

Daily Log

Monday March 16

Took photos of another 4 games on the chess set I have at home; roughly 400 images. Labelled one of them, partner labelled another.

Tuesday March 17

Labelled last two of four new games. Produced some UI diagrams for Kevin Chung.

Wednesday March 18

Trained new model, found good confusion matrix but poor "real-world" performance. Increased data augmentation to find similar dilemma.

Friday March 20

Found a few mislabelled images in dataset, corrected. Reduced channel shift data augmentation. Resplit dataset, improved readability of nnet training script on snowy. Retrained model, found much better results.

Timeline

Date	Goal	Met
Mar 2	Finish piece labelling, train new model for States (March 6th)	Done
Mar 9	Gather more data, play with ResNet types	Done
Mar 16	Label more data, add additional chess logic, increase data augmentations	Done except additional chess logic
Mar 23	Make UI graphics, see if hand occlusion is feasible	Not started
Mar 30	Add additional chess logic, consider ensemble learning	Not started

Reflection

This was another confusing week where my network's accuracy and confusion matrix did not seem to line up with its performance on real images. Luckily, it ended on a high note, with a simple re-splitting of my training and validation subsets and some minor data augmentation tweaks fixing the issue. Here's the new confusion matrix:

Confusion Matrix

```
[[ 151    0    0    1    0    0    0    0    0    0    0    0    0]
 [   0  144    0    0    1    0    0    0    0    0    0    0    0]
 [   0    1  114    0    1    0    0    0    0    0    0    0    0]
 [   0    0    0  736    0    0    2    0    0    0    2    0    0]
 [   0    2    0    0  102    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0  167    0    0    0    0    0    0    0]
 [   1    0    1    1    0    0  1474    0    0    0    2    0    0]
 [   0    0    0    0    0    0    1  144    0    0    1    0    0]
 [   0    1    0    0    0    0    0    0  147    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0  116    0    1    0]
 [   0    0    0    0    0    0    2    0    0    0  736    0    0]
 [   0    0    0    0    0    0    0    0    1    0    0  110    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0  182]]
```

with these data augmentations:

```
train_datagen = ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=0,
    shear_range=10,

    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.3,
```

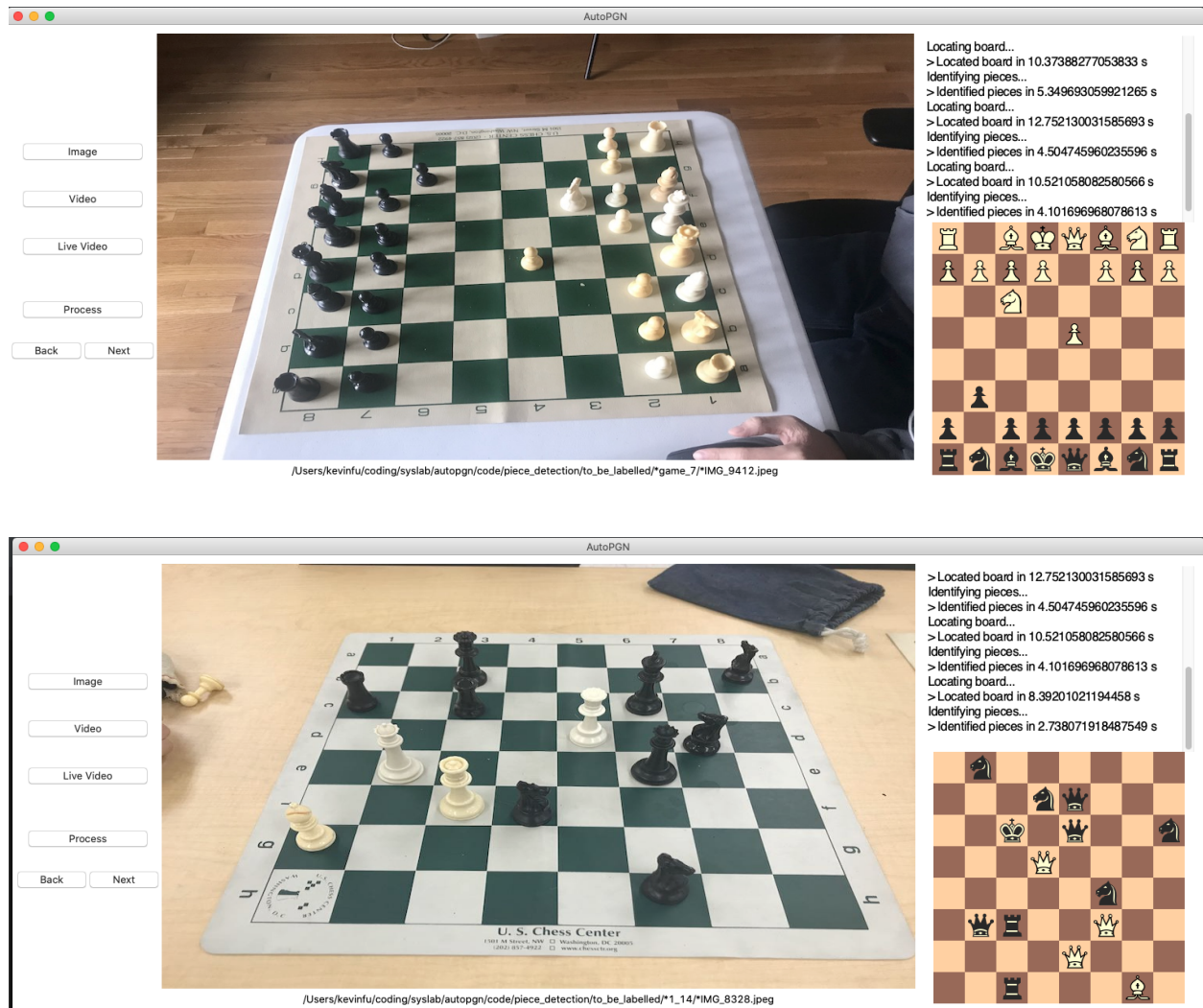
```

brightness_range=(0.8, 1.0),
channel_shift_range=50.0,

horizontal_flip=True,
)

```

That results in performance like this on real images. First two images are part of the network's dataset, last two are not:



Before "spring break" hits, my partner and I are hopeful we'll be able to have a real-time system running, with roughly half a minute of overhead at the start of a game to find the board initially. He's planning to implement tracking on the lattice points of the board, which should reduce the time taken to find the board in a live video setting significantly. As mentioned in a previous journal, board detection is fast enough for live video on a GPU-enabled machine as is. Though we haven't figured out hand occlusion, in a slightly-constrained game (players do not premove, put pieces on the squares fully, and play legally), our system should be fast enough to keep up by just processing frames as often as possible. With a half-second runtime, AutoPGN will run at 2 FPS, good enough for most time controls.

