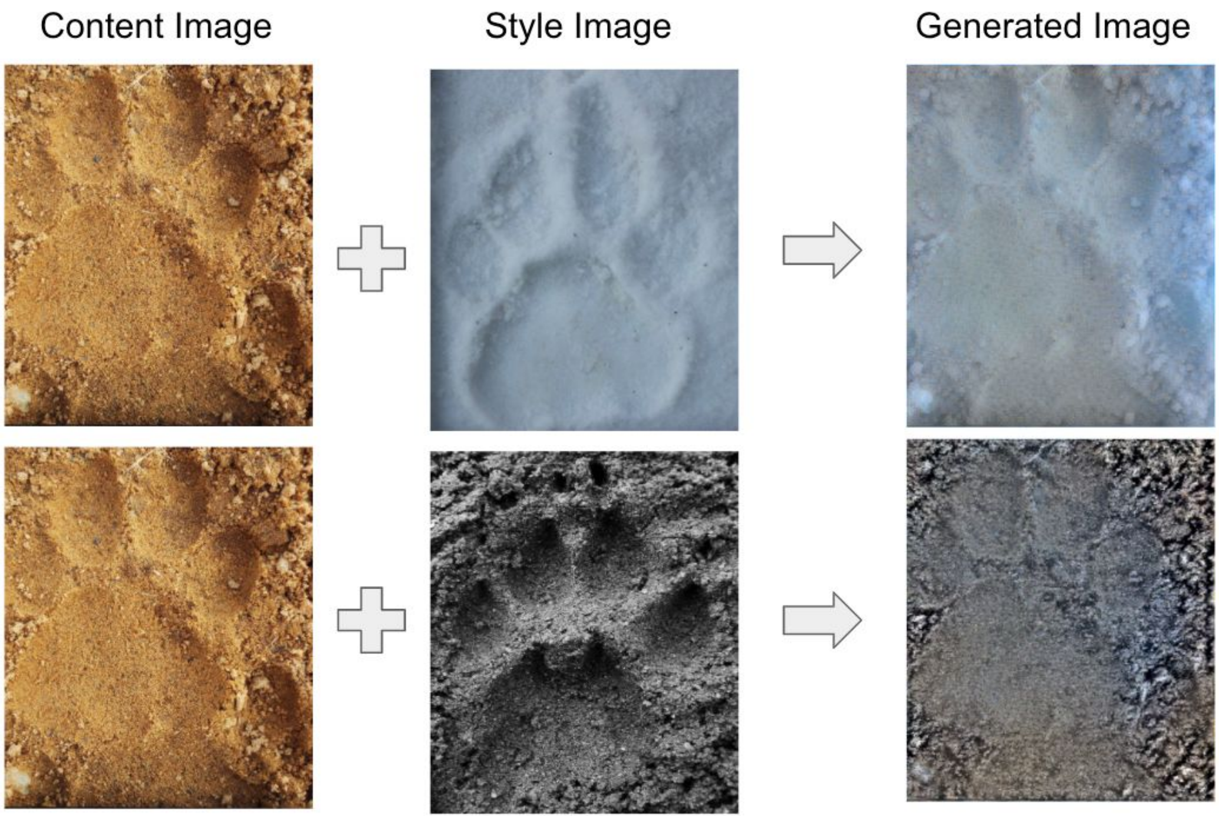
Neural Style Transfer

In addition to GAN, Neural Style Transfer (NST) is also employed for image augmentation in the project. NST is a technique to generate a new image by applying stylistic features of a style image onto a content image while retaining the content's overall structure (https://arxiv.org/abs/1508.06576). It can generate a footprint image with snow from a footprint image with dust by applying the style of snow image or it can generate a footprint image with black dust from a footprint image with brown sand by applying the style of black dust image. Therefore this technique can be used for data augmentation by generating images that are difficult to get in real situations.

The neural style transfer model is shown in figure below (https://www.mikegao.net/graphics/summary/neural_style.html). The NST takes three images, a content image, a style image, and the base image which will look like the content image with the style of the style image. It employs the pre-trained neural network model to extract the image features from the content image and the style image. The model parameters do not need to be updated during the training. The base image is the only variable that needs to be updated in the style transfer process. In the figure below, the pre-trained neural network model has five blocks of convolution layers and a pooling layer for downsampling and VGG-19 is employed as the pre-trained neural network in the project. The output of each layer of the network can be used to extract the features of content image and style image. In our model, the output of the fourth layer is used to extract the feature of content image and outputs of all five layers are used to extract the features of style image. The NST computes two loss functions. One is for the content loss and the other is for the style loss. The total loss is the sum of two loss functions. The content loss is used to make the base image become like the content image in terms of the content features. The style loss function is used to make the style of the base image become like the style image by means of the style features. The NST model finds an image that minimizes the total loss by gradient descent or other optimization.

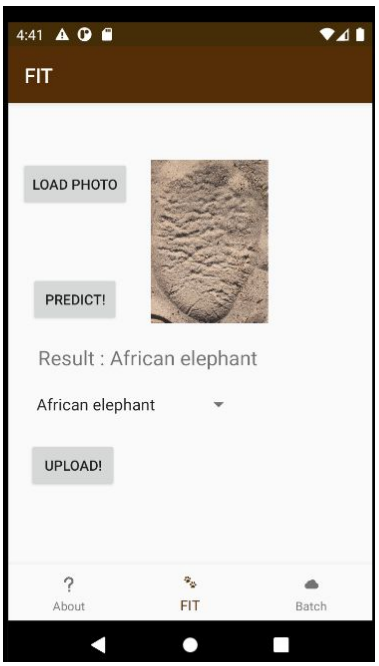


Some examples of NST applied to WildTrack footprint images are in the figure below. The base image which is the generated image in the figure is transformed to look like the content image but it is in a different environment. One is transformed to the footprint on the snow and the other is to the footprint on the black dust. NST, in addition to GAN above, can be used to generate the footprint image which is difficult to take in the real situation.


Content Image
Style Image
Generated Image

Edge - An Android App

Android Studio[1] and the Kotlin Programming Language[2] were used to write an Android smartphone app to perform classification tasks in two principal modes: a batch mode to evaluate model performance with numerous images and an engaging interactive "FIT" (footprint identification technology) mode where the user loads a photo, performs a prediction on it, and optionally uploads it to the MQTT server with a label. A third mode also provides information about the app, but is static only and not interactive. Testing and development used virtual android devices including the Galaxy Nexus API 30 and the Piex_3a_API_30_x86 ; both devices were running Android 11.



The batch mode, accessed via pressing the "Batch" button at the bottom-right, presents to the user two text inputs. The first is a URL interpreted by the app as a file-of-URLs ("fou"): a list of URLs of images. Each file in the list is interpreted as an image to be classified with a known/true label. Upon hitting the "Classify Batch" button, the app downloads each of these images and runs each of the three models on them. The second input presented to the user is the analysis results URL. After each of the images in the "fou" is classified, its results are uploaded to a web server at the user-provided analysis results URL.

The interactive mode engages the user with images, prediction messages, an upload "spinner", and an upload button. A typical workflow first involves the user hitting the "Load Photo" button to select a photo from the camera roll or from the images files on the device. After that, the image is loaded to the UI and the user hits the "Predict" button. After about 4 seconds of inference via tflite, the inference result is displayed on the screen. At this point, the spinner value is updated to reflect the prediction result. If the user is satisfied with the result, they can hit the "Upload" button to send to the MQTT server the image as well as the label from the spinner. If the user is not satisfied with the result, they can use the spinner to choose their one prediction label and then upload the image with the label to thus override the inference output.

TFLITE PERFORMANCE ON THE ANDROID APP

To explore and quantify the performance of the tflite models on the android device, the “batch” processing was carried out using the batch mode previously described. A total of 360 files were processed. Counts of the various labels are shown in the table ; the Otter being most explored while the Leopard, least.

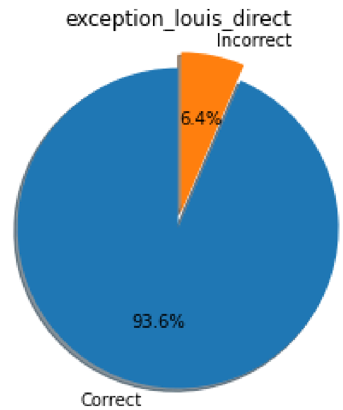
Count	Animal
53	Otter
37	Cheetah
32	African lion
31	Black Rhino
28	African elephant
28	Jaguar
27	White Rhino
25	Puma
24	Bengal Tiger
24	Bongo
19	Lowland Tapir
18	Amur Tiger
14	Leopard

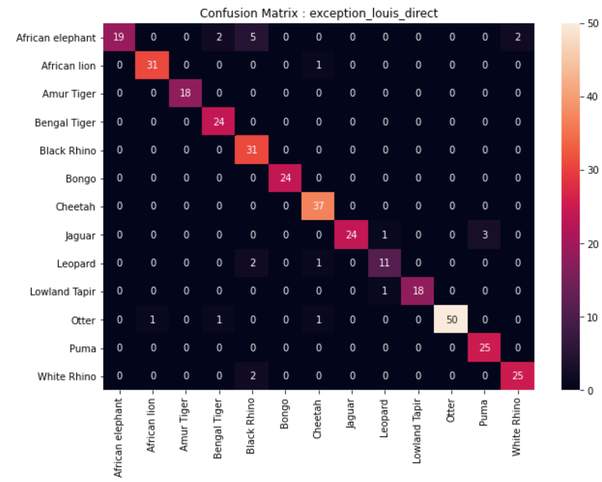
Table: counts of data labels in the batch processing

Overall, performance of the Exception and Inception models are good with accuracies of 94% and 93%. However, performance of the NasNet model is very poor with accuracy of 48.3%. The differences between performance in the TFLITE batch and the regular models are remarkable. The NasNet model is the model on the app with most opportunity for improvement, it is the best model on the cloud; this way it is a concern but also intriguing. Being smaller in size, tflite models may have lower precision and we speculate this might be a cause of such differences. Detailed inspection of the tflite models and the component layers side-by-side with the regular models has not been done and could be a fruitful next step to explore and perhaps discover the reasons for the discrepancies.

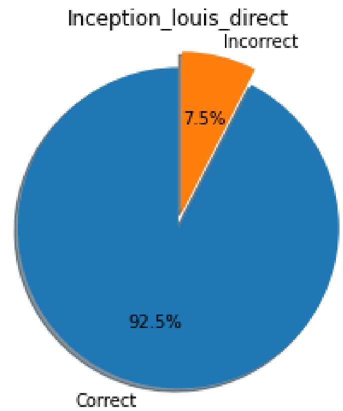
This table shows the performance of the 3 models on the Android edge device. The NASNet model clearly shows the most room for improvement on the edge device.

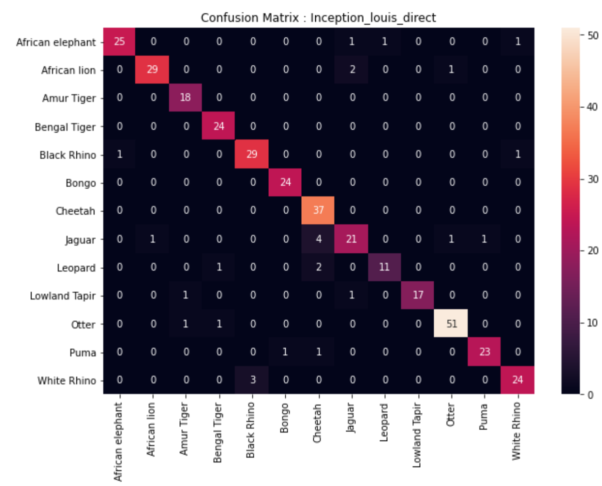
Exception Model - 93.% Accuracy



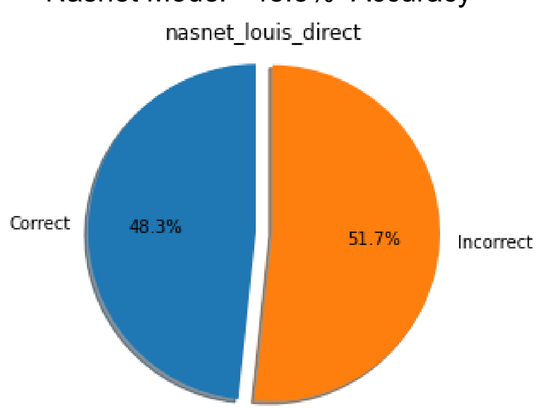


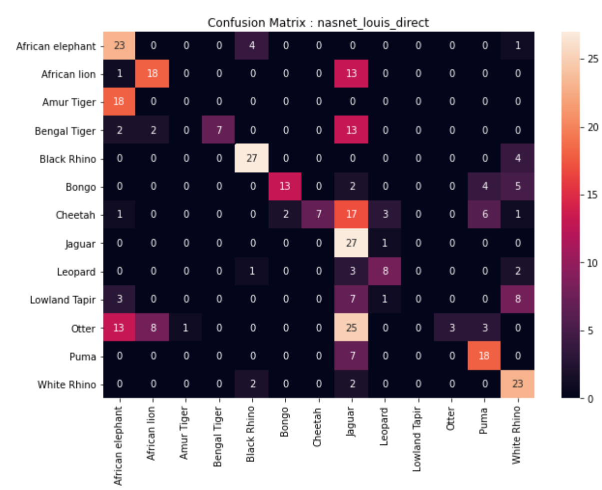
Inception Model - 92.5% Accuracy





Nasnet Model - 48.3% Accuracy





CONCLUSION AND DELIVERABLES

In conclusion we have implemented a cloud and edge-based architecture for footprint classification as well as routines implementing data augmentation (GAN/NST). Models trained via “transfer learning”, namely Xception, Inception, and NasNet now offer improvements relative to the existing models inherited from the previous MIDS/capstone group : their validation accuracy 95.22% with our group’s performance offering validation accuracy of 96.39% (NasNet 98.61%). Using MQTT, our android app classifies and uploads a labeled image to the cloud taken by the device’s camera. We are pleased to offer the WildTrack group these improvements.

We are delivering to the wildtrack team:

1. Code for this group’s contributions via github links
    a. For cloud-based code as well as Android/App code
    b. Code implementation of the MQTT pipeline/architecture
2. Improved models (TF Models)
3. Any technical assistance required to use the code
4. Generated data (GAN/NST)
    a. GAN (data augmentation & low-to-high resolution conversion) and NST model files (weather conditions ; e.g. “to snow”)

SUBMISSION ENGINEERING/GIT DETAILS

The project git repo is here : https://github.com/louis-li/w251_final
The Android App git repo is here : https://github.com/eddie-a-salinas/WildTrackMobile

REFERENCES

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