

Modern Data Mining - Final Project

An Automated Method for Malaria Diagnosis

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Abstract: Malaria is a mosquito-borne infectious disease that can cause death. In 2016, there were 216 million cases of malaria worldwide resulting in an estimated 445,000 to 731,000 deaths. Approximately 90% of both cases and deaths occurred in Africa. Diagnosis of malaria is usually constrained by the availability of doctors and other medical resources, especially in less-developed areas where malaria is more common. Current diagnosis methods include microscopic examination of blood using blood films and antigen-based rapid diagnostic tests, both require the involvement of a skilled lab inspector for accurate detection of the illness. In this study, we explore different techniques to build a predictive model for malaria diagnosis based on thin blood smear slide images. We recommend a final model (accuracy $\approx 95\%$) to be used as a prototype of a timely, cost-effective way of diagnosing malaria by automating the diagnosis through image recognition and removing the heavy reliance on a skilled lab inspector. We aspire for the model to be a powerful tool for diagnosing malaria in countries and areas that lack medical resources – e.g. through incorporation into a mobile app.

Data: We use a repository of segmented cells from the thin blood smear slide images from the Malaria Screener research activity. Source of data: <https://www.kaggle.com/iarunava/cell-images-for-detecting-malaria>

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Background

Malaria is a mosquito-borne infectious disease that can cause death. In 2016, there were 216 million cases of malaria worldwide resulting in an estimated 445,000 to 731,000 deaths. Approximately 90% of both cases and deaths occurred in Africa. Diagnosis of malaria is usually constrained by the availability of doctors and other medical resources, especially in less-developed areas where malaria is more common.

Owing to the non-specific nature of the presentation of symptoms, current diagnosis confirmation relies on microscopic examination of blood using blood films or antigen-based rapid diagnostic tests. Microscopy is the most commonly used method to detect malarial parasite.

Despite its widespread usage, diagnosis by microscopy suffers from two main drawbacks:

1. many settings (especially rural) are not equipped to perform the test
2. the **accuracy** of the results depends on both the skill of the person examining the blood film and the levels of the parasite in the blood.

Description of problem

In this study, we build 5 different predictive models using 3 different modern data mining techniques (ElasticNet Regression, Random Forests, and Artificial Neural Networks) to perform malaria diagnosis based on a 50x50 picture of a thin blood smear slide (microscopy). To choose the best final model, we compare the predictive power of the models using the AUC and accuracy criteria on the validation dataset.

The final model can be a useful prototype of a timely, cost-effective way of diagnosing malaria by automating the diagnosis through image recognition. We aspire for the model to be a powerful tool for diagnosing malaria in countries and areas that lack medical resources – e.g. our model can be incorporated into a mobile phone app to diagnosing malaria with a mobile phone!! Our final model can also be used to improve the accuracy of diagnosis result as well as availability and quality consistency across regions.

Summary of Data

The dataset was obtained from Kaggle (originally taken from the official US National Institutes of Health Website) and contains a total of 27,558, which have been classified into two groups, “Infected” (13,778 images) or “Uninfected” (13,780 images). The raw images are in the PNG file format and are various resolutions, from 40x55 pixel to 241x394 pixels.

Data Cleanup and Extraction

Python data cleaning routines (Exhibit 1) were used to extract and clean up the images. Each image was pulled from the “tar” archive and analyzed to create a 3D matrix (w,h,d; where w=width of the image in pixels, h=height of the image in pixels, d=3;). In the image matrix, the third dimension represented the components of the color channels for each pixel (i.e. the Red, Green, and Blue values). The below operations were then performed on these image matrices:

- Since the images needed to have been fed into different models that had an expected shape, we found it easier to first modify the images to make them have a square aspect ratio by removing the necessary pixels from either side of the dimension that was larger.
- Each image matrix had $w \times h \times d$ numbers and for even a relatively small 100x100 pixel image represented 30,000 different numbers! Since these numbers were fed to our models, the models became very large, complex, and difficult to train. We thus decided to resize all our images to 50x50 pixels. Note that we considered removing the color channels (make the image grayscale) but we decided to

keep them since our observation of the images revealed that the infected images had a dot that was usually purple.

- The entire cleaned dataset was then divided into a training set (14,697 rows with 0.499 positive response proportion) – used to train all the models explored in this paper; a validation set (7,349 rows with 0.496 positive response proportion) – used to evaluate the models explored after they were trained and iteratively improved; a test set (5,512 rows with 0.507 positive response proportion) – never touched during the training or improvement of any of the explored model but instead used to compute the final evaluation metrics for the model recommended for implementation by this paper.
 - Note that all our datasets were very balanced (i.e. no response skew) so accuracy was an acceptable measure of performance for each explored model

The figure below shows a sample of the raw cell images before and after cleaning with the Python routines:

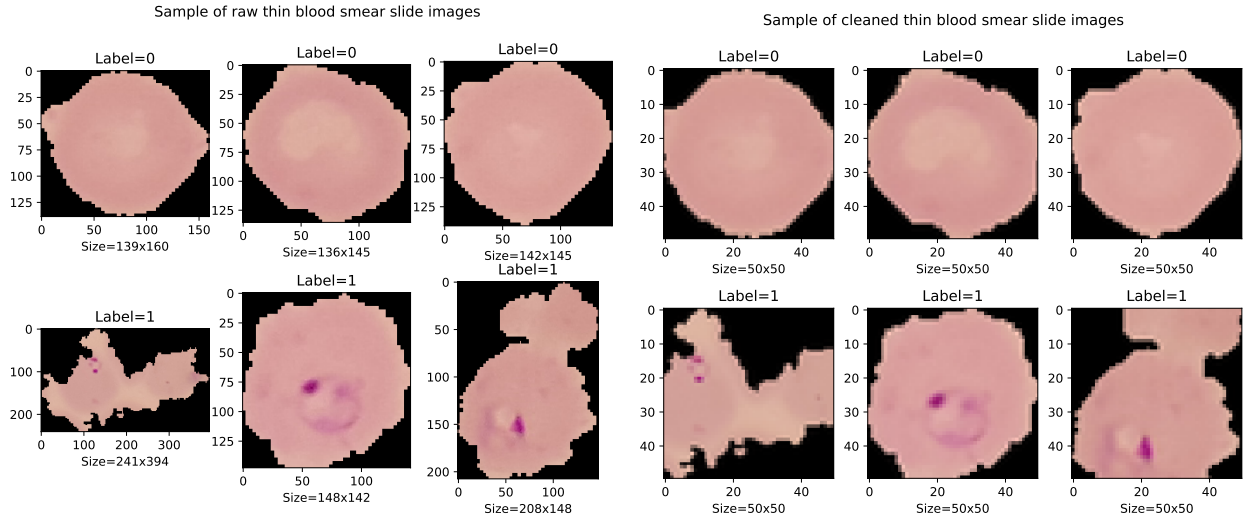


Figure 1: A sample of raw thin blood smear slide images before and after they were cleaned by our Python routines

Predictor Variables

For this study, the “predictor variables” were the matrices of the pixels of the image. Some of our models required a single dimensional vector (e.g. Random Forest), in which case we flattened each 3D matrix into a (1x7500) vector for training and evaluating the models.

The response variable was a binary indicator variable that was 1 if the image represented an infected cell or 0 if the cell wasn’t infected.

Analysis

In this study, we took an approach to evaluate different models with different configurations. Each model’s accuracy on the validation dataset was measured and used for evaluating the model. Additionally, the AUC was used to compare the models to avoid any bias from an assumed loss importance ratio in selecting a classification threshold when necessary. 5 of the explored models are presented in this study. The models used different data mining techniques, specifically: ElasticNet, Random Forest and Artificial Neural Network (3 different architectures)

ElasticNet

The ElasticNet algorithm was also used to analyze the images (Exhibit 2). The L1 L2 penalty was selected to be 0.95 and the optimal alpha was determined from analyzing the CV Error.

- The best lambda was determined to be 0.26004
- The model had an acceptable validation dataset accuracy of 0.679004, at a 0.5 classification threshold
- The model had an acceptable validation dataset AUC of 0.739080

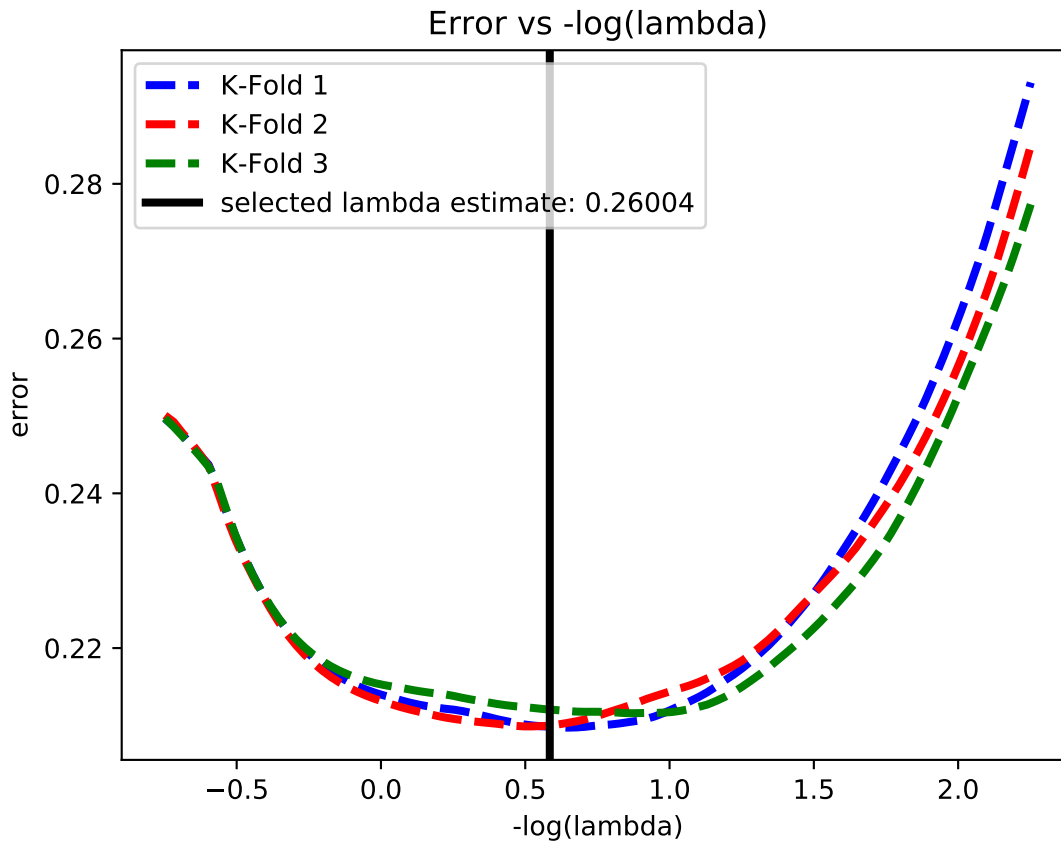


Figure 2: The CV Error as lambda was varied

Random Forest

The Random Forest algorithm was used to analyze the images (Exhibit 3). 200 trees were used in the implementation after running an extensive diagnosis of how the error varied with the number of trees. The $\sqrt{\#}$ of features was used as the number of features to consider at each split.

- The model had an acceptable validation dataset accuracy of 0.798340
- The model had an acceptable validation dataset AUC of 0.798453

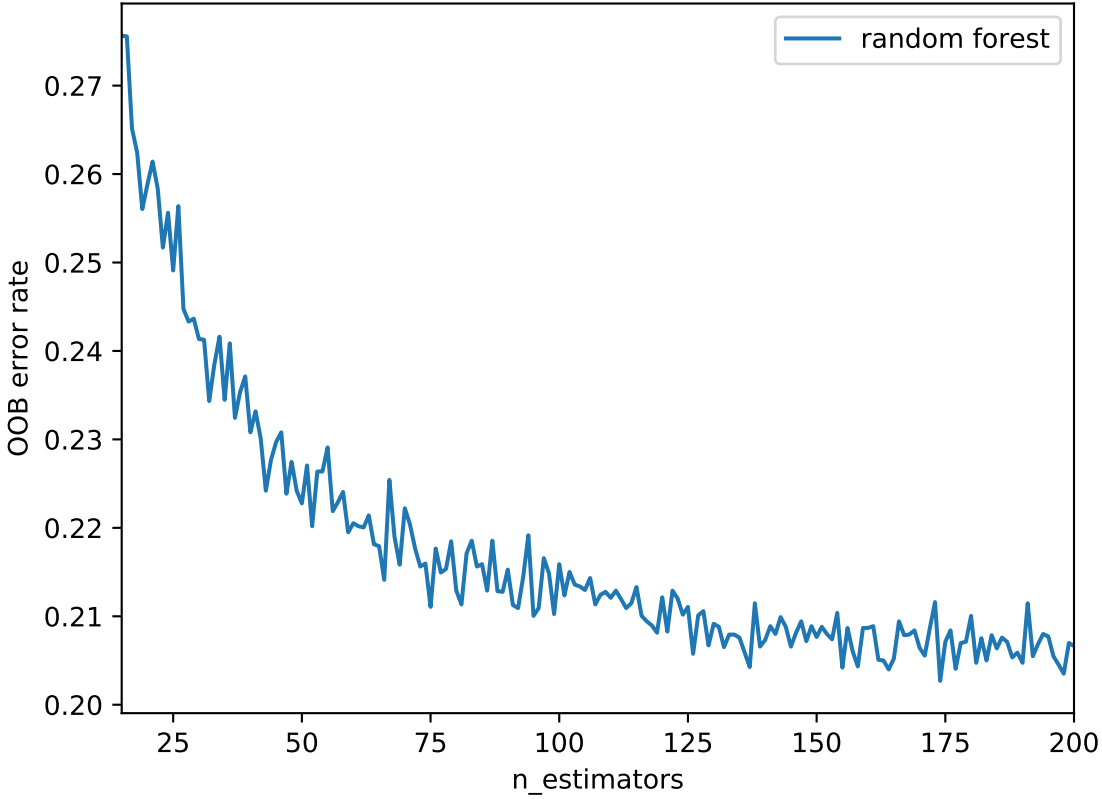


Figure 3: The error as number of trees was varied

Artificial Neural Network

The Artificial Neural Network algorithm was also used to analyze the images. We explored the three different architectures: Multi-layer Perceptron, Convolutional Neural Networks and Google's Inception v3 Architecture. For all the ANN architectures, the output node with the highest value is used as the prediction of the classification.

Multi-layer Perceptron

This was the simplest of the Neural Network Architectures. We used three hidden layers (1024, 256, 128 neurons respectively). The input image matrices were flattened to 7,500 unit vectors and used as the input layer of the network and the output layer had 2 neurons (1 for each class). The model had a total of 7,976,578 parameters.

- The model had an acceptable validation dataset accuracy of 0.663355
- As shown in the plots below, by the end of the training, the training dataset error was high, and this (combined with a high validation set error) prompted us that the model was not sufficiently complex or not converging effectively.

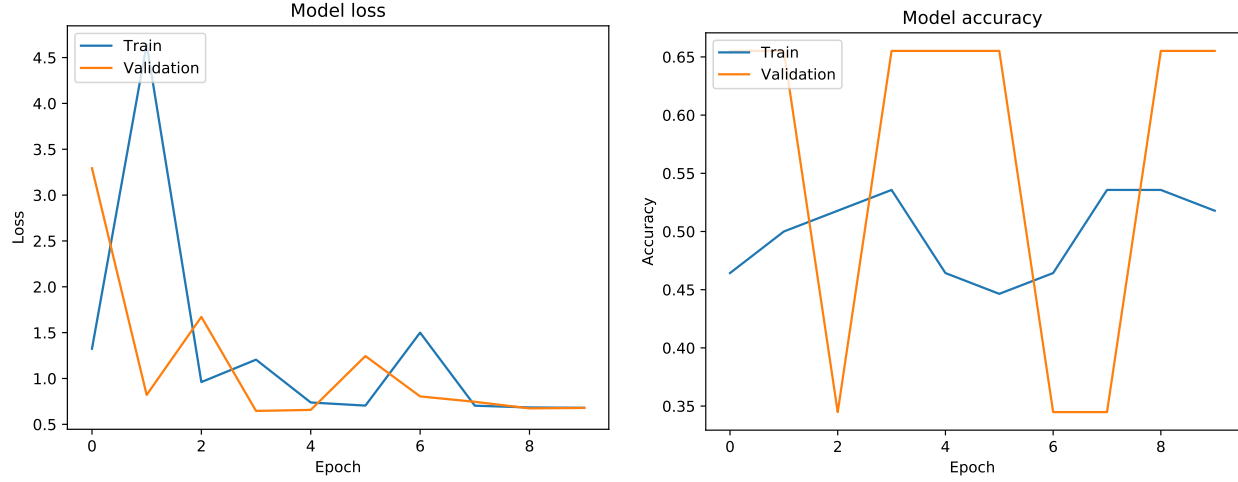


Figure 4: MLP arch. performance on the training and validation datasets over 10 training iterations

Convolutional Neural Networks

We designed another architecture that leveraged Convolutional layers. Convolutional layers are described by research to be very effective for applying Artificial Neural Networks to image recognition tasks. These layers are good for making the network robust to a translation of important image features, which applies very well to our task, where we observed that the images tagged as infected primarily had a “purple dot” at different parts in the image. The model had a total of 2,425,538 parameters.

- The model had an acceptable validation dataset accuracy of 0.953326
- The plots below show that the training loss was decreasing which indicates that the data is being modeled well. The low loss of the validation set also shows that the model wasn’t overfitting. The simultaneously high model accuracies by the end of training (i.e. on the training and validation set simultaneously) also support that this model architecture offers good performance and generalizability.

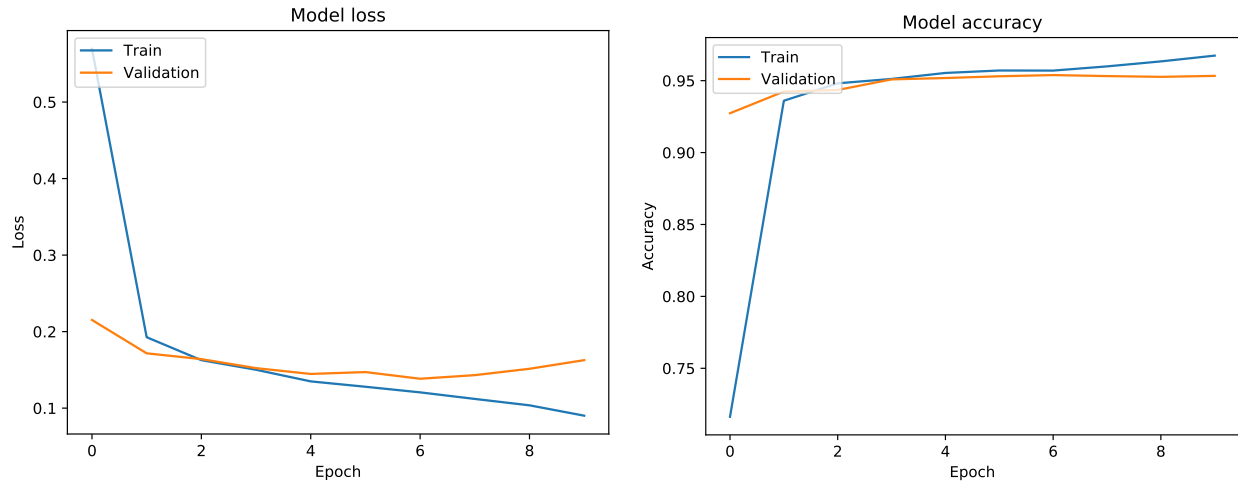


Figure 5: Convolutional arch. performance on the training and validation datasets over 10 training iterations

Inception v3 Architecture

For the third model, we explored Google’s proposed Inception architecture (version 3). This architecture also leverages convolutional layers and other advanced complexities that enable it to excel. Convolutional layers are described by research to be very effective for applying Artificial Neural Networks to image recognition tasks. These layers are good for making the network robust to a translation of important image features, which applies very well to our task, where we observed that the images tagged as infected primarily had a “purple dot” at different parts in the image. The model had a total of 22,327,842 parameters.

- The model had an acceptable validation dataset accuracy of 0.951966
- The plots below show that the training loss was decreasing to very low amounts with the validation dataset loss, which indicates that this model’s architecture is modeling the data very well and with good generalizability. The anomalous drop in the validation set accuracy around iteration 5 is probably just an anomaly in the interaction of the data and the training weights, but the immediate recovery in the subsequent iterations gives us confidence that we can ignore this drop. Thus we conclude that this model performs well with good generalizability.

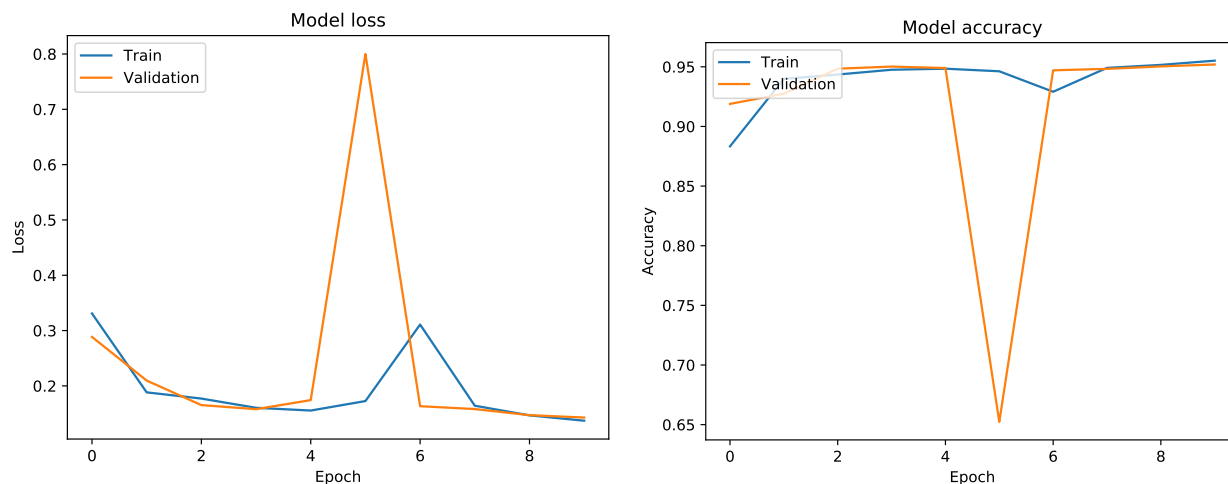


Figure 6: Inception v3 arch. performance on the training and validation datasets over 10 training iterations

Conclusion

We recommend moving forward with the Convolutional Architecture (Exhibit 7). The performance was very similar to the state of the art Inception v3 architecture but the Convolutional architecture that we used is much simpler – it’s relative simplicity was important considering that our intended use of the model is integration into low-end devices in developing countries where Malaria is a big problem.

- The final model’s test set accuracy is 0.950653
- The confusion matrix for the test dataset performance of the final model is shown below. The misclassified errors are very low and indicates the model is very performant. A sample of the misclassified images in the test dataset is shown below, and we think misclassified samples of these types are acceptable for moving forward with the model.

Next Steps: We recommend continuing to extend the model to not just classify when an image is indicative of being infected with Malaria but also to identify which one of the 5 types of malaria is indicated in the image.

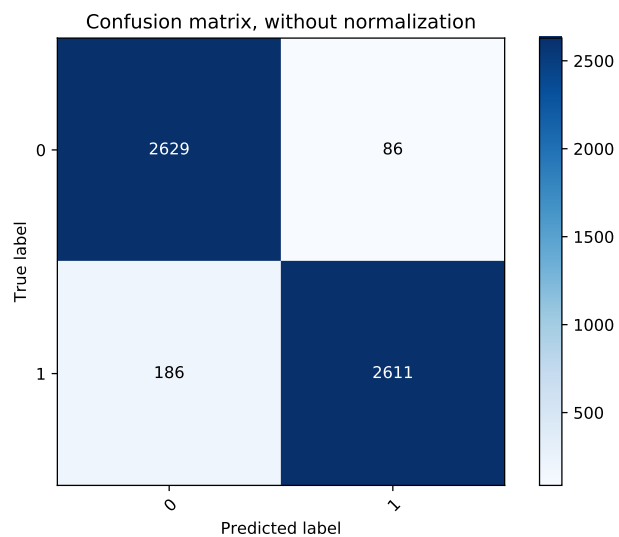


Figure 7: Confusion Matrix of the final model on the test dataset

Sample of the Misclassified Images

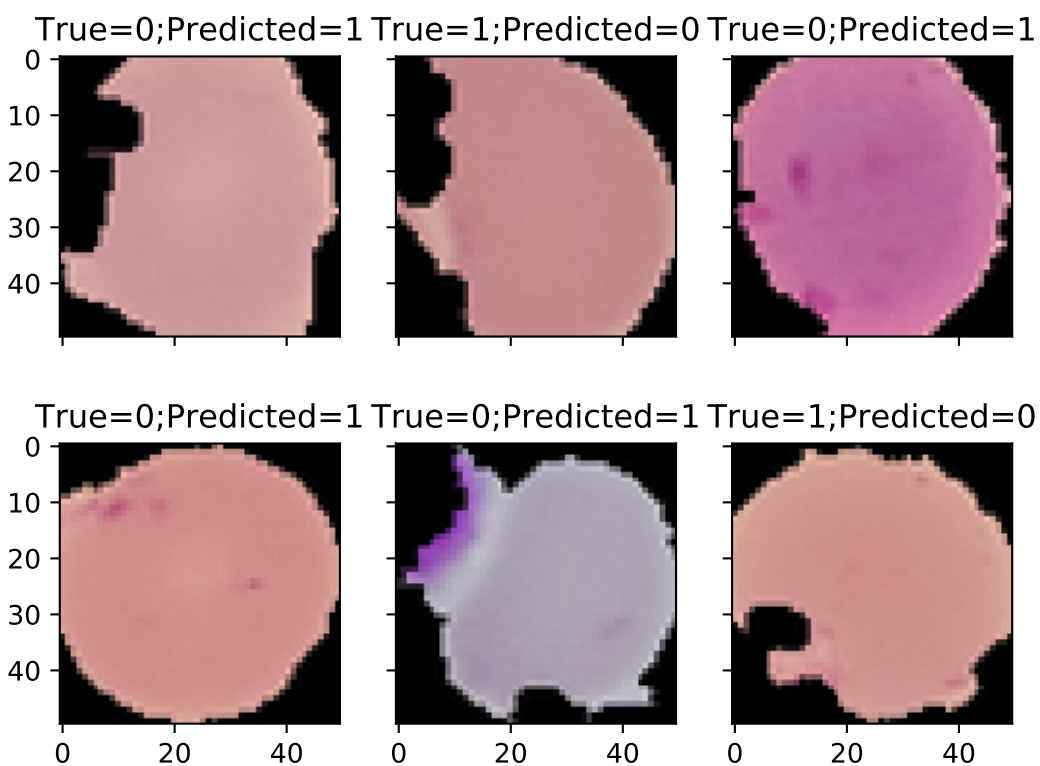


Figure 8: Sample of misclassified images using the final model on the test dataset

Appendix

Exhibit 1

- The Python code used to extract and clean the thin blood smear slide images:

```
import cv2
import numpy as np
import tarfile
import scipy.io
import math
from PIL import Image

from sklearn.model_selection import train_test_split

# Configuration variables for the script
IMAGE_RESIZE_TARGET_HINT = 50
IN_TAR_FILE_FN = 'data/cell_images_full.tar.gz'
OUT_FILE_FN = 'data/cell_images_full_32.mat'

# read filenames directly from tar
def get_all_filenames(tar_fn):
    with tarfile.open(tar_fn) as f:
        return [m.name for m in f.getmembers() if m.isfile()]

# reads bytes directly from tar by filename
def read_raw_from_tar(tar_fn, fn):
    with tarfile.open(tar_fn) as f:
        m = f.getmember(fn)
        return f.extractfile(m).read()

# creates RGB 3D matrix from raw image data
def decode_image_from_raw_bytes(raw_bytes):
    img = cv2.imdecode(np.asarray(bytearray(raw_bytes), dtype=np.uint8), 1)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    return img

# standardizes the images to a uniform size
def standardize_image_pixels(pixels, img_size):
    # centers the image and crops it so that it is square
    def _helper_center_crop_image(img):
        h, w = img.shape[0], img.shape[1]
        shift = math.floor(np.abs(h - w) / 2.0)
        if w > h:
            return img[:, shift:shift + h, :]

        return img[shift:shift + w, :, :]

    centered_cropped = _helper_center_crop_image(pixels)
    return np.array(Image.fromarray(centered_cropped))
```

```

        .resize([img_size, img_size], Image.ANTIALIAS))

# generator to yield each image from tar raw_bytes, label, and file_path
def gn_load_image_observations_from_tar(tar_fn):
    with tarfile.open(tar_fn) as f:
        for m in f.getmembers():
            if m.isfile() and m.name.endswith('.png'):
                raw_bytes = f.extractfile(m).read()
                img = decode_image_from_raw_bytes(raw_bytes)
                yield (
                    img, (1 if m.name.startswith('cell_images/infected/') else 0),
                    m.name
                )

# entry point
def _kernel():
    # %%
    # pull raw images from the tar archive
    image_dataset = list(gn_load_image_observations_from_tar(IN_TAR_FILE_FN))

    # find the smallest image and scale everything to that size
    # or use preconfigured size if it is defined
    IMG_SIZE = IMAGE_RESIZE_TARGET_HINT if IMAGE_RESIZE_TARGET_HINT is not None else (
        math.ceil(
            min([d for e in image_dataset for d in e[0].shape[0:2]]) / 25
        ) * 25)

    # %%
    # standardize all images (e.g. uniform size)
    image_dataset = [
        (standardize_image_pixels(e[0], img_size=IMG_SIZE),) + e[1:]
        for e in image_dataset
    ]

    # split training and test set
    image_dataset_train, image_dataset_test = train_test_split(
        image_dataset,
        test_size=2 / 10,
        random_state=42
    )

    # split optional training and validation set
    image_dataset_model_train, image_dataset_train_model_val = train_test_split(
        image_dataset_train,
        test_size=2 / 6,
        random_state=73
    )

    # package everything for export
    scipy.io.savemat(OUT_FILE_FN, mdict=dict(
        img_size=IMG_SIZE,

```

```

nrow_train=len(image_dataset_train),
train_X=[e[0] for e in image_dataset_train],
train_Y=[e[1] for e in image_dataset_train],
train_fns=[e[2] for e in image_dataset_train],

nrow_model_train=len(image_dataset_model_train),
model_train_X=[e[0] for e in image_dataset_model_train],
model_train_Y=[e[1] for e in image_dataset_model_train],
model_train_fns=[e[2] for e in image_dataset_model_train],

nrow_model_val=len(image_dataset_train_model_val),
model_val_X=[e[0] for e in image_dataset_train_model_val],
model_val_Y=[e[1] for e in image_dataset_train_model_val],
model_val_fns=[e[2] for e in image_dataset_train_model_val],

nrow_test=len(image_dataset_test),
test_X=[e[0] for e in image_dataset_test],
test_Y=[e[1] for e in image_dataset_test],
test_fns=[e[2] for e in image_dataset_test]
), do_compression=True, oned_as='column')

# print summary
print('Cleaned data summary:')
print(dict(
    img_size=IMG_SIZE,
    nrow_train=len(image_dataset_train),
    nrow_model_train=len(image_dataset_model_train),
    nrow_model_val=len(image_dataset_train_model_val),
    nrow_test=len(image_dataset_test)
))

# %%
# boot
_kernel()

```

Exhibit 2

- The Python code used to train a ElasticNet Regression analyzer to classify the cell images:

```

import scipy.io
import sklearn
from sklearn.linear_model import ElasticNetCV

TRAIN_DATASET_FN = 'data/cell_images_full_32.mat'

# Flatten an matrix for ElasticNet Regression
def _helper_flatten_matrix(arr):
    return arr.reshape(arr.shape[0], -1)

# entry point

```

```

def _kernel():
    # %%
    image_dataset = scipy.io.loadmat(
        TRAIN_DATASET_FN,
        variable_names=(
            'img_size',
            'nrow_model_train',
            'model_train_X', 'model_train_Y', 'model_train_fns',
            'nrow_model_val',
            'model_val_X', 'model_val_Y', 'model_train_fns'
        ),
        squeeze_me=True
    )

    # %%
    print('Building ElasticNet:')
    clf = ElasticNetCV(l1_ratio=0.95, verbose=2)
    clf.fit(
        _helper_flatten_matrix(image_dataset['model_train_X']),
        image_dataset['model_train_Y']
    )
    print('Model training complete!!')

    # %%
    # compute validation metric
    val_Y_pred = clf.predict(_helper_flatten_matrix(
        image_dataset['model_val_X']
    ))

    val_Y_pred_classes = (val_Y_pred > 0.5).astype(int)

    print("Validation accuracy:", sklearn.metrics.accuracy_score(
        image_dataset['model_val_Y'], val_Y_pred_classes
    ))

    fpr, tpr, thresholds = sklearn.metrics.roc_curve(
        image_dataset['model_val_Y'], val_Y_pred, pos_label=1
    )
    print('AUC Score:', sklearn.metrics.auc(fpr, tpr))

    # %%
    # boot
    _kernel()

```

Exhibit 3

- The Python code used to train a Random Forest analyzer to classify the cell images:

```
import scipy.io
import sklearn
from sklearn.ensemble import RandomForestClassifier

TRAIN_DATASET_FN = 'data/cell_images_full_32.mat'

# Flatten an matrix for Random Forest input
def _helper_flatten_matrix(arr):
    return arr.reshape(arr.shape[0], -1)

# entry point
def _kernel():
    # %%
    image_dataset = scipy.io.loadmat(
        TRAIN_DATASET_FN,
        variable_names=(
            'img_size',
            'nrow_model_train',
            'model_train_X', 'model_train_Y', 'model_train_fns',
            'nrow_model_val',
            'model_val_X', 'model_val_Y', 'model_val_fns'
        ),
        squeeze_me=True
    )

    # %%
    # Train the model
    print('Training model:')
    clf = RandomForestClassifier(n_estimators=200, verbose=2)
    clf.fit(
        _helper_flatten_matrix(image_dataset['model_train_X']),
        image_dataset['model_train_Y']
    )
    print('Model training complete!!!')

    # %%
    # compute validation metric
    val_Y_pred = clf.predict(_helper_flatten_matrix(
        image_dataset['model_val_X']
    ))
    print("Validation accuracy:", sklearn.metrics.accuracy_score(
        image_dataset['model_val_Y'], val_Y_pred
    ))

    fpr, tpr, thresholds = sklearn.metrics.roc_curve(
        image_dataset['model_val_Y'], val_Y_pred, pos_label=1
    )
    print('AUC Score:', sklearn.metrics.auc(fpr, tpr))

# %%
```

```
# boot
_kernel()
```

Exhibit 4

- The Python code used to train a MLP ANN to classify the cell images:

```
import numpy as np
import scipy.io
import math

import tensorflow as tf
import keras
import sklearn

TRAIN_DATASET_FN = 'data/cell_images_full_32.mat'

TRAIN_BATCH_SIZE = 50
TRAIN_EPOCHS = 10

FLG_SHIM_FLATTEN_MODEL_INPUTS = True

# this decorator will selectively flatten the model inputs
# based on the noted flag
def _deco_flatten_model_input_matrix(arr):
    if FLG_SHIM_FLATTEN_MODEL_INPUTS:
        return _helper_flatten_matrix(arr)
    return arr

# Flatten an matrix for a dense MLP
def _helper_flatten_matrix(arr):
    return arr.reshape(arr.shape[0], -1)

# Build deep net with a few layers
def build_model_mlp(input_shape):
    model = keras.models.Sequential()
    model.add(keras.layers.Dense(1024, input_shape=(np.prod(input_shape),)))
    model.add(keras.layers.Activation('sigmoid'))
    model.add(keras.layers.Dense(256))
    model.add(keras.layers.Activation('sigmoid'))
    model.add(keras.layers.Dense(128))
    model.add(keras.layers.Activation('sigmoid'))
    model.add(keras.layers.Dense(2))
    model.add(keras.layers.Activation('softmax'))
    return model

# entry point
def _kernel():
    # %%
```

```

image_dataset = scipy.io.loadmat(
    TRAIN_DATASET_FN,
    variable_names=(
        'img_size',
        'nrow_model_train',
        'model_train_X', 'model_train_Y', 'model_train_fns',
        'nrow_model_val',
        'model_val_X', 'model_val_Y', 'model_val_fns'
    ),
    squeeze_me=True
)

# %%
n_training_batches = math.ceil(image_dataset['nrow_model_train'] / TRAIN_BATCH_SIZE)

# Print some statistics on the training data
print('Training data shape:', image_dataset['model_train_X'].shape)
print('Number training batches:', n_training_batches)

print(
    "Proportion of training 1's:",
    sum(image_dataset['model_train_Y']),
    sum(image_dataset['model_train_Y']) / image_dataset['nrow_model_train']
)

# Print some statistics on the validation data
print('Validation data shape:', image_dataset['model_val_X'].shape)
print('Number validation batches:', n_training_batches)

print(
    "Proportion of validation 1's:",
    sum(image_dataset['model_val_Y']),
    sum(image_dataset['model_val_Y']) / image_dataset['nrow_model_val']
)

# %%
# helper functions
# Resets the TF graph
def helper_reset_tf_session():
    curr_session = tf.get_default_session()
    # if current session exists then close it
    if curr_session is not None:
        curr_session.close()
    # reset the tf graph
    keras.backend.clear_session()
    # create a new tf session
    config = tf.ConfigProto()
    config.gpu_options.allow_growth = True # use GPU memory as needed
    s = tf.InteractiveSession(config=config)
    keras.backend.set_session(s)
    return s

# %%

```



```

helper_reset_tf_session()

# %%
# A small abstraction to enable switching between models
model = build_model_mlp((image_dataset['img_size'], image_dataset['img_size'], 3))

# %%
# compile the model
model.compile(
    loss='categorical_crossentropy',
    optimizer=keras.optimizers.adamax(lr=1e-2),
    metrics=['accuracy'] # report accuracy during training
)

# %%
# train the model on the dataset
model_fit_history = model.fit(
    _deco_flatten_model_input_matrix(np.stack(map(
        keras.applications.inception_v3.preprocess_input,
        image_dataset['model_train_X']
    ))),
    keras.utils.np_utils.to_categorical(image_dataset['model_train_Y'], 2),
    epochs=TRAIN_EPOCHS,
    batch_size=TRAIN_BATCH_SIZE,
    validation_data=(
        _deco_flatten_model_input_matrix(np.stack(map(
            keras.applications.inception_v3.preprocess_input,
            image_dataset['model_val_X']
        ))),
        keras.utils.np_utils.to_categorical(image_dataset['model_val_Y'], 2)
    ),
    verbose=0
)

print('Model training complete!!!')

# %%
# boot
_kernel()

```

Exhibit 5

- The architecture of the trained MLP ANN:

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 1024)	7681024
activation_1 (Activation)	(None, 1024)	0
dense_2 (Dense)	(None, 256)	262400

activation_2 (Activation)	(None, 256)	0

dense_3 (Dense)	(None, 128)	32896

activation_3 (Activation)	(None, 128)	0

dense_4 (Dense)	(None, 2)	258

activation_4 (Activation)	(None, 2)	0
=====		
Total params:		7,976,578

Exhibit 6

- The Python code used to train the Convolutional ANN to classify the cell images:

```
import numpy as np
import scipy.io
import math

import tensorflow as tf
import keras
import sklearn

TRAIN_DATASET_FN = 'data/cell_images_full_32.mat'

TRAIN_BATCH_SIZE = 50
TRAIN_EPOCHS = 10

FLG_SHIM_FLATTEN_MODEL_INPUTS = False

# this decorator will selectively flatten the model inputs
# based on the noted flag
def _deco_flatten_model_input_matrix(arr):
    if FLG_SHIM_FLATTEN_MODEL_INPUTS:
        return _helper_flatten_matrix(arr)
    return arr

# Flatten an matrix for a dense MLP
def _helper_flatten_matrix(arr):
    return arr.reshape(arr.shape[0], -1)

# Build deep net with a few convolutional layers
def build_model_conv_net(input_shape):
    model = keras.Sequential()
    model.add(keras.layers.Conv2D(
        filters=16, kernel_size=3, strides=1, padding='same', input_shape=input_shape
    ))
    model.add(keras.layers.LeakyReLU(0.1))
    model.add(keras.layers.Conv2D(filters=32, kernel_size=3, strides=1, padding='same'))
```

```

model.add(keras.layers.LeakyReLU(0.1))
model.add(keras.layers.AveragePooling2D())
model.add(keras.layers.Dropout(0.25))
model.add(keras.layers.Conv2D(filters=32, kernel_size=3, strides=1, padding='same'))
model.add(keras.layers.LeakyReLU(0.1))
model.add(keras.layers.Conv2D(filters=64, kernel_size=3, strides=1, padding='same'))
model.add(keras.layers.LeakyReLU(0.1))
model.add(keras.layers.AveragePooling2D())
model.add(keras.layers.Dropout(0.25))
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(256))
model.add(keras.layers.LeakyReLU(0.1))
model.add(keras.layers.Dense(128))
model.add(keras.layers.LeakyReLU(0.1))
model.add(keras.layers.Dense(2))
model.add(keras.layers.Activation('softmax'))
return model

# entry point
def _kernel():
    # %%
    image_dataset = scipy.io.loadmat(
        TRAIN_DATASET_FN,
        variable_names=(
            'img_size',
            'nrow_model_train',
            'model_train_X', 'model_train_Y', 'model_train_fns',
            'nrow_model_val',
            'model_val_X', 'model_val_Y', 'model_val_fns'
        ),
        squeeze_me=True
    )

    # %%
    n_training_batches = math.ceil(image_dataset['nrow_model_train'] / TRAIN_BATCH_SIZE)

    # Print some statistics on the training data
    print('Training data shape:', image_dataset['model_train_X'].shape)
    print('Number training batches:', n_training_batches)

    print(
        "Proportion of training 1's:",
        sum(image_dataset['model_train_Y']),
        sum(image_dataset['model_train_Y']) / image_dataset['nrow_model_train']
    )

    # Print some statistics on the validation data
    print('Validation data shape:', image_dataset['model_val_X'].shape)
    print('Number validation batches:', n_training_batches)

    print(
        "Proportion of validation 1's:",
        sum(image_dataset['model_val_Y']),

```

```

        sum(image_dataset['model_val_Y']) / image_dataset['nrow_model_val']
    )

    # %%
    # helper functions
    # Resets the TF graph
    def helper_reset_tf_session():
        curr_session = tf.get_default_session()
        # if current session exists then close it
        if curr_session is not None:
            curr_session.close()
        # reset the tf graph
        keras.backend.clear_session()
        # create a new tf session
        config = tf.ConfigProto()
        config.gpu_options.allow_growth = True # use GPU memory as needed
        s = tf.InteractiveSession(config=config)
        keras.backend.set_session(s)
        return s

    # %%
    helper_reset_tf_session()

    # %%
    # A small abstraction to enable switching between models
    model = build_model_conv_net(
        (image_dataset['img_size'], image_dataset['img_size'], 3)
    )

    # %%
    # compile the model
    model.compile(
        loss='categorical_crossentropy',
        optimizer=keras.optimizers.adamax(lr=1e-2),
        metrics=['accuracy'] # report accuracy during training
    )

    # %%
    # train the model on the dataset
    model_fit_history = model.fit(
        _deco_flatten_model_input_matrix(np.stack(map(
            keras.applications.inception_v3.preprocess_input,
            image_dataset['model_train_X']
        ))),
        keras.utils.np_utils.to_categorical(image_dataset['model_train_Y'], 2),
        epochs=TRAIN_EPOCHS,
        batch_size=TRAIN_BATCH_SIZE,
        validation_data=(
            _deco_flatten_model_input_matrix(np.stack(map(
                keras.applications.inception_v3.preprocess_input,
                image_dataset['model_val_X']
            ))),
            keras.utils.np_utils.to_categorical(image_dataset['model_val_Y'], 2)
        )
    )

```

```

    ),
    verbose=0
)

print('Model training complete!!')

# %%
# boot
_kernel()

```

Exhibit 7

- The architecture of the trained Convolutional ANN:

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 50, 50, 16)	448
leaky_re_lu_1 (LeakyReLU)	(None, 50, 50, 16)	0
conv2d_2 (Conv2D)	(None, 50, 50, 32)	4640
leaky_re_lu_2 (LeakyReLU)	(None, 50, 50, 32)	0
average_pooling2d_1 (Average)	(None, 25, 25, 32)	0
dropout_1 (Dropout)	(None, 25, 25, 32)	0
conv2d_3 (Conv2D)	(None, 25, 25, 32)	9248
leaky_re_lu_3 (LeakyReLU)	(None, 25, 25, 32)	0
conv2d_4 (Conv2D)	(None, 25, 25, 64)	18496
leaky_re_lu_4 (LeakyReLU)	(None, 25, 25, 64)	0
average_pooling2d_2 (Average)	(None, 12, 12, 64)	0
dropout_2 (Dropout)	(None, 12, 12, 64)	0
flatten_1 (Flatten)	(None, 9216)	0
dense_1 (Dense)	(None, 256)	2359552
leaky_re_lu_5 (LeakyReLU)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
leaky_re_lu_6 (LeakyReLU)	(None, 128)	0
dense_3 (Dense)	(None, 2)	258

```
activation_1 (Activation)      (None, 2)      0
=====
Total params: 2,425,538
```

Exhibit 8

- The Python code used to train the Inception v3 ANN to classify the cell images:

```
import numpy as np
import scipy.io
import math

import tensorflow as tf
import keras
import sklearn

TRAIN_DATASET_FN = 'data/cell_images_full_32.mat'

TRAIN_BATCH_SIZE = 50
TRAIN_EPOCHS = 10

FLG_SHIM_FLATTEN_MODEL_INPUTS = True

# this decorator will selectively flatten the model inputs
# based on the noted flag
def _deco_flatten_model_input_matrix(arr):
    if FLG_SHIM_FLATTEN_MODEL_INPUTS:
        return _helper_flatten_matrix(arr)
    return arr

# Flatten an matrix for a dense MLP
def _helper_flatten_matrix(arr):
    return arr.reshape(arr.shape[0], -1)

# Builds a Keras model by fine tuning inception V3 model
def build_model_inceptionV3_fine_tune(input_shape):
    # Exclude the final layer and add custom FC layer
    model = keras.applications.InceptionV3(
        include_top=False, input_shape=input_shape
    )

    # Add global max pooling
    final_layer = keras.layers.GlobalAveragePooling2D()(model.output)

    # Add new FC layer for predicting labels
    final_layer = keras.layers.Dense(256, activation='relu')(final_layer)

    # Add new output layer
    final_layer = keras.layers.Dense(2, activation='softmax')(final_layer)
```

```

model = keras.engine.training.Model(model.inputs, final_layer)

return model

# entry point
def _kernel():
    # %%
    image_dataset = scipy.io.loadmat(
        TRAIN_DATASET_FN,
        variable_names=(
            'img_size',
            'nrow_model_train',
            'model_train_X', 'model_train_Y', 'model_train_fns',
            'nrow_model_val',
            'model_val_X', 'model_val_Y', 'model_val_fns'
        ),
        squeeze_me=True
    )

    # %%
    n_training_batches = math.ceil(image_dataset['nrow_model_train'] / TRAIN_BATCH_SIZE)

    # Print some statistics on the training data
    print('Training data shape:', image_dataset['model_train_X'].shape)
    print('Number training batches:', n_training_batches)

    print(
        "Proportion of training 1's:",
        sum(image_dataset['model_train_Y']),
        sum(image_dataset['model_train_Y']) / image_dataset['nrow_model_train']
    )

    # Print some statistics on the validation data
    print('Validation data shape:', image_dataset['model_val_X'].shape)
    print('Number validation batches:', n_training_batches)

    print(
        "Proportion of validation 1's:",
        sum(image_dataset['model_val_Y']),
        sum(image_dataset['model_val_Y']) / image_dataset['nrow_model_val']
    )

    # %%
    # helper functions
    # Resets the TF graph
    def helper_reset_tf_session():
        curr_session = tf.get_default_session()
        # if current session exists then close it
        if curr_session is not None:
            curr_session.close()
        # reset the tf graph
        keras.backend.clear_session()

```

```

    # create a new tf session
    config = tf.ConfigProto()
    config.gpu_options.allow_growth = True # use GPU memory as needed
    s = tf.InteractiveSession(config=config)
    keras.backend.set_session(s)
    return s

# %%
helper_reset_tf_session()

# %%
# A small abstraction to enable switching between models
model = build_model_inceptionV3_fine_tune(
    (image_dataset['img_size'], image_dataset['img_size'], 3)
)

# %%
# compile the model
model.compile(
    loss='categorical_crossentropy',
    optimizer=keras.optimizers.adamax(lr=1e-2),
    metrics=['accuracy'] # report accuracy during training
)

# %%
# train the model on the dataset
model_fit_history = model.fit(
    _deco_flatten_model_input_matrix(np.stack(map(
        keras.applications.inception_v3.preprocess_input,
        image_dataset['model_train_X']
    ))),
    keras.utils.np_utils.to_categorical(image_dataset['model_train_Y'], 2),
    epochs=TRAIN_EPOCHS,
    batch_size=TRAIN_BATCH_SIZE,
    validation_data=(
        _deco_flatten_model_input_matrix(np.stack(map(
            keras.applications.inception_v3.preprocess_input,
            image_dataset['model_val_X']
        ))),
        keras.utils.np_utils.to_categorical(image_dataset['model_val_Y'], 2)
    ),
    verbose=0
)

print('Model training complete!!!')

# %%
# boot
_kernel()

```


Exhibit 9

- The architecture of the trained Inception v3 ANN:

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 75, 75, 3)	0	
conv2d_1 (Conv2D)	(None, 37, 37, 32)	864	input_1[0][0]
batch_normalization_1 (BatchNor	(None, 37, 37, 32)	96	conv2d_1[0][0]
activation_1 (Activation)	(None, 37, 37, 32)	0	batch_normalization_1[0][0]
conv2d_2 (Conv2D)	(None, 35, 35, 32)	9216	activation_1[0][0]
batch_normalization_2 (BatchNor	(None, 35, 35, 32)	96	conv2d_2[0][0]
activation_2 (Activation)	(None, 35, 35, 32)	0	batch_normalization_2[0][0]
conv2d_3 (Conv2D)	(None, 35, 35, 64)	18432	activation_2[0][0]
batch_normalization_3 (BatchNor	(None, 35, 35, 64)	192	conv2d_3[0][0]
activation_3 (Activation)	(None, 35, 35, 64)	0	batch_normalization_3[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 17, 17, 64)	0	activation_3[0][0]
conv2d_4 (Conv2D)	(None, 17, 17, 80)	5120	max_pooling2d_1[0][0]
batch_normalization_4 (BatchNor	(None, 17, 17, 80)	240	conv2d_4[0][0]
activation_4 (Activation)	(None, 17, 17, 80)	0	batch_normalization_4[0][0]
conv2d_5 (Conv2D)	(None, 15, 15, 192)	138240	activation_4[0][0]
batch_normalization_5 (BatchNor	(None, 15, 15, 192)	576	conv2d_5[0][0]
activation_5 (Activation)	(None, 15, 15, 192)	0	batch_normalization_5[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 192)	0	activation_5[0][0]
conv2d_9 (Conv2D)	(None, 7, 7, 64)	12288	max_pooling2d_2[0][0]
batch_normalization_9 (BatchNor	(None, 7, 7, 64)	192	conv2d_9[0][0]
activation_9 (Activation)	(None, 7, 7, 64)	0	batch_normalization_9[0][0]
conv2d_7 (Conv2D)	(None, 7, 7, 48)	9216	max_pooling2d_2[0][0]
conv2d_10 (Conv2D)	(None, 7, 7, 96)	55296	activation_9[0][0]
batch_normalization_7 (BatchNor	(None, 7, 7, 48)	144	conv2d_7[0][0]

batch_normalization_10 (BatchNo	(None, 7, 7, 96)	288	conv2d_10[0][0]
activation_7 (Activation)	(None, 7, 7, 48)	0	batch_normalization_7[0][0]
activation_10 (Activation)	(None, 7, 7, 96)	0	batch_normalization_10[0][0]
average_pooling2d_1 (AveragePoo	(None, 7, 7, 192)	0	max_pooling2d_2[0][0]
conv2d_6 (Conv2D)	(None, 7, 7, 64)	12288	max_pooling2d_2[0][0]
conv2d_8 (Conv2D)	(None, 7, 7, 64)	76800	activation_7[0][0]
conv2d_11 (Conv2D)	(None, 7, 7, 96)	82944	activation_10[0][0]
conv2d_12 (Conv2D)	(None, 7, 7, 32)	6144	average_pooling2d_1[0][0]
batch_normalization_6 (BatchNor	(None, 7, 7, 64)	192	conv2d_6[0][0]
batch_normalization_8 (BatchNor	(None, 7, 7, 64)	192	conv2d_8[0][0]
batch_normalization_11 (BatchNo	(None, 7, 7, 96)	288	conv2d_11[0][0]
batch_normalization_12 (BatchNo	(None, 7, 7, 32)	96	conv2d_12[0][0]
activation_6 (Activation)	(None, 7, 7, 64)	0	batch_normalization_6[0][0]
activation_8 (Activation)	(None, 7, 7, 64)	0	batch_normalization_8[0][0]
activation_11 (Activation)	(None, 7, 7, 96)	0	batch_normalization_11[0][0]
activation_12 (Activation)	(None, 7, 7, 32)	0	batch_normalization_12[0][0]
mixed0 (Concatenate)	(None, 7, 7, 256)	0	activation_6[0][0] activation_8[0][0] activation_11[0][0] activation_12[0][0]
conv2d_16 (Conv2D)	(None, 7, 7, 64)	16384	mixed0[0][0]
batch_normalization_16 (BatchNo	(None, 7, 7, 64)	192	conv2d_16[0][0]
activation_16 (Activation)	(None, 7, 7, 64)	0	batch_normalization_16[0][0]
conv2d_14 (Conv2D)	(None, 7, 7, 48)	12288	mixed0[0][0]
conv2d_17 (Conv2D)	(None, 7, 7, 96)	55296	activation_16[0][0]
batch_normalization_14 (BatchNo	(None, 7, 7, 48)	144	conv2d_14[0][0]
batch_normalization_17 (BatchNo	(None, 7, 7, 96)	288	conv2d_17[0][0]
activation_14 (Activation)	(None, 7, 7, 48)	0	batch_normalization_14[0][0]

activation_17 (Activation)	(None, 7, 7, 96)	0	batch_normalization_17[0][0]
average_pooling2d_2 (AveragePool)	(None, 7, 7, 256)	0	mixed0[0][0]
conv2d_13 (Conv2D)	(None, 7, 7, 64)	16384	mixed0[0][0]
conv2d_15 (Conv2D)	(None, 7, 7, 64)	76800	activation_14[0][0]
conv2d_18 (Conv2D)	(None, 7, 7, 96)	82944	activation_17[0][0]
conv2d_19 (Conv2D)	(None, 7, 7, 64)	16384	average_pooling2d_2[0][0]
batch_normalization_13 (Batch Normalization)	(None, 7, 7, 64)	192	conv2d_13[0][0]
batch_normalization_15 (Batch Normalization)	(None, 7, 7, 64)	192	conv2d_15[0][0]
batch_normalization_18 (Batch Normalization)	(None, 7, 7, 96)	288	conv2d_18[0][0]
batch_normalization_19 (Batch Normalization)	(None, 7, 7, 64)	192	conv2d_19[0][0]
activation_13 (Activation)	(None, 7, 7, 64)	0	batch_normalization_13[0][0]
activation_15 (Activation)	(None, 7, 7, 64)	0	batch_normalization_15[0][0]
activation_18 (Activation)	(None, 7, 7, 96)	0	batch_normalization_18[0][0]
activation_19 (Activation)	(None, 7, 7, 64)	0	batch_normalization_19[0][0]
mixed1 (Concatenate)	(None, 7, 7, 288)	0	activation_13[0][0] activation_15[0][0] activation_18[0][0] activation_19[0][0]
conv2d_23 (Conv2D)	(None, 7, 7, 64)	18432	mixed1[0][0]
batch_normalization_23 (Batch Normalization)	(None, 7, 7, 64)	192	conv2d_23[0][0]
activation_23 (Activation)	(None, 7, 7, 64)	0	batch_normalization_23[0][0]
conv2d_21 (Conv2D)	(None, 7, 7, 48)	13824	mixed1[0][0]
conv2d_24 (Conv2D)	(None, 7, 7, 96)	55296	activation_23[0][0]
batch_normalization_21 (Batch Normalization)	(None, 7, 7, 48)	144	conv2d_21[0][0]
batch_normalization_24 (Batch Normalization)	(None, 7, 7, 96)	288	conv2d_24[0][0]
activation_21 (Activation)	(None, 7, 7, 48)	0	batch_normalization_21[0][0]
activation_24 (Activation)	(None, 7, 7, 96)	0	batch_normalization_24[0][0]
average_pooling2d_3 (AveragePool)	(None, 7, 7, 288)	0	mixed1[0][0]

conv2d_20 (Conv2D)	(None, 7, 7, 64)	18432	mixed1[0][0]
conv2d_22 (Conv2D)	(None, 7, 7, 64)	76800	activation_21[0][0]
conv2d_25 (Conv2D)	(None, 7, 7, 96)	82944	activation_24[0][0]
conv2d_26 (Conv2D)	(None, 7, 7, 64)	18432	average_pooling2d_3[0][0]
batch_normalization_20 (BatchNo	(None, 7, 7, 64)	192	conv2d_20[0][0]
batch_normalization_22 (BatchNo	(None, 7, 7, 64)	192	conv2d_22[0][0]
batch_normalization_25 (BatchNo	(None, 7, 7, 96)	288	conv2d_25[0][0]
batch_normalization_26 (BatchNo	(None, 7, 7, 64)	192	conv2d_26[0][0]
activation_20 (Activation)	(None, 7, 7, 64)	0	batch_normalization_20[0][0]
activation_22 (Activation)	(None, 7, 7, 64)	0	batch_normalization_22[0][0]
activation_25 (Activation)	(None, 7, 7, 96)	0	batch_normalization_25[0][0]
activation_26 (Activation)	(None, 7, 7, 64)	0	batch_normalization_26[0][0]
mixed2 (Concatenate)	(None, 7, 7, 288)	0	activation_20[0][0] activation_22[0][0] activation_25[0][0] activation_26[0][0]
conv2d_28 (Conv2D)	(None, 7, 7, 64)	18432	mixed2[0][0]
batch_normalization_28 (BatchNo	(None, 7, 7, 64)	192	conv2d_28[0][0]
activation_28 (Activation)	(None, 7, 7, 64)	0	batch_normalization_28[0][0]
conv2d_29 (Conv2D)	(None, 7, 7, 96)	55296	activation_28[0][0]
batch_normalization_29 (BatchNo	(None, 7, 7, 96)	288	conv2d_29[0][0]
activation_29 (Activation)	(None, 7, 7, 96)	0	batch_normalization_29[0][0]
conv2d_27 (Conv2D)	(None, 3, 3, 384)	995328	mixed2[0][0]
conv2d_30 (Conv2D)	(None, 3, 3, 96)	82944	activation_29[0][0]
batch_normalization_27 (BatchNo	(None, 3, 3, 384)	1152	conv2d_27[0][0]
batch_normalization_30 (BatchNo	(None, 3, 3, 96)	288	conv2d_30[0][0]
activation_27 (Activation)	(None, 3, 3, 384)	0	batch_normalization_27[0][0]
activation_30 (Activation)	(None, 3, 3, 96)	0	batch_normalization_30[0][0]

max_pooling2d_3 (MaxPooling2D)	(None, 3, 3, 288)	0	mixed2[0][0]
mixed3 (Concatenate)	(None, 3, 3, 768)	0	activation_27[0][0] activation_30[0][0] max_pooling2d_3[0][0]
conv2d_35 (Conv2D)	(None, 3, 3, 128)	98304	mixed3[0][0]
batch_normalization_35 (BatchNo	(None, 3, 3, 128)	384	conv2d_35[0][0]
activation_35 (Activation)	(None, 3, 3, 128)	0	batch_normalization_35[0][0]
conv2d_36 (Conv2D)	(None, 3, 3, 128)	114688	activation_35[0][0]
batch_normalization_36 (BatchNo	(None, 3, 3, 128)	384	conv2d_36[0][0]
activation_36 (Activation)	(None, 3, 3, 128)	0	batch_normalization_36[0][0]
conv2d_32 (Conv2D)	(None, 3, 3, 128)	98304	mixed3[0][0]
conv2d_37 (Conv2D)	(None, 3, 3, 128)	114688	activation_36[0][0]
batch_normalization_32 (BatchNo	(None, 3, 3, 128)	384	conv2d_32[0][0]
batch_normalization_37 (BatchNo	(None, 3, 3, 128)	384	conv2d_37[0][0]
activation_32 (Activation)	(None, 3, 3, 128)	0	batch_normalization_32[0][0]
activation_37 (Activation)	(None, 3, 3, 128)	0	batch_normalization_37[0][0]
conv2d_33 (Conv2D)	(None, 3, 3, 128)	114688	activation_32[0][0]
conv2d_38 (Conv2D)	(None, 3, 3, 128)	114688	activation_37[0][0]
batch_normalization_33 (BatchNo	(None, 3, 3, 128)	384	conv2d_33[0][0]
batch_normalization_38 (BatchNo	(None, 3, 3, 128)	384	conv2d_38[0][0]
activation_33 (Activation)	(None, 3, 3, 128)	0	batch_normalization_33[0][0]
activation_38 (Activation)	(None, 3, 3, 128)	0	batch_normalization_38[0][0]
average_pooling2d_4 (AveragePoo	(None, 3, 3, 768)	0	mixed3[0][0]
conv2d_31 (Conv2D)	(None, 3, 3, 192)	147456	mixed3[0][0]
conv2d_34 (Conv2D)	(None, 3, 3, 192)	172032	activation_33[0][0]
conv2d_39 (Conv2D)	(None, 3, 3, 192)	172032	activation_38[0][0]
conv2d_40 (Conv2D)	(None, 3, 3, 192)	147456	average_pooling2d_4[0][0]
batch_normalization_31 (BatchNo	(None, 3, 3, 192)	576	conv2d_31[0][0]

batch_normalization_34	(BatchNo	(None, 3, 3, 192)	576	conv2d_34[0][0]
batch_normalization_39	(BatchNo	(None, 3, 3, 192)	576	conv2d_39[0][0]
batch_normalization_40	(BatchNo	(None, 3, 3, 192)	576	conv2d_40[0][0]
activation_31	(Activation)	(None, 3, 3, 192)	0	batch_normalization_31[0][0]
activation_34	(Activation)	(None, 3, 3, 192)	0	batch_normalization_34[0][0]
activation_39	(Activation)	(None, 3, 3, 192)	0	batch_normalization_39[0][0]
activation_40	(Activation)	(None, 3, 3, 192)	0	batch_normalization_40[0][0]
mixed4	(Concatenate)	(None, 3, 3, 768)	0	activation_31[0][0] activation_34[0][0] activation_39[0][0] activation_40[0][0]
conv2d_45	(Conv2D)	(None, 3, 3, 160)	122880	mixed4[0][0]
batch_normalization_45	(BatchNo	(None, 3, 3, 160)	480	conv2d_45[0][0]
activation_45	(Activation)	(None, 3, 3, 160)	0	batch_normalization_45[0][0]
conv2d_46	(Conv2D)	(None, 3, 3, 160)	179200	activation_45[0][0]
batch_normalization_46	(BatchNo	(None, 3, 3, 160)	480	conv2d_46[0][0]
activation_46	(Activation)	(None, 3, 3, 160)	0	batch_normalization_46[0][0]
conv2d_42	(Conv2D)	(None, 3, 3, 160)	122880	mixed4[0][0]
conv2d_47	(Conv2D)	(None, 3, 3, 160)	179200	activation_46[0][0]
batch_normalization_42	(BatchNo	(None, 3, 3, 160)	480	conv2d_42[0][0]
batch_normalization_47	(BatchNo	(None, 3, 3, 160)	480	conv2d_47[0][0]
activation_42	(Activation)	(None, 3, 3, 160)	0	batch_normalization_42[0][0]
activation_47	(Activation)	(None, 3, 3, 160)	0	batch_normalization_47[0][0]
conv2d_43	(Conv2D)	(None, 3, 3, 160)	179200	activation_42[0][0]
conv2d_48	(Conv2D)	(None, 3, 3, 160)	179200	activation_47[0][0]
batch_normalization_43	(BatchNo	(None, 3, 3, 160)	480	conv2d_43[0][0]
batch_normalization_48	(BatchNo	(None, 3, 3, 160)	480	conv2d_48[0][0]
activation_43	(Activation)	(None, 3, 3, 160)	0	batch_normalization_43[0][0]

activation_48 (Activation)	(None, 3, 3, 160)	0	batch_normalization_48[0][0]
average_pooling2d_5 (AveragePool)	(None, 3, 3, 768)	0	mixed4[0][0]
conv2d_41 (Conv2D)	(None, 3, 3, 192)	147456	mixed4[0][0]
conv2d_44 (Conv2D)	(None, 3, 3, 192)	215040	activation_43[0][0]
conv2d_49 (Conv2D)	(None, 3, 3, 192)	215040	activation_48[0][0]
conv2d_50 (Conv2D)	(None, 3, 3, 192)	147456	average_pooling2d_5[0][0]
batch_normalization_41 (Batch Normalization)	(None, 3, 3, 192)	576	conv2d_41[0][0]
batch_normalization_44 (Batch Normalization)	(None, 3, 3, 192)	576	conv2d_44[0][0]
batch_normalization_49 (Batch Normalization)	(None, 3, 3, 192)	576	conv2d_49[0][0]
batch_normalization_50 (Batch Normalization)	(None, 3, 3, 192)	576	conv2d_50[0][0]
activation_41 (Activation)	(None, 3, 3, 192)	0	batch_normalization_41[0][0]
activation_44 (Activation)	(None, 3, 3, 192)	0	batch_normalization_44[0][0]
activation_49 (Activation)	(None, 3, 3, 192)	0	batch_normalization_49[0][0]
activation_50 (Activation)	(None, 3, 3, 192)	0	batch_normalization_50[0][0]
mixed5 (Concatenate)	(None, 3, 3, 768)	0	activation_41[0][0] activation_44[0][0] activation_49[0][0] activation_50[0][0]
conv2d_55 (Conv2D)	(None, 3, 3, 160)	122880	mixed5[0][0]
batch_normalization_55 (Batch Normalization)	(None, 3, 3, 160)	480	conv2d_55[0][0]
activation_55 (Activation)	(None, 3, 3, 160)	0	batch_normalization_55[0][0]
conv2d_56 (Conv2D)	(None, 3, 3, 160)	179200	activation_55[0][0]
batch_normalization_56 (Batch Normalization)	(None, 3, 3, 160)	480	conv2d_56[0][0]
activation_56 (Activation)	(None, 3, 3, 160)	0	batch_normalization_56[0][0]
conv2d_52 (Conv2D)	(None, 3, 3, 160)	122880	mixed5[0][0]
conv2d_57 (Conv2D)	(None, 3, 3, 160)	179200	activation_56[0][0]
batch_normalization_52 (Batch Normalization)	(None, 3, 3, 160)	480	conv2d_52[0][0]
batch_normalization_57 (Batch Normalization)	(None, 3, 3, 160)	480	conv2d_57[0][0]

activation_52 (Activation)	(None, 3, 3, 160)	0	batch_normalization_52[0][0]
activation_57 (Activation)	(None, 3, 3, 160)	0	batch_normalization_57[0][0]
conv2d_53 (Conv2D)	(None, 3, 3, 160)	179200	activation_52[0][0]
conv2d_58 (Conv2D)	(None, 3, 3, 160)	179200	activation_57[0][0]
batch_normalization_53 (BatchNo	(None, 3, 3, 160)	480	conv2d_53[0][0]
batch_normalization_58 (BatchNo	(None, 3, 3, 160)	480	conv2d_58[0][0]
activation_53 (Activation)	(None, 3, 3, 160)	0	batch_normalization_53[0][0]
activation_58 (Activation)	(None, 3, 3, 160)	0	batch_normalization_58[0][0]
average_pooling2d_6 (AveragePoo	(None, 3, 3, 768)	0	mixed5[0][0]
conv2d_51 (Conv2D)	(None, 3, 3, 192)	147456	mixed5[0][0]
conv2d_54 (Conv2D)	(None, 3, 3, 192)	215040	activation_53[0][0]
conv2d_59 (Conv2D)	(None, 3, 3, 192)	215040	activation_58[0][0]
conv2d_60 (Conv2D)	(None, 3, 3, 192)	147456	average_pooling2d_6[0][0]
batch_normalization_51 (BatchNo	(None, 3, 3, 192)	576	conv2d_51[0][0]
batch_normalization_54 (BatchNo	(None, 3, 3, 192)	576	conv2d_54[0][0]
batch_normalization_59 (BatchNo	(None, 3, 3, 192)	576	conv2d_59[0][0]
batch_normalization_60 (BatchNo	(None, 3, 3, 192)	576	conv2d_60[0][0]
activation_51 (Activation)	(None, 3, 3, 192)	0	batch_normalization_51[0][0]
activation_54 (Activation)	(None, 3, 3, 192)	0	batch_normalization_54[0][0]
activation_59 (Activation)	(None, 3, 3, 192)	0	batch_normalization_59[0][0]
activation_60 (Activation)	(None, 3, 3, 192)	0	batch_normalization_60[0][0]
mixed6 (Concatenate)	(None, 3, 3, 768)	0	activation_51[0][0] activation_54[0][0] activation_59[0][0] activation_60[0][0]
conv2d_65 (Conv2D)	(None, 3, 3, 192)	147456	mixed6[0][0]
batch_normalization_65 (BatchNo	(None, 3, 3, 192)	576	conv2d_65[0][0]
activation_65 (Activation)	(None, 3, 3, 192)	0	batch_normalization_65[0][0]

conv2d_66 (Conv2D)	(None, 3, 3, 192)	258048	activation_65[0][0]
batch_normalization_66 (BatchNo	(None, 3, 3, 192)	576	conv2d_66[0][0]
activation_66 (Activation)	(None, 3, 3, 192)	0	batch_normalization_66[0][0]
conv2d_62 (Conv2D)	(None, 3, 3, 192)	147456	mixed6[0][0]
conv2d_67 (Conv2D)	(None, 3, 3, 192)	258048	activation_66[0][0]
batch_normalization_62 (BatchNo	(None, 3, 3, 192)	576	conv2d_62[0][0]
batch_normalization_67 (BatchNo	(None, 3, 3, 192)	576	conv2d_67[0][0]
activation_62 (Activation)	(None, 3, 3, 192)	0	batch_normalization_62[0][0]
activation_67 (Activation)	(None, 3, 3, 192)	0	batch_normalization_67[0][0]
conv2d_63 (Conv2D)	(None, 3, 3, 192)	258048	activation_62[0][0]
conv2d_68 (Conv2D)	(None, 3, 3, 192)	258048	activation_67[0][0]
batch_normalization_63 (BatchNo	(None, 3, 3, 192)	576	conv2d_63[0][0]
batch_normalization_68 (BatchNo	(None, 3, 3, 192)	576	conv2d_68[0][0]
activation_63 (Activation)	(None, 3, 3, 192)	0	batch_normalization_63[0][0]
activation_68 (Activation)	(None, 3, 3, 192)	0	batch_normalization_68[0][0]
average_pooling2d_7 (AveragePoo	(None, 3, 3, 768)	0	mixed6[0][0]
conv2d_61 (Conv2D)	(None, 3, 3, 192)	147456	mixed6[0][0]
conv2d_64 (Conv2D)	(None, 3, 3, 192)	258048	activation_63[0][0]
conv2d_69 (Conv2D)	(None, 3, 3, 192)	258048	activation_68[0][0]
conv2d_70 (Conv2D)	(None, 3, 3, 192)	147456	average_pooling2d_7[0][0]
batch_normalization_61 (BatchNo	(None, 3, 3, 192)	576	conv2d_61[0][0]
batch_normalization_64 (BatchNo	(None, 3, 3, 192)	576	conv2d_64[0][0]
batch_normalization_69 (BatchNo	(None, 3, 3, 192)	576	conv2d_69[0][0]
batch_normalization_70 (BatchNo	(None, 3, 3, 192)	576	conv2d_70[0][0]
activation_61 (Activation)	(None, 3, 3, 192)	0	batch_normalization_61[0][0]
activation_64 (Activation)	(None, 3, 3, 192)	0	batch_normalization_64[0][0]
activation_69 (Activation)	(None, 3, 3, 192)	0	batch_normalization_69[0][0]

activation_70 (Activation)	(None, 3, 3, 192)	0	batch_normalization_70[0][0]
mixed7 (Concatenate)	(None, 3, 3, 768)	0	activation_61[0][0] activation_64[0][0] activation_69[0][0] activation_70[0][0]
conv2d_73 (Conv2D)	(None, 3, 3, 192)	147456	mixed7[0][0]
batch_normalization_73 (BatchNo	(None, 3, 3, 192)	576	conv2d_73[0][0]
activation_73 (Activation)	(None, 3, 3, 192)	0	batch_normalization_73[0][0]
conv2d_74 (Conv2D)	(None, 3, 3, 192)	258048	activation_73[0][0]
batch_normalization_74 (BatchNo	(None, 3, 3, 192)	576	conv2d_74[0][0]
activation_74 (Activation)	(None, 3, 3, 192)	0	batch_normalization_74[0][0]
conv2d_71 (Conv2D)	(None, 3, 3, 192)	147456	mixed7[0][0]
conv2d_75 (Conv2D)	(None, 3, 3, 192)	258048	activation_74[0][0]
batch_normalization_71 (BatchNo	(None, 3, 3, 192)	576	conv2d_71[0][0]
batch_normalization_75 (BatchNo	(None, 3, 3, 192)	576	conv2d_75[0][0]
activation_71 (Activation)	(None, 3, 3, 192)	0	batch_normalization_71[0][0]
activation_75 (Activation)	(None, 3, 3, 192)	0	batch_normalization_75[0][0]
conv2d_72 (Conv2D)	(None, 1, 1, 320)	552960	activation_71[0][0]
conv2d_76 (Conv2D)	(None, 1, 1, 192)	331776	activation_75[0][0]
batch_normalization_72 (BatchNo	(None, 1, 1, 320)	960	conv2d_72[0][0]
batch_normalization_76 (BatchNo	(None, 1, 1, 192)	576	conv2d_76[0][0]
activation_72 (Activation)	(None, 1, 1, 320)	0	batch_normalization_72[0][0]
activation_76 (Activation)	(None, 1, 1, 192)	0	batch_normalization_76[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, 1, 1, 768)	0	mixed7[0][0]
mixed8 (Concatenate)	(None, 1, 1, 1280)	0	activation_72[0][0] activation_76[0][0] max_pooling2d_4[0][0]
conv2d_81 (Conv2D)	(None, 1, 1, 448)	573440	mixed8[0][0]
batch_normalization_81 (BatchNo	(None, 1, 1, 448)	1344	conv2d_81[0][0]

activation_81 (Activation)	(None, 1, 1, 448)	0	batch_normalization_81[0][0]
conv2d_78 (Conv2D)	(None, 1, 1, 384)	491520	mixed8[0][0]
conv2d_82 (Conv2D)	(None, 1, 1, 384)	1548288	activation_81[0][0]
batch_normalization_78 (BatchNo	(None, 1, 1, 384)	1152	conv2d_78[0][0]
batch_normalization_82 (BatchNo	(None, 1, 1, 384)	1152	conv2d_82[0][0]
activation_78 (Activation)	(None, 1, 1, 384)	0	batch_normalization_78[0][0]
activation_82 (Activation)	(None, 1, 1, 384)	0	batch_normalization_82[0][0]
conv2d_79 (Conv2D)	(None, 1, 1, 384)	442368	activation_78[0][0]
conv2d_80 (Conv2D)	(None, 1, 1, 384)	442368	activation_78[0][0]
conv2d_83 (Conv2D)	(None, 1, 1, 384)	442368	activation_82[0][0]
conv2d_84 (Conv2D)	(None, 1, 1, 384)	442368	activation_82[0][0]
average_pooling2d_8 (AveragePoo	(None, 1, 1, 1280)	0	mixed8[0][0]
conv2d_77 (Conv2D)	(None, 1, 1, 320)	409600	mixed8[0][0]
batch_normalization_79 (BatchNo	(None, 1, 1, 384)	1152	conv2d_79[0][0]
batch_normalization_80 (BatchNo	(None, 1, 1, 384)	1152	conv2d_80[0][0]
batch_normalization_83 (BatchNo	(None, 1, 1, 384)	1152	conv2d_83[0][0]
batch_normalization_84 (BatchNo	(None, 1, 1, 384)	1152	conv2d_84[0][0]
conv2d_85 (Conv2D)	(None, 1, 1, 192)	245760	average_pooling2d_8[0][0]
batch_normalization_77 (BatchNo	(None, 1, 1, 320)	960	conv2d_77[0][0]
activation_79 (Activation)	(None, 1, 1, 384)	0	batch_normalization_79[0][0]
activation_80 (Activation)	(None, 1, 1, 384)	0	batch_normalization_80[0][0]
activation_83 (Activation)	(None, 1, 1, 384)	0	batch_normalization_83[0][0]
activation_84 (Activation)	(None, 1, 1, 384)	0	batch_normalization_84[0][0]
batch_normalization_85 (BatchNo	(None, 1, 1, 192)	576	conv2d_85[0][0]
activation_77 (Activation)	(None, 1, 1, 320)	0	batch_normalization_77[0][0]
mixed9_0 (Concatenate)	(None, 1, 1, 768)	0	activation_79[0][0] activation_80[0][0]

concatenate_1 (Concatenate)	(None, 1, 1, 768)	0	activation_83[0][0] activation_84[0][0]
activation_85 (Activation)	(None, 1, 1, 192)	0	batch_normalization_85[0][0]
mixed9 (Concatenate)	(None, 1, 1, 2048)	0	activation_77[0][0] mixed9_0[0][0] concatenate_1[0][0] activation_85[0][0]
conv2d_90 (Conv2D)	(None, 1, 1, 448)	917504	mixed9[0][0]
batch_normalization_90 (BatchNo	(None, 1, 1, 448)	1344	conv2d_90[0][0]
activation_90 (Activation)	(None, 1, 1, 448)	0	batch_normalization_90[0][0]
conv2d_87 (Conv2D)	(None, 1, 1, 384)	786432	mixed9[0][0]
conv2d_91 (Conv2D)	(None, 1, 1, 384)	1548288	activation_90[0][0]
batch_normalization_87 (BatchNo	(None, 1, 1, 384)	1152	conv2d_87[0][0]
batch_normalization_91 (BatchNo	(None, 1, 1, 384)	1152	conv2d_91[0][0]
activation_87 (Activation)	(None, 1, 1, 384)	0	batch_normalization_87[0][0]
activation_91 (Activation)	(None, 1, 1, 384)	0	batch_normalization_91[0][0]
conv2d_88 (Conv2D)	(None, 1, 1, 384)	442368	activation_87[0][0]
conv2d_89 (Conv2D)	(None, 1, 1, 384)	442368	activation_87[0][0]
conv2d_92 (Conv2D)	(None, 1, 1, 384)	442368	activation_91[0][0]
conv2d_93 (Conv2D)	(None, 1, 1, 384)	442368	activation_91[0][0]
average_pooling2d_9 (AveragePoo	(None, 1, 1, 2048)	0	mixed9[0][0]
conv2d_86 (Conv2D)	(None, 1, 1, 320)	655360	mixed9[0][0]
batch_normalization_88 (BatchNo	(None, 1, 1, 384)	1152	conv2d_88[0][0]
batch_normalization_89 (BatchNo	(None, 1, 1, 384)	1152	conv2d_89[0][0]
batch_normalization_92 (BatchNo	(None, 1, 1, 384)	1152	conv2d_92[0][0]
batch_normalization_93 (BatchNo	(None, 1, 1, 384)	1152	conv2d_93[0][0]
conv2d_94 (Conv2D)	(None, 1, 1, 192)	393216	average_pooling2d_9[0][0]
batch_normalization_86 (BatchNo	(None, 1, 1, 320)	960	conv2d_86[0][0]
activation_88 (Activation)	(None, 1, 1, 384)	0	batch_normalization_88[0][0]

activation_89 (Activation)	(None, 1, 1, 384)	0	batch_normalization_89[0][0]
activation_92 (Activation)	(None, 1, 1, 384)	0	batch_normalization_92[0][0]
activation_93 (Activation)	(None, 1, 1, 384)	0	batch_normalization_93[0][0]
batch_normalization_94 (BatchNo	(None, 1, 1, 192)	576	conv2d_94[0][0]
activation_86 (Activation)	(None, 1, 1, 320)	0	batch_normalization_86[0][0]
mixed9_1 (Concatenate)	(None, 1, 1, 768)	0	activation_88[0][0] activation_89[0][0]
concatenate_2 (Concatenate)	(None, 1, 1, 768)	0	activation_92[0][0] activation_93[0][0]
activation_94 (Activation)	(None, 1, 1, 192)	0	batch_normalization_94[0][0]
mixed10 (Concatenate)	(None, 1, 1, 2048)	0	activation_86[0][0] mixed9_1[0][0] concatenate_2[0][0] activation_94[0][0]
global_average_pooling2d_1 (Glo	(None, 2048)	0	mixed10[0][0]
dense_1 (Dense)	(None, 256)	524544	global_average_pooling2d_1[0][0]
dense_2 (Dense)	(None, 2)	514	dense_1[0][0]
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Total params: 22,327,842			