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Capstone Project -
'Predicting Video Game Ratings Through Image Classification with CNNs'

1 Objective

For this project, we are trying to use convolutional neural networks to try to identify the ESRB rating of video games based on images from the game. This could have applications in live content moderation on platforms such as Twitch or YouTube, where a streamer might be streaming games with mature content without identifying their stream as containing mature content. If we can train a CNN to identify mature content or at least flag that content for human review, we can help reduce the amount of content that human reviewers would have to sift through. We could also hopefully identify a greater amount of mature content without the need of user reporting, ideally leading to less consumption by young audiences before the content is reported.

2 Obtain

In [1]:
```
# Imports
import pandas as pd
```
executed in 384ms, finished 20:18:25 2021-06-23

First, we want a list of games and their respective ratings. We'll pull that information from the ESRB website, and we'll use games released for the PlayStation 4, Xbox One, and Nintendo Switch. The notebook 'data_scrape_titles' details the process of scraping the information using Selenium. A pandas DataFrame containing the data is saved as 'esrb_ratings.pkl'.

In [2]:
```
df = pd.read_pickle('esrb_ratings.pkl')
df.head()
```
executed in 31ms, finished 20:18:26 2021-06-23

Out[2]:

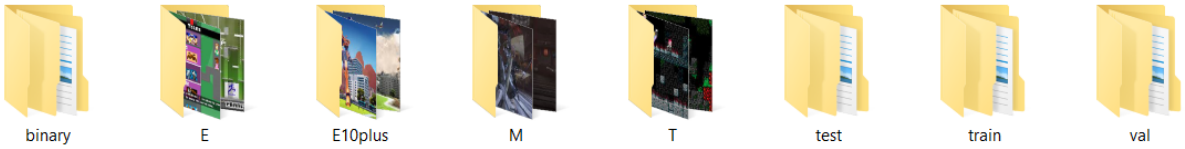
	title	consoles	descriptors	rating
0	Blizzard Arcade Collection	[PlayStation 4, Nintendo Switch, Xbox One]	[Blood, Fantasy Violence, Language, Use of Tob...	T
1	Rez Infinite	[PlayStation 4]	[Fantasy Violence]	E10plus
2	Hotshot Racing	[PlayStation 4, Nintendo Switch]	[Alcohol Reference, Language, Mild Violence]	E10plus
3	Sea of Solitude : The Director's Cut	[Nintendo Switch]	[Fantasy Violence, Language]	T
4	Ape Out	[Nintendo Switch]	[Blood and Gore, Violence]	T

With this data, we'll use Selenium once again to go through the game titles and pull 10 images of

each game from Google Images. This process is detailed in the notebook 'data_scrape_images'. After running the notebook, the images are saved in an 'images' directory, with each image being saved in a subdirectory corresponding to the game's rating.

3 Scrub

With our images gathered and sorted, we then run the code in the notebook 'data_split' to split our images into training, validation, and test sets. We do two different splits. In the first split, the game images are sorted according to the specific ratings of their games(E, E10plus, M, T). In the second split, The game images are sorted into groups of E-T and M.



The first will allow us to do a 4-class categorical classification. The second will allow us to do a binary classification. Our main goal is to identify M-rated games, and we'll have to see whether a categorical or binary model is better-equipped to do that.

4 Explore

In [3]:
```
# Imports
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator

import matplotlib.pyplot as plt
%matplotlib inline

import my_module as custom
```

executed in 3.85s, finished 20:18:29 2021-06-23

```
C:\Users\katma\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tools\_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

To get a feel for the data, we'll create some image generators, and then use that to check out some of our training images.

In [4]:
```
# Create generators
train_data = ImageDataGenerator(rescale=1/255,
                                horizontal_flip=True,
                                shear_range=0.2,
                                zoom_range=0.2)
val_data = ImageDataGenerator(rescale=1/255)
test_data = ImageDataGenerator(rescale=1/255)
```

executed in 14ms, finished 20:18:29 2021-06-23

In [5]:
```
train_gen = train_data.flow_from_directory('images/train', target_size=(224,224
val_gen = val_data.flow_from_directory('images/val', target_size=(224,224))
test_gen = test_data.flow_from_directory('images/test', target_size=(224,224),
```

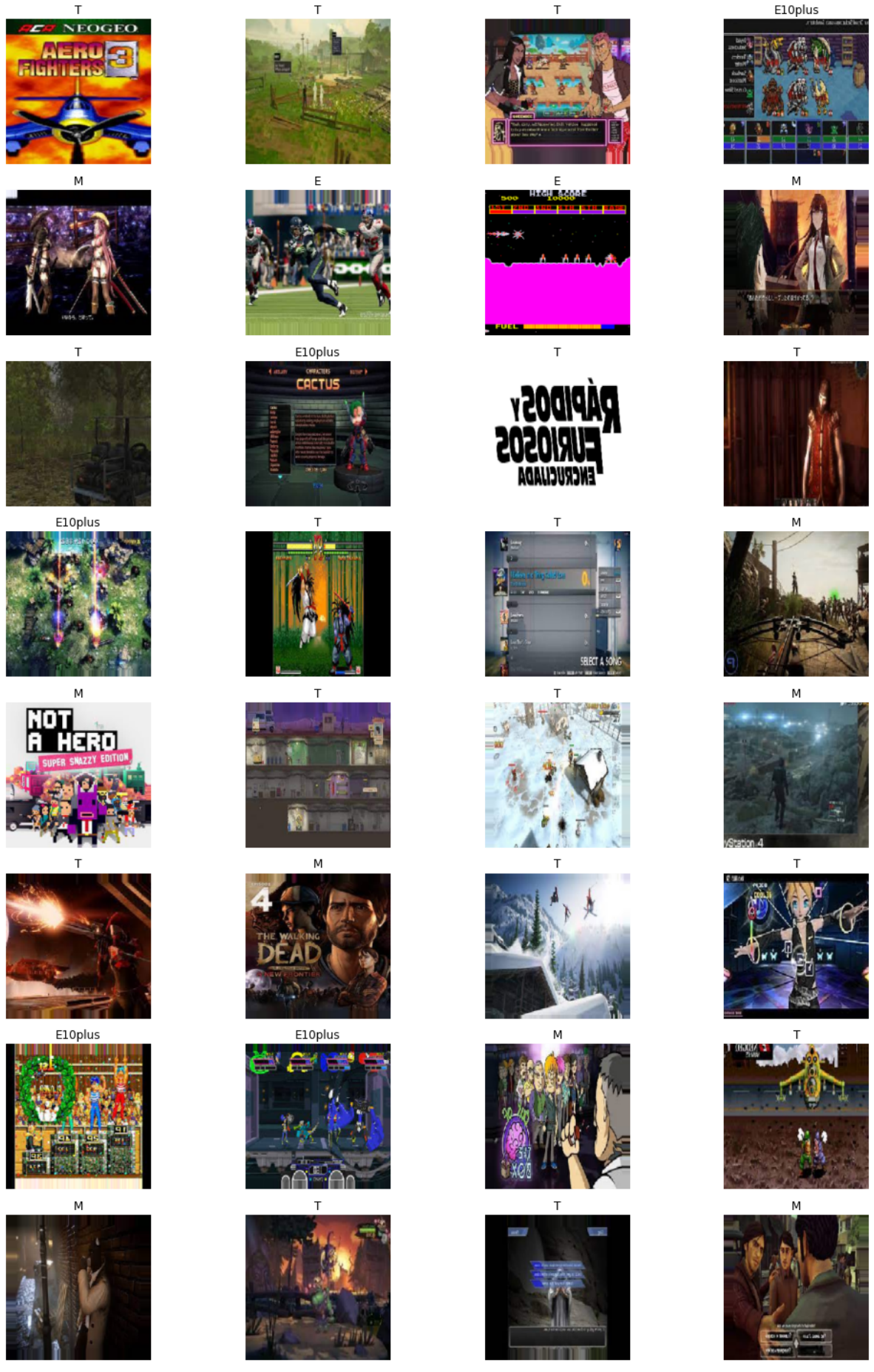
executed in 1.72s, finished 20:18:31 2021-06-23

```
Found 33620 images belonging to 4 classes.
Found 2240 images belonging to 4 classes.
Found 8970 images belonging to 4 classes.
```

In [6]:

```
# Get a batch of images
img, labels = train_gen.next()
ratings = ['E', 'E10plus', 'M', 'T']

# Show the images and labels
plt.figure(figsize=(15,20))
for i in range(len(img)):
    plt.subplot(8,4,i+1)
    plt.title(ratings[labels[i].argmax()])
    plt.imshow(img[i])
    plt.axis('off')
plt.tight_layout()
```

executed in 1.86s, finished 20:18:33 2021-06-23



Upon viewing this batch of images, I would not personally be able to accurately label many of the

games just based on the given image. Hopefully our neural networks can pick out features that are not obvious to me.

5 Model

In [7]:
```
# Imports
from tensorflow.keras.models import *
from tensorflow.keras.layers import *
from tensorflow.keras.callbacks import ModelCheckpoint
```

executed in 15ms, finished 20:18:33 2021-06-23

Before modeling, we'll use a simple function to save our best model weights in case we need to revert back to them later.

In [8]:
```
def init_callbacks(number):
    model_checkpoint = ModelCheckpoint(f'best_model_{str(number)}.h5', monitor=
                                       verbose=1, save_best_only=True,
                                       save_weights_only=True)
    return model_checkpoint

epochs = 10
input_shape = (224,224,3)
```

executed in 13ms, finished 20:18:33 2021-06-23

5.1 Model 1 (Simple Neural Network)

Our first model is just a simple neural network with a couple of dense layers and an output layer. This neural net probably lacks the complexity to make good predictions for our particular case, but if nothing else it provides a decent baseline for determining whether or not future models are an improvement.

In [9]:
```
model_1 = Sequential()
model_1.add(Dense(128, activation='relu', input_shape=input_shape))
model_1.add(Dense(64, activation='relu'))
model_1.add(Flatten())
model_1.add(Dense(4, activation='softmax'))

model_1.compile(loss='categorical_crossentropy',
                optimizer=tf.keras.optimizers.RMSprop(learning_rate=1e-4),
                metrics=['acc'])

model_1.summary()
```

executed in 788ms, finished 20:18:34 2021-06-23

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 224, 224, 128)     512
_________________________________________________________________
dense_1 (Dense)              (None, 224, 224, 64)      8256
_________________________________________________________________
flatten (Flatten)            (None, 3211264)           0
_________________________________________________________________
dense_2 (Dense)              (None, 4)                 12845060
=================================================================
Total params: 12,853,828
Trainable params: 12,853,828
Non-trainable params: 0
_________________________________________________________________
```

In [10]:
```
history_1 = model_1.fit(train_gen,
                        steps_per_epoch=100,
                        epochs=epochs,
                        validation_data=val_gen,
                        callbacks=init_callbacks(1))
```

executed in 5m 8s, finished 20:23:41 2021-06-23

```
Epoch 1/10
100/100 [==============================] - 32s 307ms/step - loss: 4.7256 - ac
c: 0.2689 - val_loss: 1.9811 - val_acc: 0.3478

Epoch 00001: val_loss improved from inf to 1.98107, saving model to best_mode
l_1.h5
Epoch 2/10
100/100 [==============================] - 30s 303ms/step - loss: 1.4824 - ac
c: 0.3331 - val_loss: 1.3180 - val_acc: 0.3737

Epoch 00002: val_loss improved from 1.98107 to 1.31802, saving model to best_
model_1.h5
Epoch 3/10
100/100 [==============================] - 31s 304ms/step - loss: 1.3275 - ac
c: 0.3625 - val_loss: 1.3208 - val_acc: 0.3737

Epoch 00003: val_loss did not improve from 1.31802
Epoch 4/10
100/100 [==============================] - 30s 302ms/step - loss: 1.3074 - ac
c: 0.3688 - val_loss: 1.3069 - val_acc: 0.3938

Epoch 00004: val_loss improved from 1.31802 to 1.30689, saving model to best_
model_1.h5
Epoch 5/10
100/100 [==============================] - 30s 303ms/step - loss: 1.2875 - ac
c: 0.3912 - val_loss: 1.3009 - val_acc: 0.4013

Epoch 00005: val_loss improved from 1.30689 to 1.30092, saving model to best_
model_1.h5
Epoch 6/10
100/100 [==============================] - 30s 302ms/step - loss: 1.2934 - ac
c: 0.4143 - val_loss: 1.2932 - val_acc: 0.3960

Epoch 00006: val_loss improved from 1.30092 to 1.29323, saving model to best_
model_1.h5
Epoch 7/10
100/100 [==============================] - 30s 303ms/step - loss: 1.2668 - ac
c: 0.4072 - val_loss: 1.2942 - val_acc: 0.4040

Epoch 00007: val_loss did not improve from 1.29323
Epoch 8/10
100/100 [==============================] - 31s 306ms/step - loss: 1.2816 - ac
c: 0.3954 - val_loss: 1.3006 - val_acc: 0.3848

Epoch 00008: val_loss did not improve from 1.29323
Epoch 9/10
100/100 [==============================] - 31s 310ms/step - loss: 1.2789 - ac
c: 0.4045 - val_loss: 1.2884 - val_acc: 0.3906
```

```
Epoch 00009: val_loss improved from 1.29323 to 1.28839, saving model to best_
model_1.h5
Epoch 10/10
100/100 [==============================] - 31s 308ms/step - loss: 1.2701 - ac
c: 0.4015 - val_loss: 1.2970 - val_acc: 0.3951

Epoch 00010: val_loss did not improve from 1.28839
```

5.1.1 Results

The evaluate function in my_module.py gives us a good deal of information about the model. First, it shows accuracy and loss over each epoch, which is useful in determining whether a model has started to overfit. Since we're only running 10 epochs, this shouldn't be a big concern, but if we see accuracy or loss for our validation set start to go off course at the end of training, we can always revert to the weights saved by our ModelCheckpoint callback.

Next we see a couple of pie charts. The first shows the distribution of classes in the test set, and the second shows the distribution of classes in the model's predictions for the test set. While similar distributions don't necessarily mean that our model is performing well, it does help us to see if biases in our model may need to be offset.

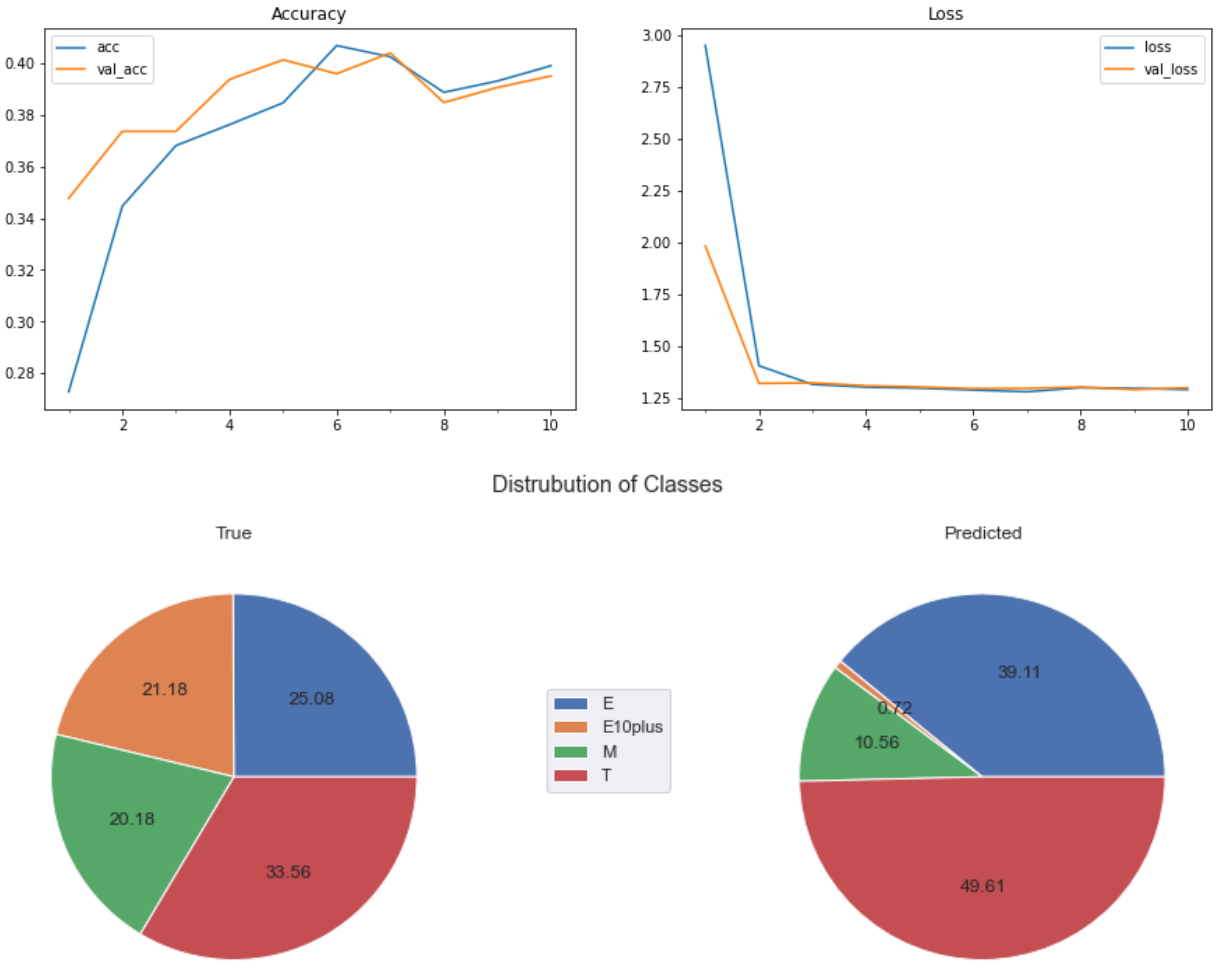
Next is a very nice confusion matrix plot by Wagner Cipriano. It shows both the true numbers and overall percentage for each prediction as well as showing accuracy and recall right on the confusion matrix.

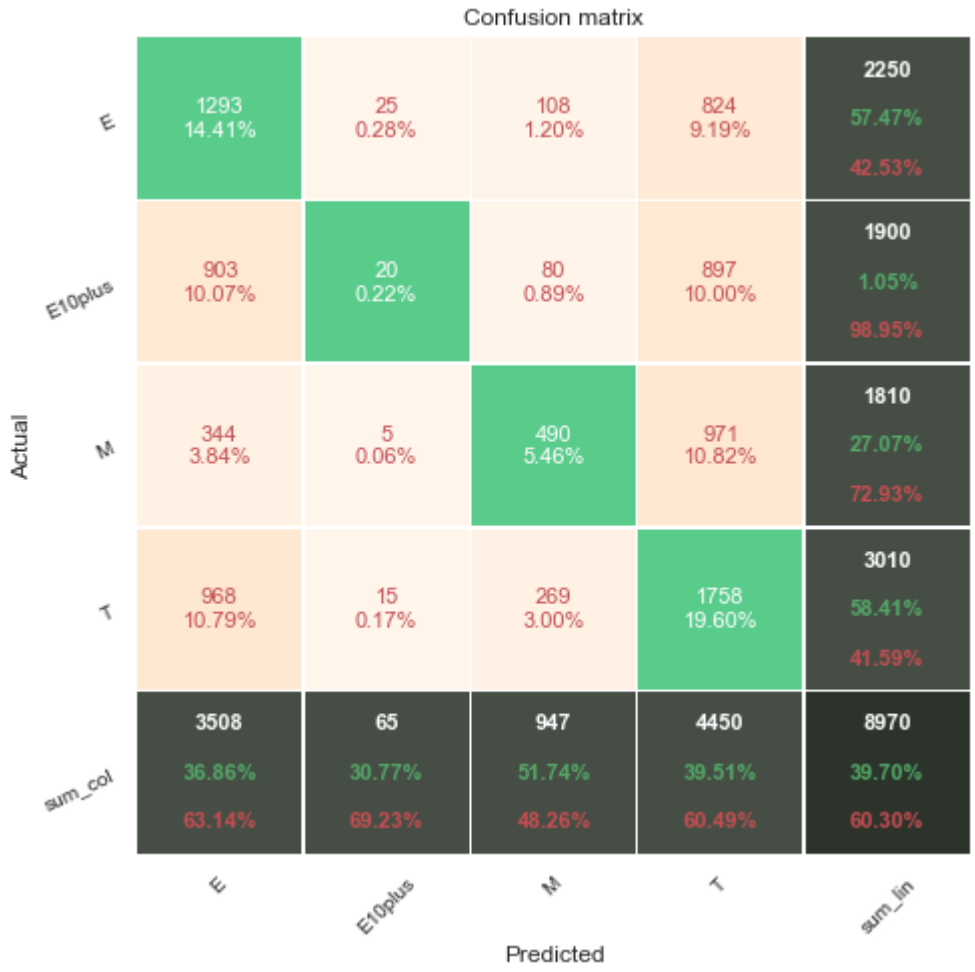
While the confusion matrix makes the classification report largely unnecessary, I do like having it to see the f1 score for the M-rated class. As this project is mostly about being able to identify these M-rated games, a model with high recall on the M class is preferable. However, if that high recall comes at the cost of an overly poor precision, it defeats the purpose of the model, as the model would cause a lot of unnecessary human review.

In [11]:
```
custom.evaluate(model_1, history_1, test_gen)
```

executed in 41.7s, finished 20:24:23 2021-06-23

```
281/281 [==============================] - 21s 75ms/step - loss: 1.3041 - acc:
0.3970
[1.3041287660598755, 0.39698997139930725]

C:\Users\katma\course_materials\capstone-project\my_module.py:20: MatplotlibDep
recationWarning: Passing the minor parameter of set_ticks() positionally is dep
recated since Matplotlib 3.2; the parameter will become keyword-only two minor
releases later.
  ax[0].set_xticks(range(1,(len(history['acc']))+1),5)
C:\Users\katma\course_materials\capstone-project\my_module.py:25: MatplotlibDep
recationWarning: Passing the minor parameter of set_ticks() positionally is dep
recated since Matplotlib 3.2; the parameter will become keyword-only two minor
releases later.
  ax[1].set_xticks(range(1,(len(history['loss']))+1),5)
```





	precision	recall	f1-score	support
E	0.37	0.57	0.45	2250
E10plus	0.31	0.01	0.02	1900
M	0.52	0.27	0.36	1810
T	0.40	0.58	0.47	3010
accuracy			0.40	8970
macro avg	0.40	0.36	0.32	8970
weighted avg	0.39	0.40	0.35	8970

<Figure size 432x288 with 0 Axes>

We can see that this model is definitely biased toward E and T predictions. Understandable, as those are the two most prominent classes. This model gives us only 27% recall for the M class, making it pretty ineffective at identifying M-rated games based on screenshots.

5.2 Model 2 (CNN - 4 Convolutional Blocks)

As the simple neural network proved ineffective, we'll move on to a convolutional neural network. CNNs are often used for image classification projects as the convolutional layers are much better than dense layers at discovering patterns in images. This model uses four convolutional blocks, each containing two Conv2D layers and a MaxPooling2D layer. Each block also includes a Dropout layer, which helps prevent overfitting. After the convolutional blocks, we flatten the inputs and pass them to a Dense layer before outputting predictions.

In [12]:

```
model_2 = Sequential()

model_2.add(Conv2D(filters=32, kernel_size=(3,3), padding='same',
                   activation='relu', input_shape=input_shape))
model_2.add(Conv2D(32, (3,3), activation='relu'))
model_2.add(MaxPooling2D((2,2)))
model_2.add(Dropout(0.2))

model_2.add(Conv2D(64, (3,3), padding='same', activation='relu'))
model_2.add(Conv2D(64, (3,3), activation='relu'))
model_2.add(MaxPooling2D((2,2)))
model_2.add(Dropout(0.2))

model_2.add(Conv2D(128, (3,3), padding='same', activation='relu'))
model_2.add(Conv2D(128, (3,3), activation='relu'))
model_2.add(MaxPooling2D((2,2)))
model_2.add(Dropout(0.2))

model_2.add(Conv2D(256, (3,3), padding='same', activation='relu'))
model_2.add(Conv2D(256, (3,3), activation='relu'))
model_2.add(MaxPooling2D((2,2)))
model_2.add(Dropout(0.2))

model_2.add(Flatten())
model_2.add(Dense(512, activation='relu'))
model_2.add(Dropout(0.2))
model_2.add(Dense(4, activation='softmax'))

optimizer = tf.keras.optimizers.RMSprop(learning_rate=1e-4)

model_2.compile(loss='categorical_crossentropy',
              optimizer=optimizer,
              metrics=['acc'])

model_2.summary()
```

executed in 140ms, finished 20:24:23 2021-06-23

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 224, 224, 32)      896
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 222, 222, 32)      9248
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 111, 111, 32)      0
_________________________________________________________________
dropout (Dropout)            (None, 111, 111, 32)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 111, 111, 64)      18496
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 109, 109, 64)      36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 54, 54, 64)        0
```

```
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 54, 54, 128)       73856
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 52, 52, 128)       147584
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 26, 26, 128)       0
_________________________________________________________________
dropout_2 (Dropout)          (None, 26, 26, 128)       0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 26, 26, 256)       295168
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 24, 24, 256)       590080
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 12, 12, 256)       0
_________________________________________________________________
dropout_3 (Dropout)          (None, 12, 12, 256)       0
_________________________________________________________________
flatten_1 (Flatten)          (None, 36864)             0
_________________________________________________________________
dense_3 (Dense)              (None, 512)               18874880
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_4 (Dense)              (None, 4)                 2052
=================================================================
Total params: 20,049,188
Trainable params: 20,049,188
Non-trainable params: 0
_________________________________________________________________
```

In [13]:
```
history_2 = model_2.fit(train_gen,
                        epochs=epochs,
                        validation_data=val_gen,
                        callbacks=init_callbacks(2))
```

executed in 43m 45s, finished 21:08:09 2021-06-23

```
Epoch 1/10
1051/1051 [==============================] - 274s 255ms/step - loss: 1.3243 -
acc: 0.3528 - val_loss: 1.2697 - val_acc: 0.4009

Epoch 00001: val_loss improved from inf to 1.26973, saving model to best_mode
l_2.h5
Epoch 2/10
1051/1051 [==============================] - 261s 248ms/step - loss: 1.2505 -
acc: 0.4110 - val_loss: 1.2465 - val_acc: 0.4232

Epoch 00002: val_loss improved from 1.26973 to 1.24649, saving model to best_
model_2.h5
Epoch 3/10
1051/1051 [==============================] - 263s 250ms/step - loss: 1.2246 -
acc: 0.4267 - val_loss: 1.2353 - val_acc: 0.4254

Epoch 00003: val_loss improved from 1.24649 to 1.23527, saving model to best_
model_2.h5
Epoch 4/10
1051/1051 [==============================] - 259s 246ms/step - loss: 1.2126 -
acc: 0.4465 - val_loss: 1.2360 - val_acc: 0.4268

Epoch 00004: val_loss did not improve from 1.23527
Epoch 5/10
1051/1051 [==============================] - 260s 247ms/step - loss: 1.1934 -
acc: 0.4533 - val_loss: 1.2756 - val_acc: 0.4152

Epoch 00005: val_loss did not improve from 1.23527
Epoch 6/10
1051/1051 [==============================] - 263s 250ms/step - loss: 1.1834 -
acc: 0.4598 - val_loss: 1.2071 - val_acc: 0.4487

Epoch 00006: val_loss improved from 1.23527 to 1.20713, saving model to best_
model_2.h5
Epoch 7/10
1051/1051 [==============================] - 260s 247ms/step - loss: 1.1773 -
acc: 0.4672 - val_loss: 1.1935 - val_acc: 0.4545

Epoch 00007: val_loss improved from 1.20713 to 1.19353, saving model to best_
model_2.h5
Epoch 8/10
1051/1051 [==============================] - 260s 248ms/step - loss: 1.1720 -
acc: 0.4676 - val_loss: 1.2641 - val_acc: 0.4326

Epoch 00008: val_loss did not improve from 1.19353
Epoch 9/10
1051/1051 [==============================] - 262s 249ms/step - loss: 1.1634 -
acc: 0.4731 - val_loss: 1.1862 - val_acc: 0.4688

Epoch 00009: val_loss improved from 1.19353 to 1.18619, saving model to best_
```

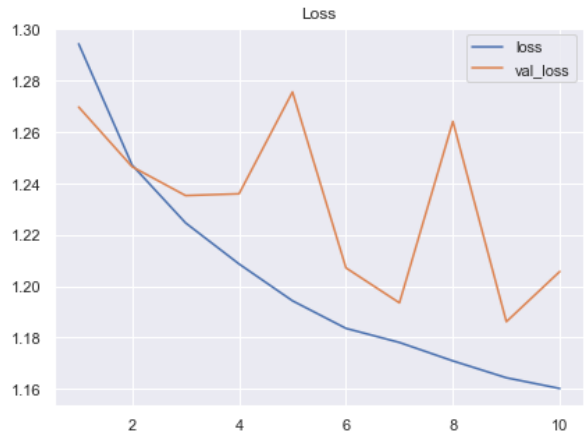
```
model_2.h5
Epoch 10/10
1051/1051 [==============================] - 262s 249ms/step - loss: 1.1538 -
acc: 0.4763 - val_loss: 1.2057 - val_acc: 0.4728

Epoch 00010: val_loss did not improve from 1.18619
```

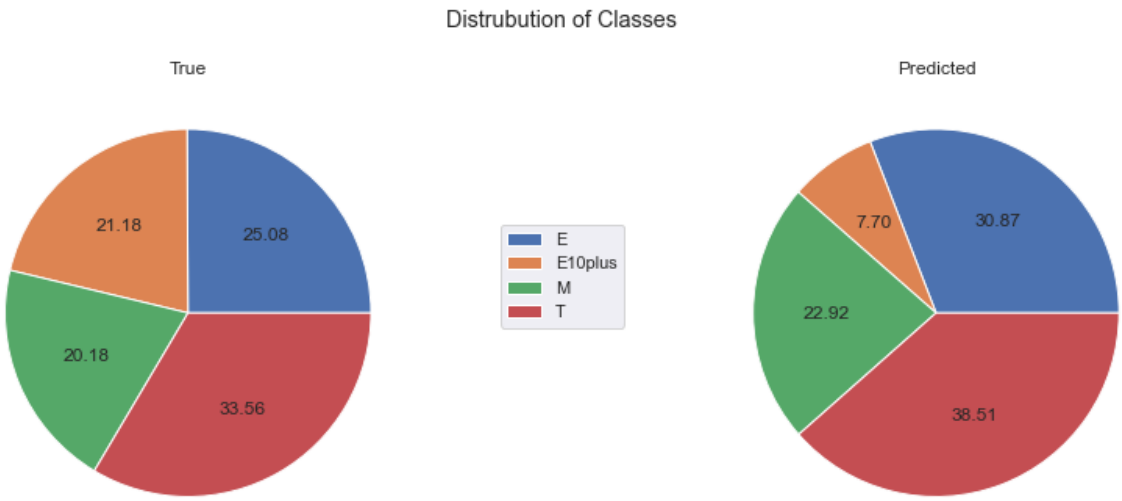
5.2.1 Results

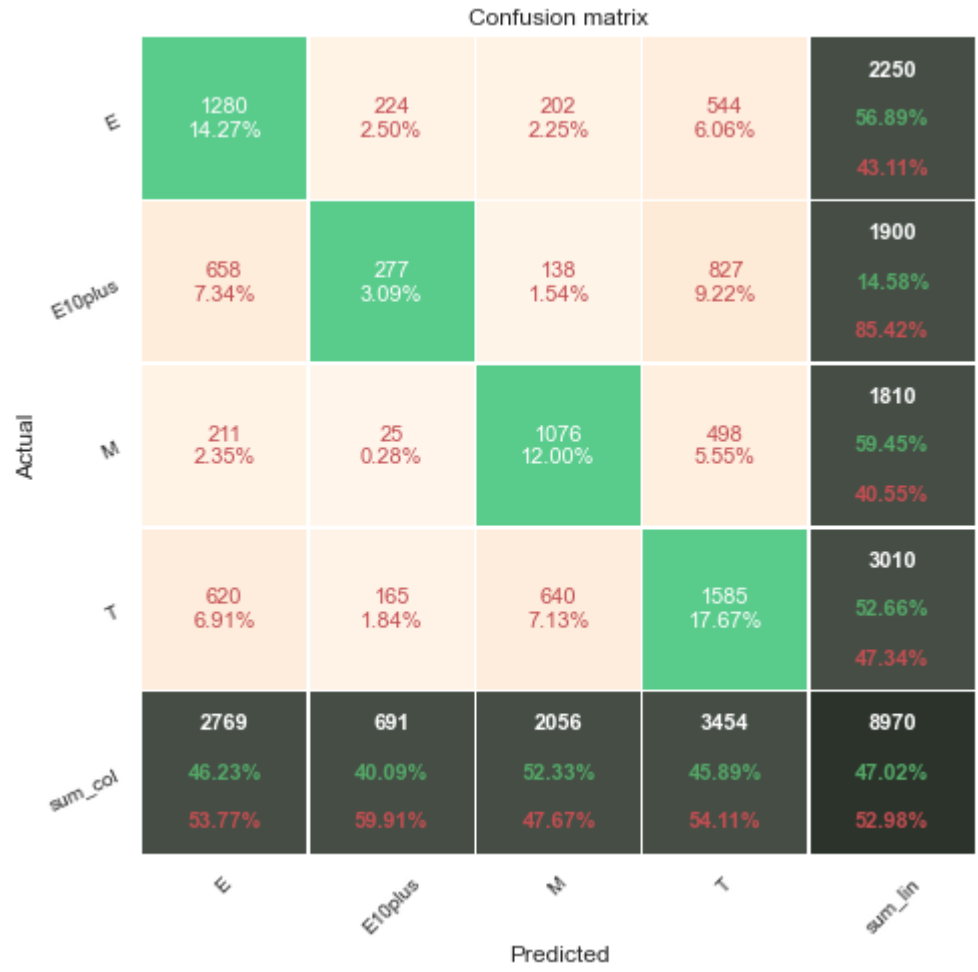
In [14]:
```
custom.evaluate(model_2, history_2, test_gen)
```

executed in 22.2s, finished 21:08:31 2021-06-23

```
281/281 [==============================] - 12s 41ms/step - loss: 1.1915 - acc:
0.4702
[1.1915004253387451, 0.47023412585258484]
```







	precision	recall	f1-score	support
E	0.46	0.57	0.51	2250
E10plus	0.40	0.15	0.21	1900
M	0.52	0.59	0.56	1810
T	0.46	0.53	0.49	3010
accuracy			0.47	8970
macro avg	0.46	0.46	0.44	8970
weighted avg	0.46	0.47	0.45	8970

```
<Figure size 432x288 with 0 Axes>
```

Our accuracy improved quite a bit with this model, and we can see from the pie charts that the distributions are much closer than last time, although this model still does have a bit of an aversion to the E10plus class. We've also reached 59% recall on the M class with 52% precision. That's a big improvement. In fact, the M class has the highest f1 score in this model at 0.56.

5.3 Model 3 (With Class Weights)

While our last model showed good improvement, we might be able to further improve by adding class weights to the model. While our data isn't terribly imbalanced, we have seen that our models do have some bias toward the more prominent classes. We'll use the same model structure as last

time, except this time we're adding a BatchNormalization layer to each convolutional block and adding a class_weight argument to the compile function.

In [15]:
```
model_3 = Sequential()

model_3.add(Conv2D(filters=32, kernel_size=(3,3), padding='same',
                   activation='relu', input_shape=input_shape))
model_3.add(Conv2D(32, (3,3), activation='relu'))
model_3.add(BatchNormalization())
model_3.add(MaxPooling2D((2,2)))
model_3.add(Dropout(0.2))

model_3.add(Conv2D(64, (3,3), padding='same', activation='relu'))
model_3.add(Conv2D(64, (3,3), activation='relu'))
model_3.add(BatchNormalization())
model_3.add(MaxPooling2D((2,2)))
model_3.add(Dropout(0.2))

model_3.add(Conv2D(128, (3,3), padding='same', activation='relu'))
model_3.add(Conv2D(128, (3,3), activation='relu'))
model_3.add(BatchNormalization())
model_3.add(MaxPooling2D((2,2)))
model_3.add(Dropout(0.2))

model_3.add(Conv2D(256, (3,3), padding='same', activation='relu'))
model_3.add(Conv2D(256, (3,3), activation='relu'))
model_3.add(BatchNormalization())
model_3.add(MaxPooling2D((2,2)))
model_3.add(Dropout(0.2))

model_3.add(Flatten())
model_3.add(Dense(512, activation='relu'))
model_3.add(Dropout(0.2))
model_3.add(Dense(4, activation='softmax'))

optimizer = tf.keras.optimizers.RMSprop(learning_rate=1e-4)

model_3.compile(loss='categorical_crossentropy',
                optimizer=optimizer,
                metrics=['acc'])

model_3.summary()
```

executed in 157ms, finished 21:08:31 2021-06-23

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 224, 224, 32)      896
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 222, 222, 32)      9248
_________________________________________________________________
batch_normalization (BatchNo (None, 222, 222, 32)      128
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 111, 111, 32)      0
_________________________________________________________________
dropout_5 (Dropout)          (None, 111, 111, 32)      0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 111, 111, 64)      18496
```

```
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 109, 109, 64)      36928
_________________________________________________________________
batch_normalization_1 (Batch (None, 109, 109, 64)      256
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 54, 54, 64)        0
_________________________________________________________________
dropout_6 (Dropout)          (None, 54, 54, 64)        0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 54, 54, 128)       73856
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 52, 52, 128)       147584
_________________________________________________________________
batch_normalization_2 (Batch (None, 52, 52, 128)       512
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 26, 26, 128)       0
_________________________________________________________________
dropout_7 (Dropout)          (None, 26, 26, 128)       0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 26, 26, 256)       295168
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 24, 24, 256)       590080
_________________________________________________________________
batch_normalization_3 (Batch (None, 24, 24, 256)       1024
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 12, 12, 256)       0
_________________________________________________________________
dropout_8 (Dropout)          (None, 12, 12, 256)       0
_________________________________________________________________
flatten_2 (Flatten)          (None, 36864)             0
_________________________________________________________________
dense_5 (Dense)              (None, 512)               18874880
_________________________________________________________________
dropout_9 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_6 (Dense)              (None, 4)                 2052
=================================================================
Total params: 20,051,108
Trainable params: 20,050,148
Non-trainable params: 960
_________________________________________________________________
```

In [16]:

```
class_counts = [11240, 9480, 15070, 9040]
class_weights = {x:15070/y for x,y in enumerate(class_counts)}
```

executed in 15ms, finished 21:08:31 2021-06-23

In [17]:
```
history_3 = model_3.fit(train_gen,
                        epochs=epochs,
                        validation_data=val_gen,
                        callbacks=init_callbacks(3),
                        class_weight=class_weights)
```

executed in 43m 46s, finished 21:52:17 2021-06-23

```
Epoch 1/10
1051/1051 [==============================] - 262s 248ms/step - loss: 3.1996 - a
cc: 0.3258 - val_loss: 1.7291 - val_acc: 0.3754

Epoch 00001: val_loss improved from inf to 1.72911, saving model to best_model_
3.h5
Epoch 2/10
1051/1051 [==============================] - 262s 249ms/step - loss: 1.8292 - a
cc: 0.3781 - val_loss: 2.1966 - val_acc: 0.3308

Epoch 00002: val_loss did not improve from 1.72911
Epoch 3/10
1051/1051 [==============================] - 264s 251ms/step - loss: 1.8037 - a
cc: 0.3859 - val_loss: 1.3647 - val_acc: 0.3951

Epoch 00003: val_loss improved from 1.72911 to 1.36467, saving model to best_mo
del_3.h5
Epoch 4/10
1051/1051 [==============================] - 263s 250ms/step - loss: 1.7846 - a
cc: 0.4014 - val_loss: 1.4402 - val_acc: 0.3987

Epoch 00004: val_loss did not improve from 1.36467
Epoch 5/10
1051/1051 [==============================] - 261s 248ms/step - loss: 1.7649 - a
cc: 0.4119 - val_loss: 1.3330 - val_acc: 0.4192

Epoch 00005: val_loss improved from 1.36467 to 1.33296, saving model to best_mo
del_3.h5
Epoch 6/10
1051/1051 [==============================] - 264s 251ms/step - loss: 1.7419 - a
cc: 0.4173 - val_loss: 1.3595 - val_acc: 0.4259

Epoch 00006: val_loss did not improve from 1.33296
Epoch 7/10
1051/1051 [==============================] - 262s 250ms/step - loss: 1.7405 - a
cc: 0.4181 - val_loss: 1.4315 - val_acc: 0.4362

Epoch 00007: val_loss did not improve from 1.33296
Epoch 8/10
1051/1051 [==============================] - 261s 248ms/step - loss: 1.7415 - a
cc: 0.4147 - val_loss: 1.2764 - val_acc: 0.4170

Epoch 00008: val_loss improved from 1.33296 to 1.27636, saving model to best_mo
del_3.h5
Epoch 9/10
1051/1051 [==============================] - 261s 249ms/step - loss: 1.7216 - a
cc: 0.4271 - val_loss: 1.5753 - val_acc: 0.4286

Epoch 00009: val_loss did not improve from 1.27636
```

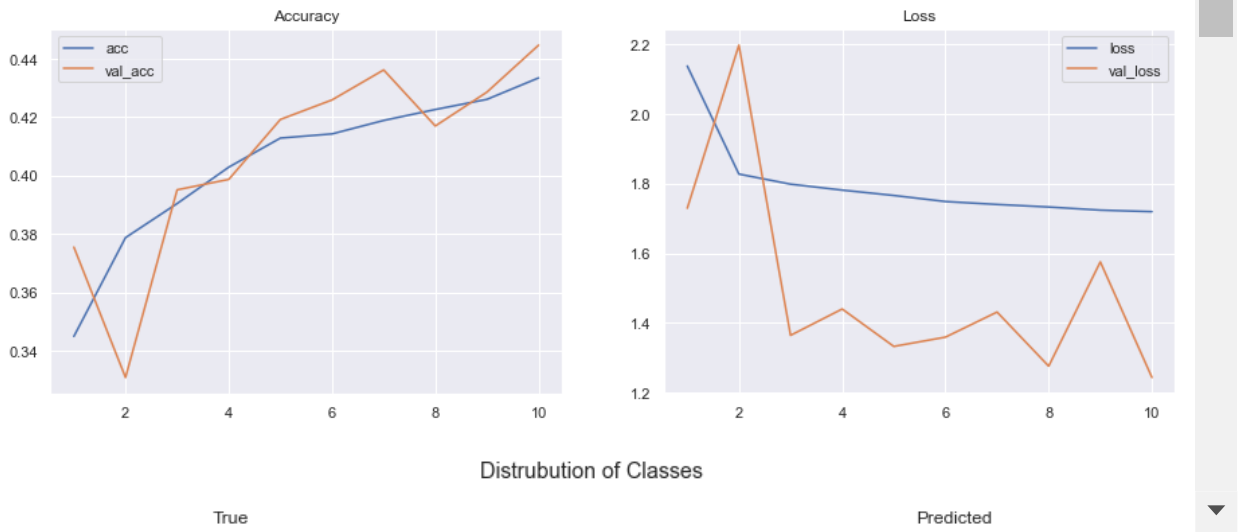
```
Epoch 10/10
1051/1051 [==============================] - 264s 251ms/step - loss: 1.7126 - a
cc: 0.4356 - val_loss: 1.2439 - val_acc: 0.4446

Epoch 00010: val_loss improved from 1.27636 to 1.24389, saving model to best_mo
del_3.h5
```

5.3.1 Results

In [18]:
```
custom.evaluate(model_3, history_3, test_gen)
```

executed in 23.3s, finished 21:52:40 2021-06-23

```
281/281 [==============================] - 12s 42ms/step - loss: 1.2418 - ac
c: 0.4486
[1.2417646646499634, 0.4486064612865448]
```



Our overall accuracy went down by a couple percentage points with this model, but the accuracy and loss charts show that this model could probably do with some further training. Looking at the pie charts, it looks like adding class weights had the opposite of our intended effect, with the T class taking over the majority of predictions. We also lost almost 12% on recall for the M class. This is definitely not an improvement on our second model.

5.4 Model 4 (Pretrained CNN)

One of the great things about using CNNs for image classification is that a bunch of other data scientists have done it already. As such, there are several pretrained CNN architectures available. For this model, we'll use the VGG-16 architecture, which is available for import straight from Keras. We'll keep the VGG-16 layers untrainable, but we'll add a few layers at the end of the model to allow the model to shape itself to our particular data.

In [19]:
```
from tensorflow.keras.applications.vgg16 import VGG16

base_model = VGG16(input_shape=input_shape,
                   include_top=False)

for layer in base_model.layers:
    layer.trainable = False

x = Flatten()(base_model.output)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(4, activation='softmax')(x)

model_4 = Model(base_model.input, x)

optimizer = tf.keras.optimizers.RMSprop(learning_rate=1e-4)

model_4.compile(optimizer=optimizer,
                loss='categorical_crossentropy',
                metrics=['acc'])

model_4.summary()
```

executed in 315ms, finished 21:52:40 2021-06-23

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
```

```
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten_3 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_7 (Dense)              (None, 512)               12845568
_________________________________________________________________
dropout_10 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_8 (Dense)              (None, 4)                 2052
=================================================================
Total params: 27,562,308
Trainable params: 12,847,620
Non-trainable params: 14,714,688
_________________________________________________________________
```

In [20]:
```
history_4 = model_4.fit(train_gen,
                        validation_data=val_gen,
                        epochs=epochs,
                        callbacks=init_callbacks(4))
```

executed in 46m 11s, finished 22:38:51 2021-06-23

```
Epoch 1/10
1051/1051 [==============================] - 282s 263ms/step - loss: 1.3727 -
acc: 0.3905 - val_loss: 1.1799 - val_acc: 0.4929

Epoch 00001: val_loss improved from inf to 1.17991, saving model to best_mode
l_4.h5
Epoch 2/10
1051/1051 [==============================] - 273s 259ms/step - loss: 1.1994 -
acc: 0.4591 - val_loss: 1.1515 - val_acc: 0.4938

Epoch 00002: val_loss improved from 1.17991 to 1.15154, saving model to best_
model_4.h5
Epoch 3/10
1051/1051 [==============================] - 283s 269ms/step - loss: 1.1717 -
acc: 0.4709 - val_loss: 1.1568 - val_acc: 0.5080

Epoch 00003: val_loss did not improve from 1.15154
Epoch 4/10
1051/1051 [==============================] - 274s 261ms/step - loss: 1.1678 -
acc: 0.4751 - val_loss: 1.1413 - val_acc: 0.5085

Epoch 00004: val_loss improved from 1.15154 to 1.14128, saving model to best_
model_4.h5
Epoch 5/10
1051/1051 [==============================] - 280s 266ms/step - loss: 1.1532 -
acc: 0.4875 - val_loss: 1.1304 - val_acc: 0.5165

Epoch 00005: val_loss improved from 1.14128 to 1.13039, saving model to best_
model_4.h5
Epoch 6/10
1051/1051 [==============================] - 276s 263ms/step - loss: 1.1334 -
acc: 0.4982 - val_loss: 1.1230 - val_acc: 0.5143

Epoch 00006: val_loss improved from 1.13039 to 1.12298, saving model to best_
model_4.h5
Epoch 7/10
1051/1051 [==============================] - 274s 261ms/step - loss: 1.1226 -
acc: 0.5066 - val_loss: 1.1239 - val_acc: 0.5201

Epoch 00007: val_loss did not improve from 1.12298
Epoch 8/10
1051/1051 [==============================] - 273s 259ms/step - loss: 1.1188 -
acc: 0.5087 - val_loss: 1.1397 - val_acc: 0.5054

Epoch 00008: val_loss did not improve from 1.12298
Epoch 9/10
1051/1051 [==============================] - 274s 261ms/step - loss: 1.1169 -
acc: 0.5138 - val_loss: 1.1434 - val_acc: 0.5049

Epoch 00009: val_loss did not improve from 1.12298
```

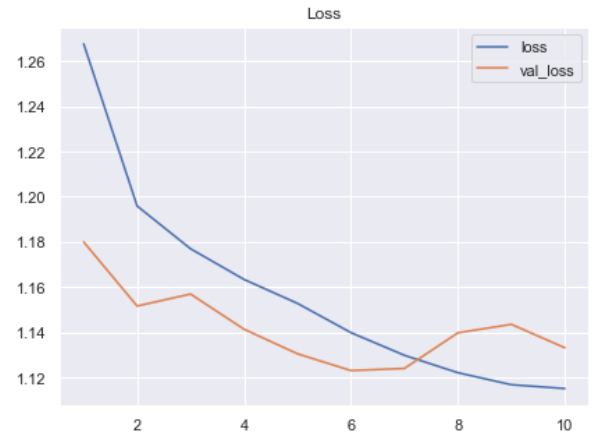
```
Epoch 10/10
1051/1051 [==============================] - 280s 266ms/step - loss: 1.1177 -
acc: 0.5071 - val_loss: 1.1331 - val_acc: 0.5183

Epoch 00010: val_loss did not improve from 1.12298
```

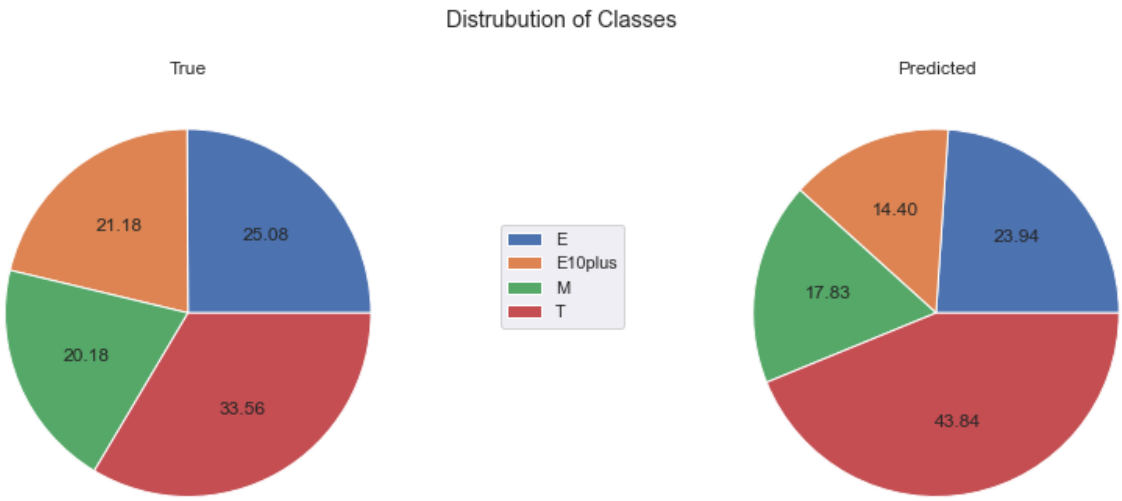
5.4.1 Results

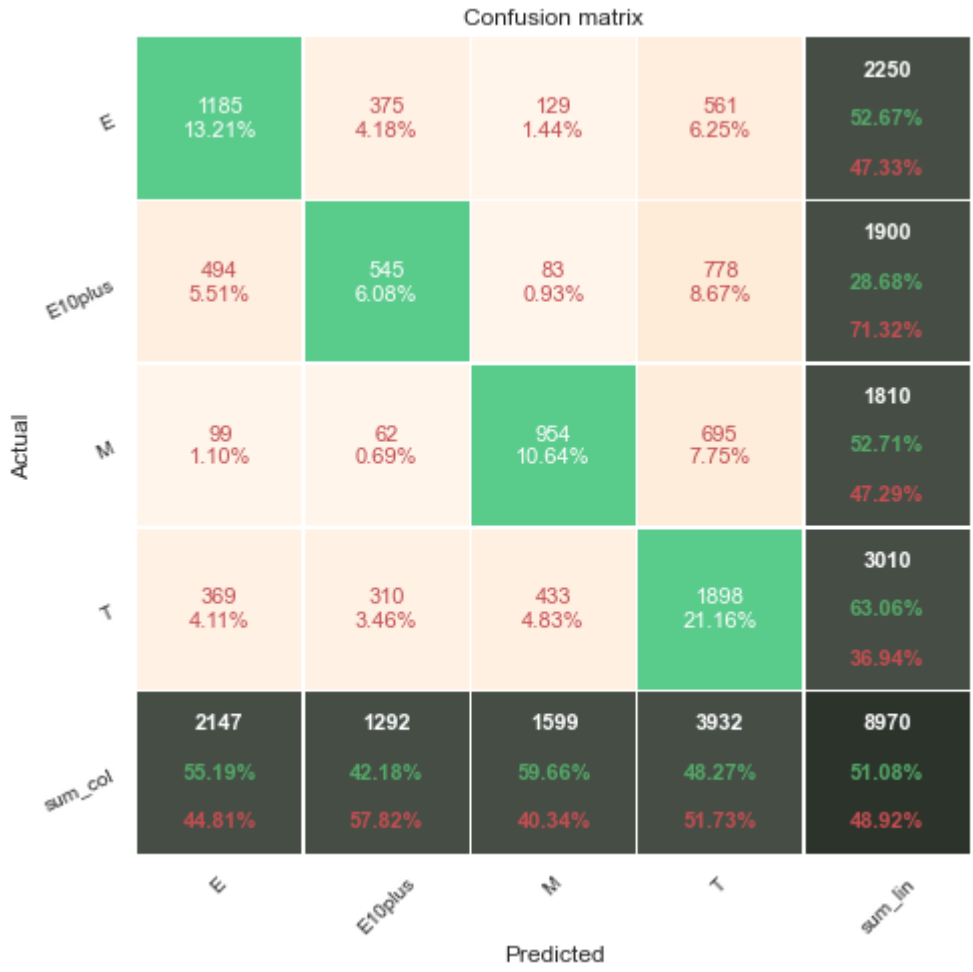
In [21]:
```
custom.evaluate(model_4, history_4, test_gen)
```

executed in 1m 22.5s, finished 22:40:14 2021-06-23

```
281/281 [==============================] - 43s 152ms/step - loss: 1.1392 - acc:
0.5108
[1.139237880706787, 0.51081383228302]
```







	precision	recall	f1-score	support
E	0.55	0.53	0.54	2250
E10plus	0.42	0.29	0.34	1900
M	0.60	0.53	0.56	1810
T	0.48	0.63	0.55	3010
accuracy			0.51	8970
macro avg	0.51	0.49	0.50	8970
weighted avg	0.51	0.51	0.50	8970

```
<Figure size 432x288 with 0 Axes>
```

And with that, we've finally broken above 50% overall accuracy! The class distributions look decent as well, although still about 10% heavy on the T predictions and 6% light on E10plus. Our M class recall is about 53% with 60% precision, giving us an f1 score of 0.56, similar to our first CNN model. It's a close call on which model is preferable.

5.5 Model 5 (Binary)

Since the main concern of this project is identifying M-rated games, it seems reasonable that a binary approach could prove effective. By combining all of the data for classes E-T, we could train a model to simply pull the M-rated games from the rest. This will, however, drastically alter the

class imbalance problem. Allowing for class weights did not help us in the past, but in this case the imbalance will be too great to ignore.

In [22]:
```
train_gen_bin = train_data.flow_from_directory('images/binary/train',
                                               target_size=(224,224),
                                               class_mode='binary')
val_gen_bin = val_data.flow_from_directory('images/binary/val',
                                           target_size=(224,224),
                                           class_mode='binary')
test_gen_bin = test_data.flow_from_directory('images/binary/test',
                                             target_size=(224,224),
                                             class_mode='binary',
                                             shuffle=False)
```

executed in 3.32s, finished 22:40:17 2021-06-23

```
Found 33598 images belonging to 2 classes.
Found 2240 images belonging to 2 classes.
Found 8970 images belonging to 2 classes.
```

In [23]:
```
# View a batch of binary train data
img, labels = train_gen_bin.next()
classes = list(train_gen_bin.class_indices.keys())
str_labels = [classes[x] for x in labels.astype('int')]

plt.figure(figsize=(15,20))
for i in range(len(img)):
    plt.subplot(8,4,i+1)
    plt.title(f'{str_labels[i]}')
    plt.imshow(img[i])
    plt.axis('off')
plt.tight_layout()
```

executed in 2.65s, finished 22:40:20 2021-06-23

E-T

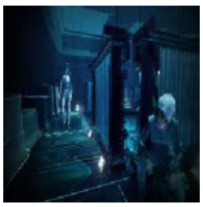
E-T

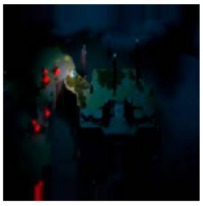
M

E-T

E-T

E-T

M

E-T

E-T

E-T


E-T

E-T

E-T

E-T


E-T

E-T

E-T

E-T

E-T

E-T

E-T

E-T

E-T

E-T

E-T

E-T


E-T

E-T

M

M

M

E-T


In [24]:
```
base_model_bin = VGG16(include_top=False,
                       input_shape=input_shape)
for layer in base_model_bin.layers:
    layer.trainable = False

x = Flatten()(base_model_bin.output)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(1, activation='sigmoid')(x)

model_5 = Model(base_model_bin.input, x)

optimizer = tf.keras.optimizers.Adam(learning_rate=1e-4)

model_5.compile(optimizer=optimizer,
                loss='binary_crossentropy',
                metrics=['acc'])

model_5.summary()
```

executed in 297ms, finished 22:40:20 2021-06-23

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
```

```
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten_4 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_9 (Dense)              (None, 512)               12845568
_________________________________________________________________
dropout_11 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_10 (Dense)             (None, 1)                 513
=================================================================
Total params: 27,560,769
Trainable params: 12,846,081
Non-trainable params: 14,714,688
_________________________________________________________________
```

In [25]:

```
total = train_gen_bin.classes.shape[0]
ones = train_gen_bin.classes.sum()
zeroes = total - ones

print(zeroes, ones)
```

executed in 14ms, finished 22:40:20 2021-06-23

```
26818 6780
```

In [26]:

```
class_weights = {x:zeroes/y for x,y in enumerate([zeroes, ones])}
class_weights
```

executed in 14ms, finished 22:40:20 2021-06-23

Out[26]:

```
{0: 1.0, 1: 3.955457227138643}
```

In [27]:
```
history_5 = model_5.fit(train_gen_bin,
                        validation_data=val_gen_bin,
                        epochs=epochs,
                        class_weight=class_weights,
                        callbacks=init_callbacks(5))
```

executed in 45m 46s, finished 23:26:07 2021-06-23

```
Epoch 1/10
1050/1050 [==============================] - 288s 274ms/step - loss: 0.9863 -
acc: 0.6795 - val_loss: 0.5429 - val_acc: 0.7433

Epoch 00001: val_loss improved from inf to 0.54288, saving model to best_mode
l_5.h5
Epoch 2/10
1050/1050 [==============================] - 272s 259ms/step - loss: 0.8701 -
acc: 0.7344 - val_loss: 0.5015 - val_acc: 0.7674

Epoch 00002: val_loss improved from 0.54288 to 0.50150, saving model to best_
model_5.h5
Epoch 3/10
1050/1050 [==============================] - 271s 258ms/step - loss: 0.8259 -
acc: 0.7506 - val_loss: 0.5677 - val_acc: 0.7196

Epoch 00003: val_loss did not improve from 0.50150
Epoch 4/10
1050/1050 [==============================] - 273s 260ms/step - loss: 0.8120 -
acc: 0.7552 - val_loss: 0.4883 - val_acc: 0.7688

Epoch 00004: val_loss improved from 0.50150 to 0.48831, saving model to best_
model_5.h5
Epoch 5/10
1050/1050 [==============================] - 271s 258ms/step - loss: 0.8045 -
acc: 0.7570 - val_loss: 0.4253 - val_acc: 0.8098

Epoch 00005: val_loss improved from 0.48831 to 0.42530, saving model to best_
model_5.h5
Epoch 6/10
1050/1050 [==============================] - 277s 263ms/step - loss: 0.7824 -
acc: 0.7672 - val_loss: 0.5107 - val_acc: 0.7536

Epoch 00006: val_loss did not improve from 0.42530
Epoch 7/10
1050/1050 [==============================] - 273s 259ms/step - loss: 0.7696 -
acc: 0.7712 - val_loss: 0.5330 - val_acc: 0.7429

Epoch 00007: val_loss did not improve from 0.42530
Epoch 8/10
1050/1050 [==============================] - 276s 262ms/step - loss: 0.7553 -
acc: 0.7748 - val_loss: 0.5210 - val_acc: 0.7491

Epoch 00008: val_loss did not improve from 0.42530
Epoch 9/10
1050/1050 [==============================] - 271s 258ms/step - loss: 0.7523 -
acc: 0.7729 - val_loss: 0.4807 - val_acc: 0.7696

Epoch 00009: val_loss did not improve from 0.42530
```

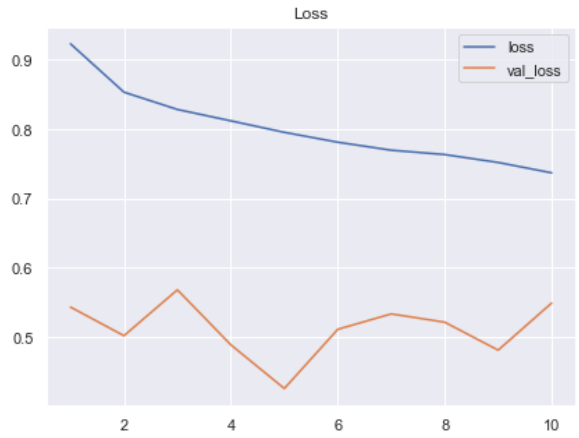
```
Epoch 10/10
1050/1050 [==============================] - 273s 260ms/step - loss: 0.7407 -
acc: 0.7799 - val_loss: 0.5487 - val_acc: 0.7415

Epoch 00010: val_loss did not improve from 0.42530
```

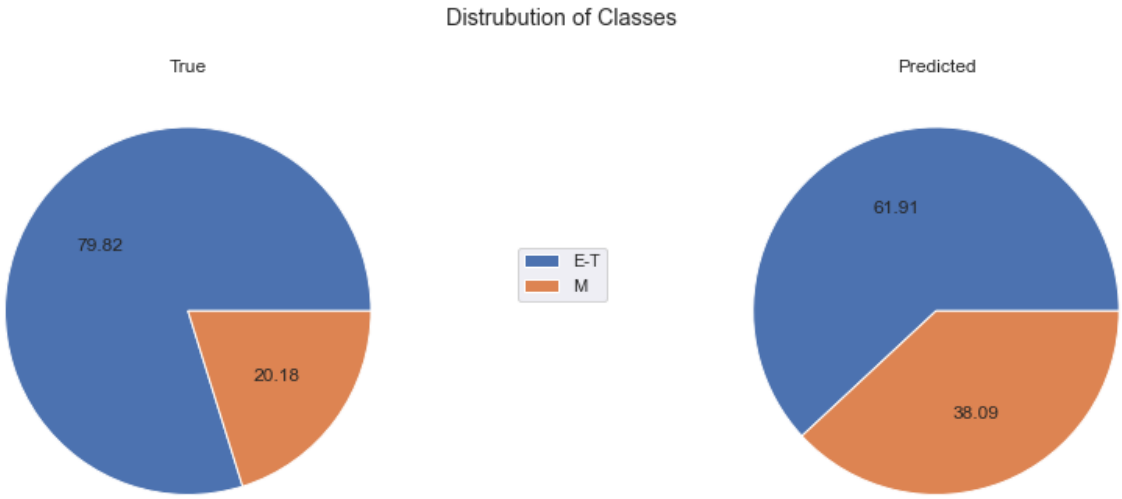
5.5.1 Results

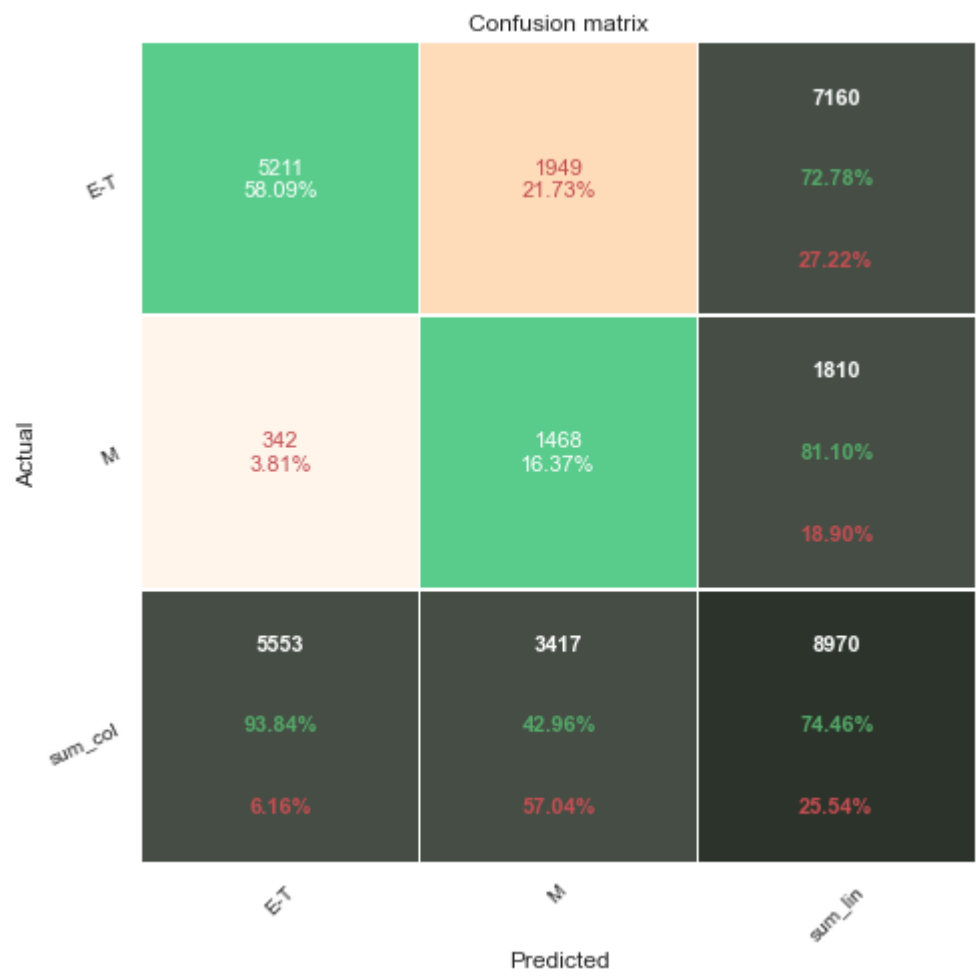
In [28]:
```
custom.evaluate(model_5, history_5, test_gen_bin)
```

executed in 1m 19.8s, finished 23:27:27 2021-06-23

```
281/281 [==============================] - 40s 143ms/step - loss: 0.5416 - acc:
0.7446
[0.5415802001953125, 0.74459308385849]
```







	precision	recall	f1-score	support
E-T	0.94	0.73	0.82	7160
M	0.43	0.81	0.56	1810
accuracy			0.74	8970
macro avg	0.68	0.77	0.69	8970
weighted avg	0.84	0.74	0.77	8970

```
<Figure size 432x288 with 0 Axes>
```

We ended up with an overall accuracy of about 74%, and while that sounds much higher than the previous models, it's worth remembering that only about 20% of the images are M class. The model could achieve 80% accuracy by simply predicting the majority class for every prediction. Judging by the pie charts, it looks like adding the class weights definitely gave a healthy boost to M-class predictions. We also achieved an 81% recall on the M class. The precision is only 43%, leaving the f1 score once again at 0.56. I think that boost in recall is too good to pass up, though. Of the five, I would definitely deploy this model.

6 iNterpret

When using neural networks, it can be difficult to see what's happening with the model. What is the model doing with the image data, and what patterns is it finding. Luckily, we can grab the outputs

of individual layers and see what that layer has done to our original images. Below, I've put together some code to see the VGG-16 model's interpretations of an image after each of the 5 convolutional blocks. For each block, we see the image altered in 64 different ways to focus on different aspects of the original image.

In [29]:
```
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.applications.vgg16 import preprocess_input
import os
import numpy as np
```

executed in 13ms, finished 23:27:27 2021-06-23

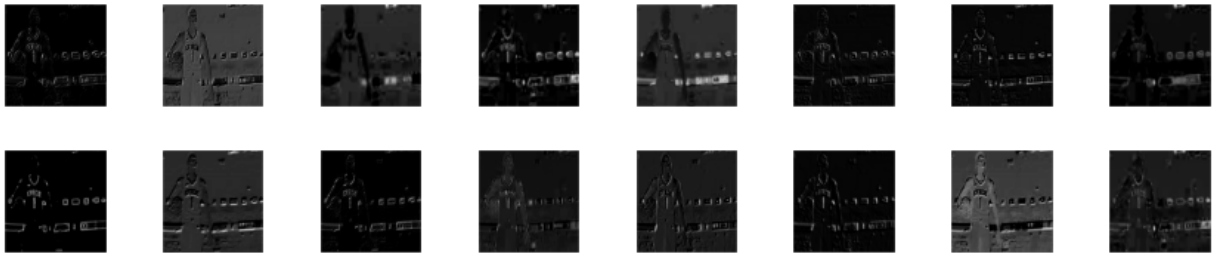
In [30]:
```
model = VGG16()
ixs = [2, 5, 9, 13, 17]
outputs = [model.layers[i].output for i in ixs]
model = Model(inputs=model.inputs, outputs=outputs)
```

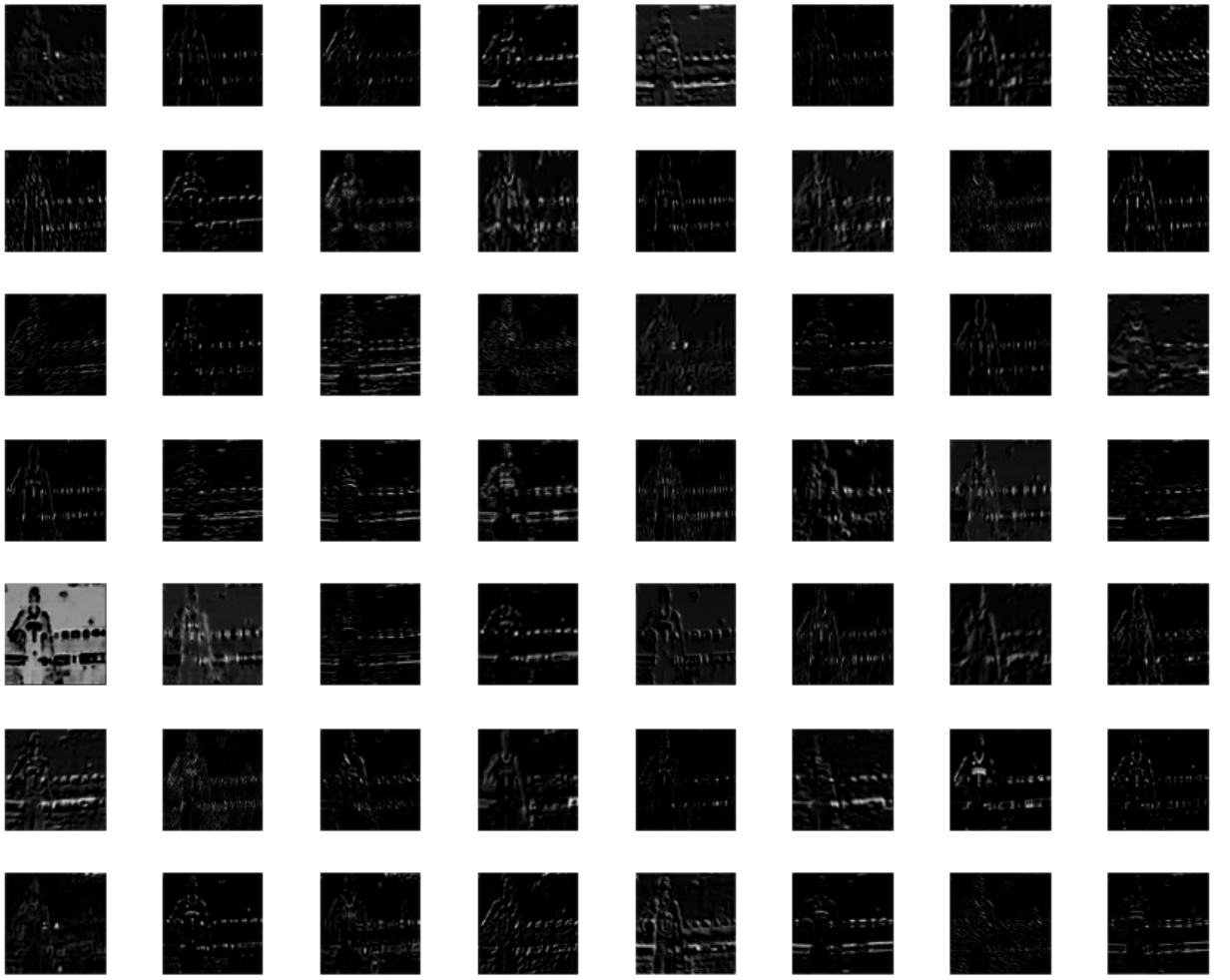
executed in 1.40s, finished 23:27:28 2021-06-23

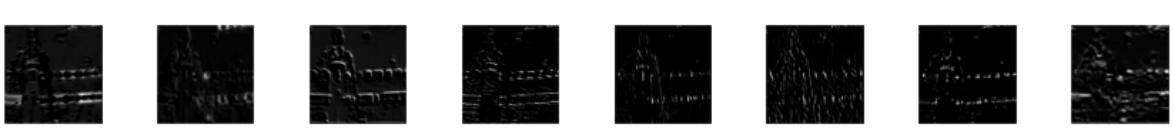
In [31]:
```
random_rating = np.random.choice(['E', 'E10plus', 'M', 'T'])
random_image = np.random.choice(os.listdir('images/' + random_rating))
random_path = 'images/' + random_rating + '/' + random_image

test_img = load_img(random_path, target_size=(224,224))
test_img = img_to_array(test_img)
test_img = np.expand_dims(test_img, axis=0)
test_img = preprocess_input(test_img)

feature_maps = model.predict(test_img)

square = 8
print(f'Image from: {random_image[:-6]}')
print(f'Rated: {random_rating}')
plt.imshow(load_img(random_path))
plt.axis('off')
for fmap in feature_maps:
    ix = 1
    for _ in range(square):
        plt.figure(figsize=(15,12))
        for _ in range(square):
            ax = plt.subplot(square, square, ix)
            ax.set_xticks([])
            ax.set_yticks([])
            plt.imshow(fmap[0,:,:,ix-1], cmap='gray')
            ix += 1
    plt.show()
    print('-----' * 21 + '---')
```

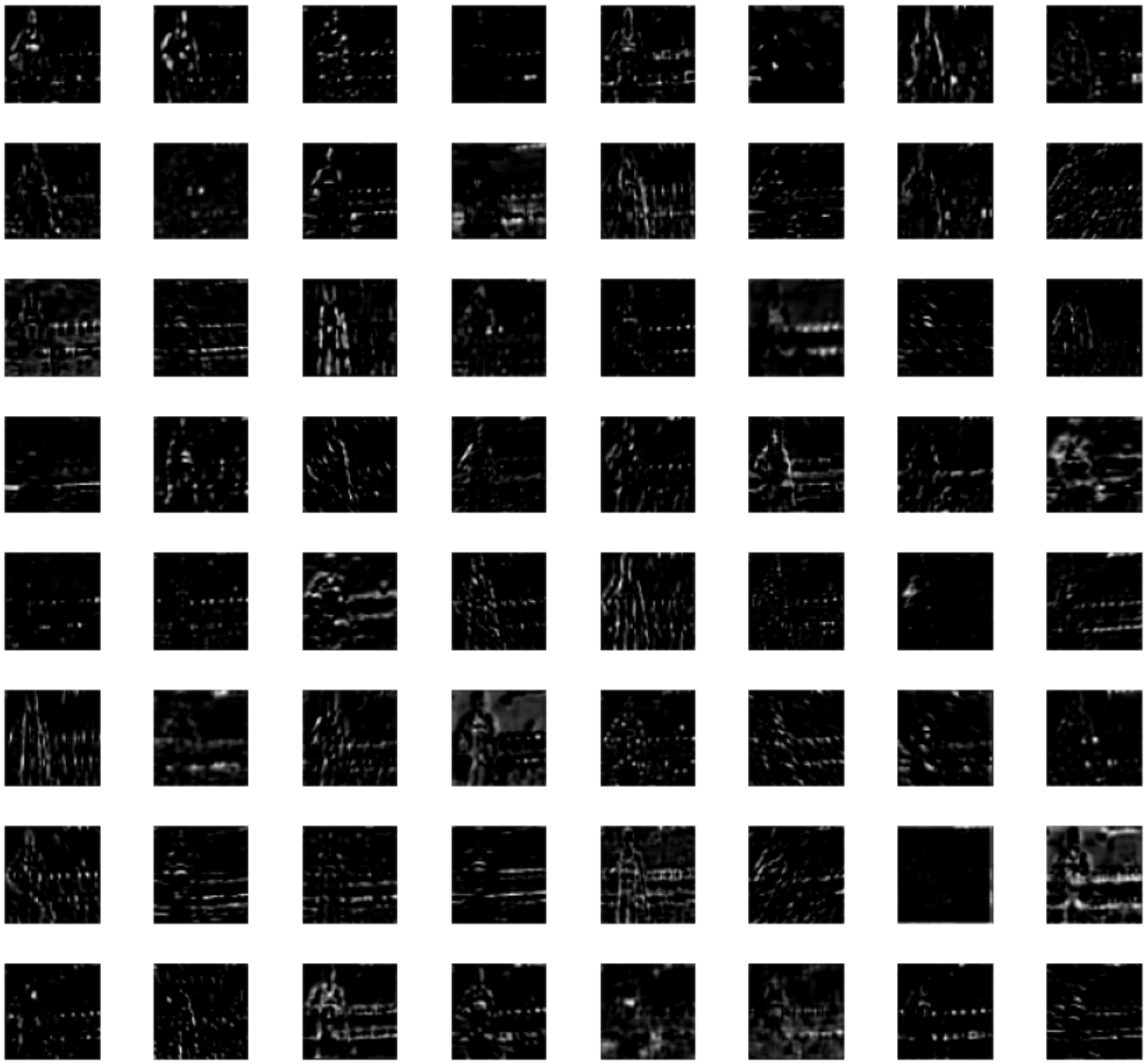
executed in 10.2s, finished 23:27:38 2021-06-23

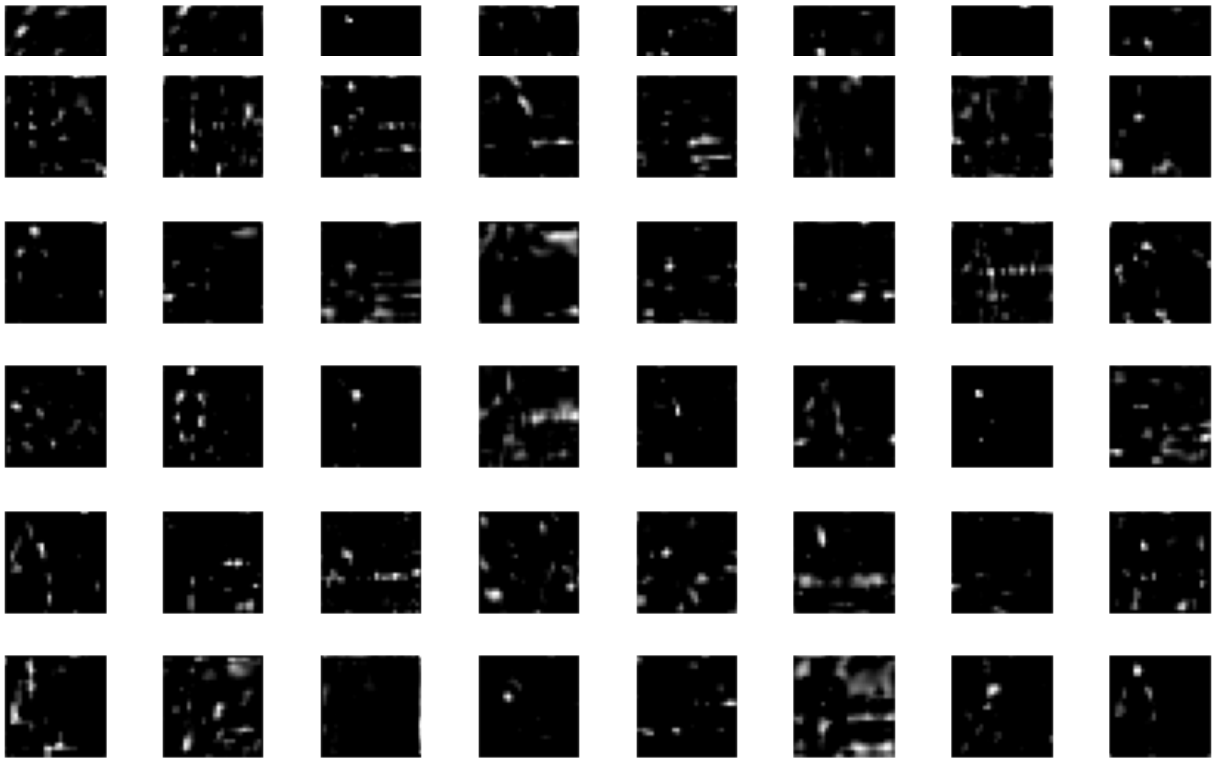
```
Image from: NBA 2K21
Rated: E
```

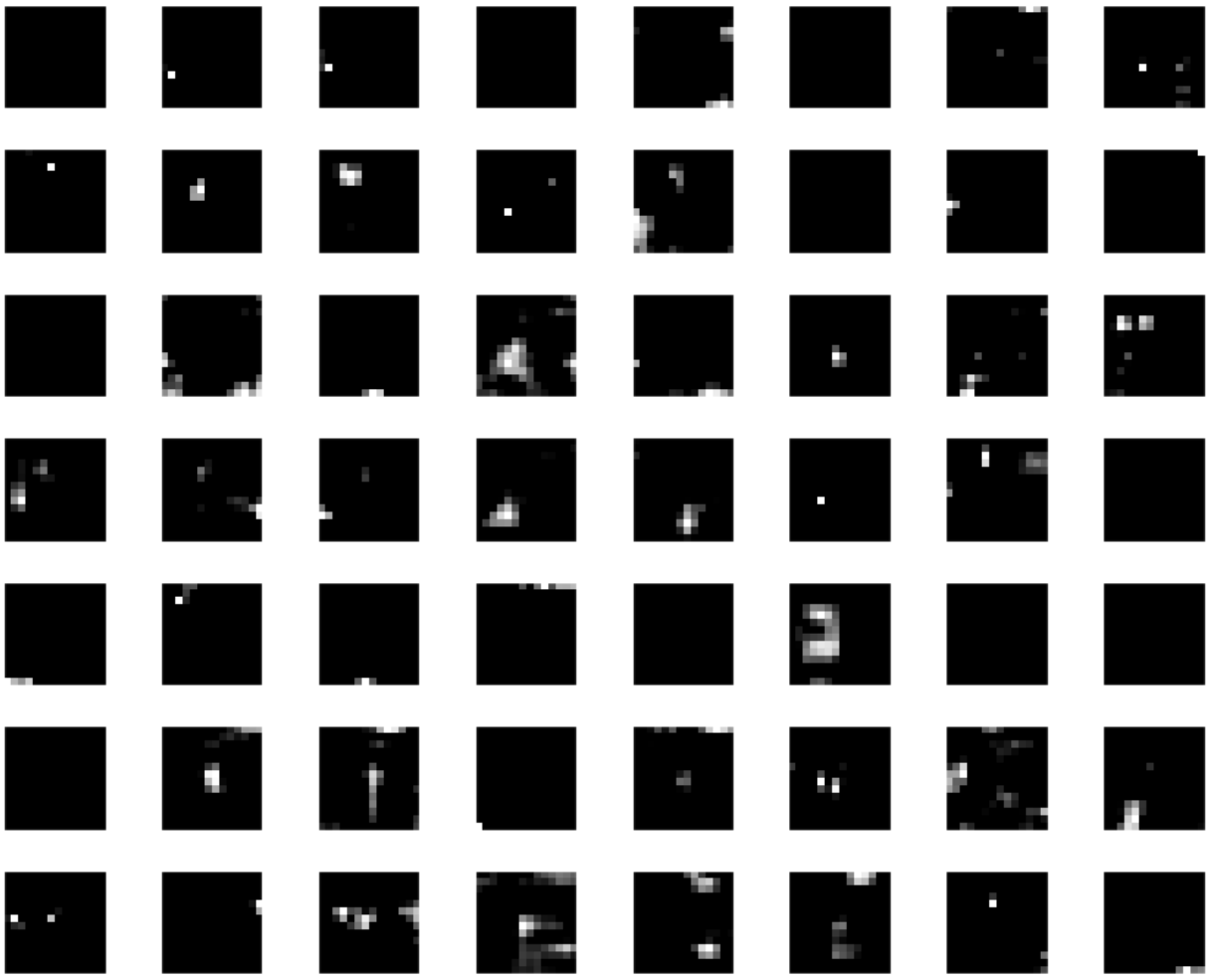












In [32]:
```
model_5.predict(test_img)
```
executed in 300ms, finished 23:27:38 2021-06-23

Out[32]:
```
array([[0.]], dtype=float32)
```

Above we can see an image from the game NBA 2K21. The image undergoes many convolutions, and while the image is still quite recognizable in many of the first-layer outputs, it is broken down further and further in subsequent layers. While we may still not be able to make much sense of the patterns that the model is drawing out, we can see in layer 5 that the model has definitely found specifics aspects of the image to focus on. And running this specific image though our binary model's predict function, we can see that our model was able to correctly predict that this is not an M-rated title.

7 Conclusion

While the models here are not perfect predictors of M-rated games, we did achieve 81% recall for M-rated games in our binary model. While the precision for this model is too low to implement in any sort of automated content restriction program, I do believe that it could be effective for automated content flagging. This flagged content could then be put up for human review by Twitch, YouTube, or any video game content hosting service.

7.1 Suggestions

- These particular models were trained on data scraped directly from Google Images using the game titles and the keywords 'video game screenshot.' While I did find this to be a fairly reliable source of images, it is certainly not a perfect sampling of data. More reliable data could probably obtained in bulk by the streaming services themselves by grabbing random gameplay screenshots during streams, though this would require confirmation that the pulled images were correctly labeled, and Twitch streamers are not always necessarily playing the game that they indicate they're playing. It would also be more difficult to obtain images from more obscure, less-streamed games.
- I think it could also be effective to stack models to get a single prediction from several screenshots, though my experiments with this so far have not proved to be any more accurate than the models shown here.
- In the same vein as the last suggestion, it might also prove effective to train models on short gameplay video clips rather than single-frame images, though this would certainly involve exponentially greater computational power.