

Get Chess Board

Chess Screenshot → Analysis Board



r1b1k2r/pp2ppbp/2n3p1/q7/2BPP3/4B3/P3NPPP/R2QK2R

Motivation & Goals

Motivation

Watching chess on YouTube:

-But why not <random_chess_move>??

The video moves on without hearing you...

In a parallel universe:

The video still moves on without hearing you... but you open that position on a chess engine.

Goals

Decrease the friction to study a chess game played on a video platform. Some benefits:

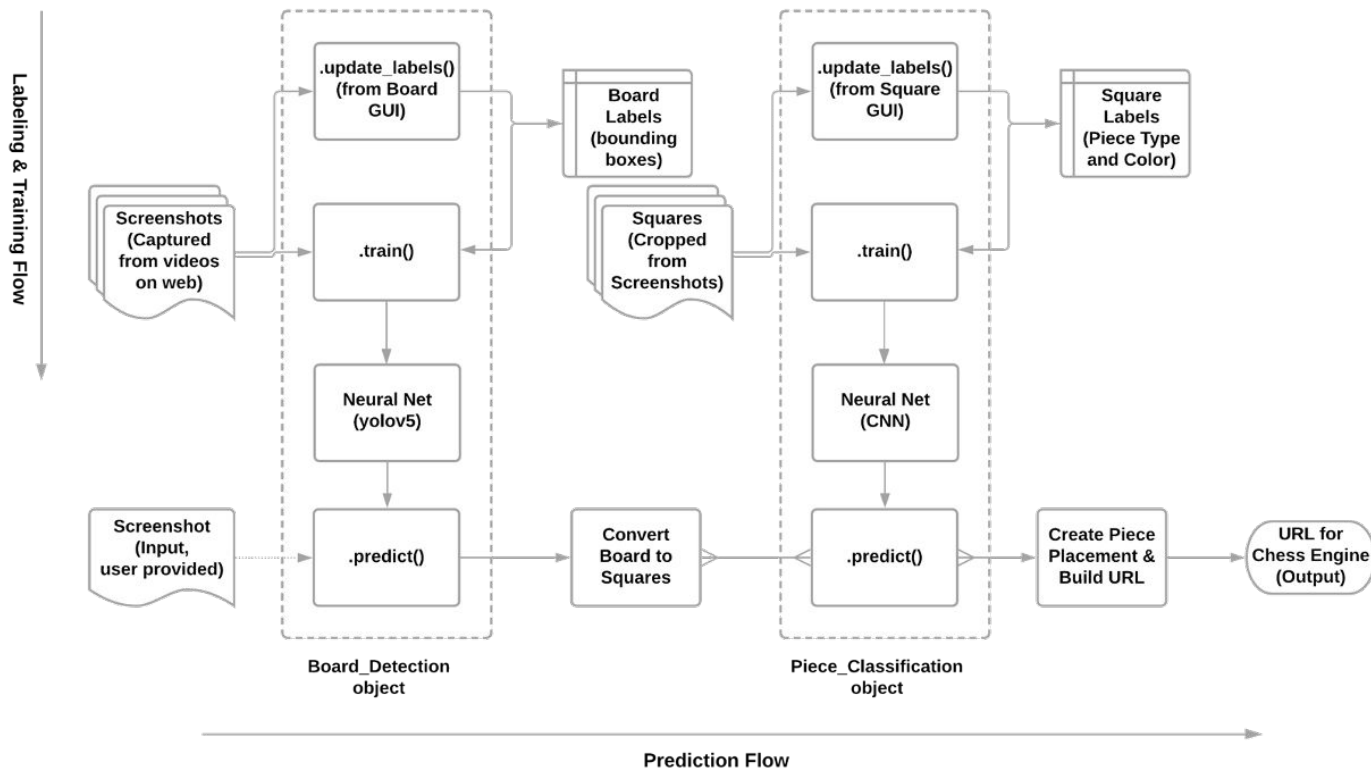
1. Shorten the feedback-loop on learning by making the analysis board available
2. Introduce a programmatic tool for capturing chess games from videos
3. Make watching chess more fun!

Project Objective: Take in a screenshot of a chess game on a video platform and return a string the represents the piece placement.

Methodology Design

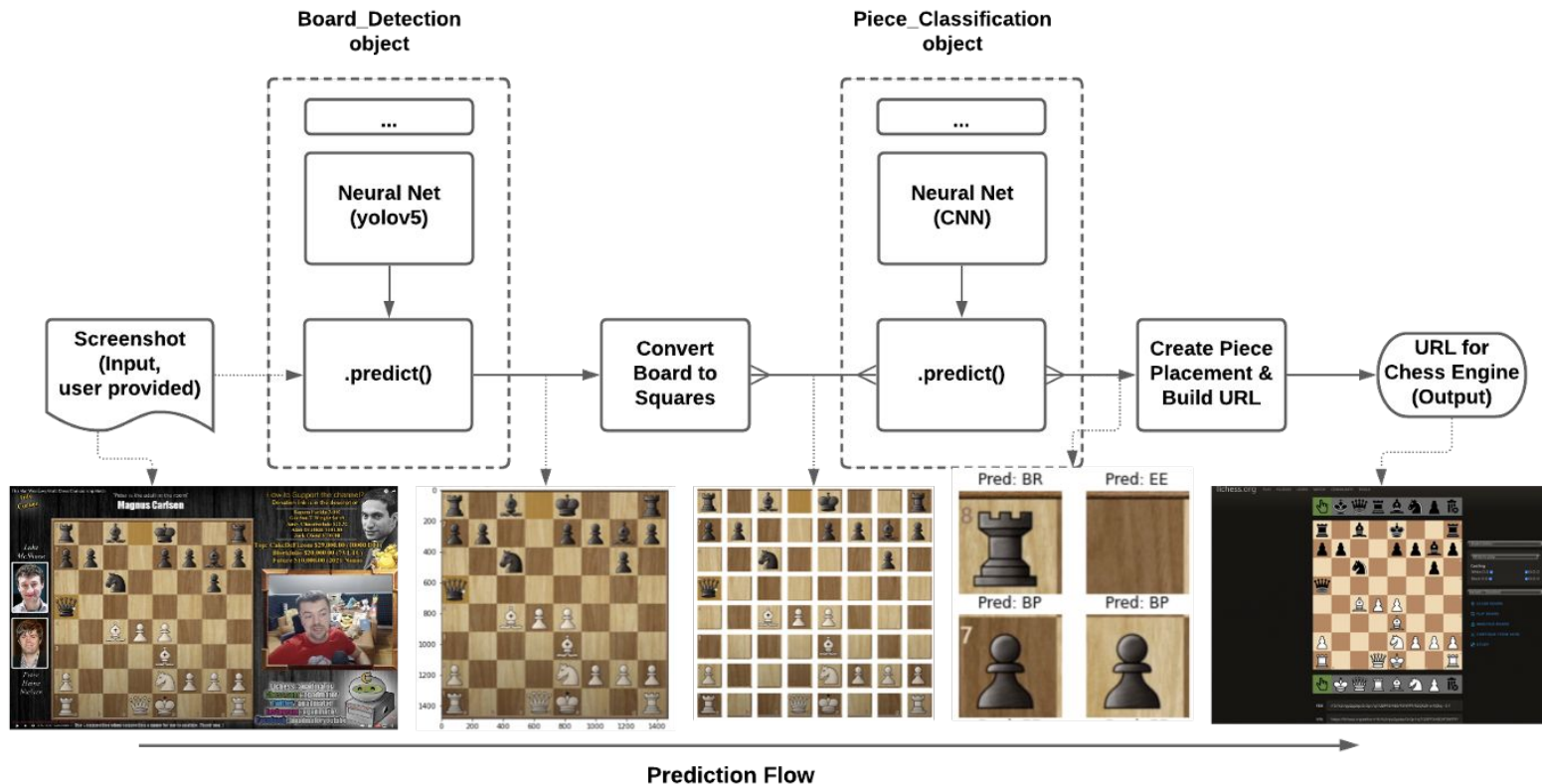
-Break the problem down into manageable and relatively independent subproblems.

Get Chess Board Solution Design - Flowchart



Focusing On Prediction Flow

Get Chess Board Solution Design - Prediction Flow



Methodology Steps

0. **Data Acquisition & Labeling GUI:**
 - a. **for Boards**
 - b. **for Squares**
1. **Board Detection**
2. **Convert Board to Squares**
3. **Piece Classification**
4. **Creating Piece Placement & Building URL**

Steps: Data Acquisition & Labeling GUI - Boards

Design Goal: Lessen the cognitive load of the labeler. Abstract away the data handling.

To this end, the user should be able to:

- Label a chessboard object (set a bounding box) within the GUI with a mouse drag**
- Label multiple objects**
- Delete any labels that are not desired**
- Label screenshots in succession**
- Move to the next image (or exit) without worrying about the saving status**

Steps: Data Acquisition & Labeling GUI - Boards



- Labeled around 80 screenshots in 2-3 hours
- Label data held in a csv - two rows can be seen in the image
- Has functions to handle randomization into training, validation and test
- Handles any conversions and requirements for yolov5.

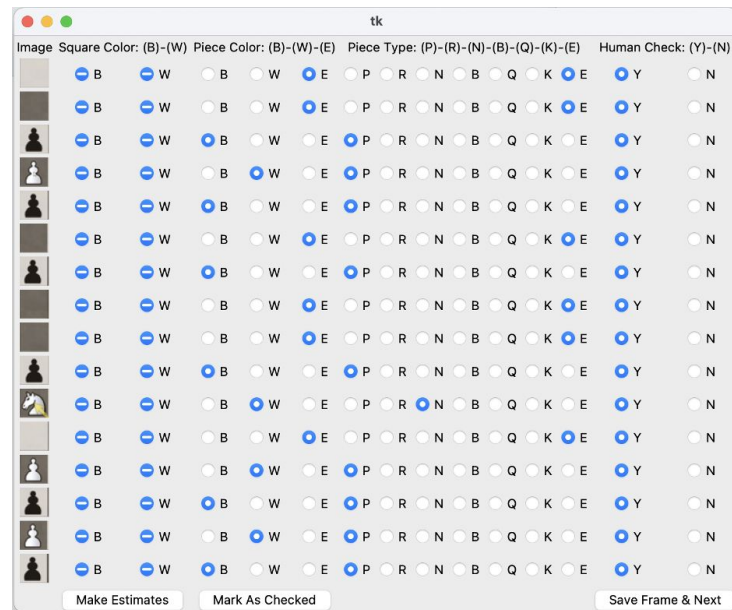
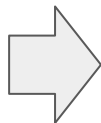
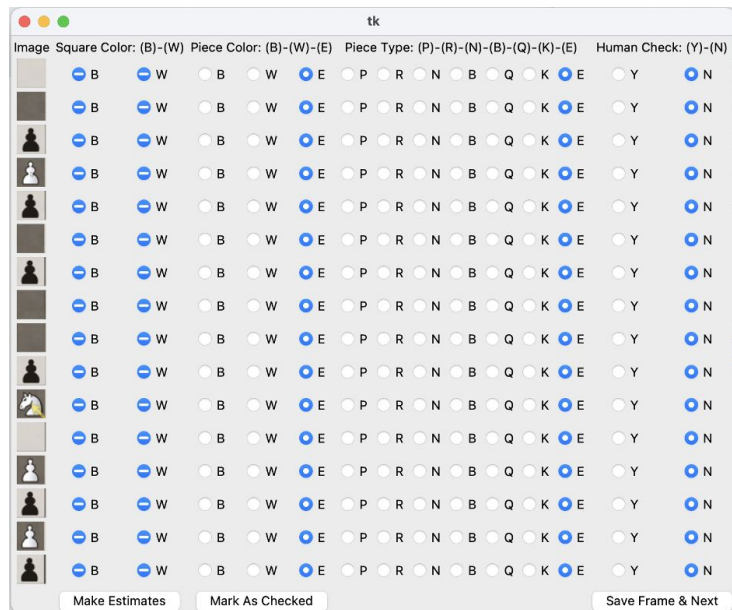
Steps: Data Acquisition & Labeling GUI - Squares

Design Goal: Lessen the cognitive load of the labeler. Abstract away the data handling.

To this end, the user should be able to:

- Label a square with mouse click - use radio buttons for their toggle property**
- Use minimum clicks:**
 - Default state of any square is set to E(mpty) - more than half of squares are empty**
 - Button added to confirm “Human Check” wholesale for the screen**
- Label sets of squares in succession**
- Move to the next image (or exit) without worrying about the saving status**

Steps: Data Acquisition & Labeling GUI - Squares



- Labeled around 5600 squares in 5-6hours
- Label data held in a csv - sixteen rows can be seen in the image
- Has functions to handle randomization into training, validation and test
- Handles any conversions and requirements for yolov5.

Steps: Data Acquisition & Labeling GUI - Square Counts

Count of Pieces by Color and Type – includes E(mpty) squares

		fname						
PcType-PRNBQKE	B	E	K	N	P	Q	R	All
PcColor-BWE								
B	115.0	-	87.0	110.0	524.0	64.0	143.0	1043
E	-	3540.0	-	-	-	-	-	3540
W	118.0	-	87.0	114.0	531.0	66.0	143.0	1059
All	233	3540	174	224	1055	130	286	5642

- Empty squares more than half (62.7%), Pawns (18.7%), Rooks (5.1%), Bishops (4.1%), kNights (4%), Kings (3.1%), Queens (2.3%)
- Labels indicate unbalanced classes for classification
- With color split - the unbalance becomes more pronounced.
- Silver lining is black and white pieces seem balanced.

Steps: Board Detection - Training

- Uses a relatively lightweight detection algorithm: yolov5 implemented on PyTorch, see yolo** for the originating paper.
- Goal: Detect the chessboard: Algorithm producing bounding boxes and chessboards being a box helps.
- Training:
 - used 64 screenshots for training and 18 for validation
 - Initial weights are those of the small pretrained model provided by yolov5
- Results:
 - Each epoch took ~4 minutes for a total of 599 (best @ 499) epochs at 39 hours.
 - Over validation set mAP@.5=0.96 and mAP@.5:.95=95.3

Results of the experiment (actual best set, took over 39 hours, best epoch 498, end at 599.)

Epoch	gpu_mem	box	obj	cls	labels	img_size
498/1499	0G	0.0154	0.006404	0	49	1440: 100% ██████████ 4/4 [04:00<00:00, 60.11s/it]
	Class	Images	Labels	P	R	mAP@.5 mAP@.5:.95: 100% ██████████ 1/1 [00:05<00:00, 5.33s/it]
	all	18	24	0.96	1	0.987 0.953
Epoch	gpu_mem	box	obj	cls	labels	img_size
598/1499	0G	0.01687	0.004755	0	52	1440: 100% ██████████ 4/4 [03:32<00:00, 53.17s/it]
	Class	Images	Labels	P	R	mAP@.5 mAP@.5:.95: 100% ██████████ 1/1 [00:05<00:00, 5.32s/it]
	all	18	24	0.96	1	0.96 0.911

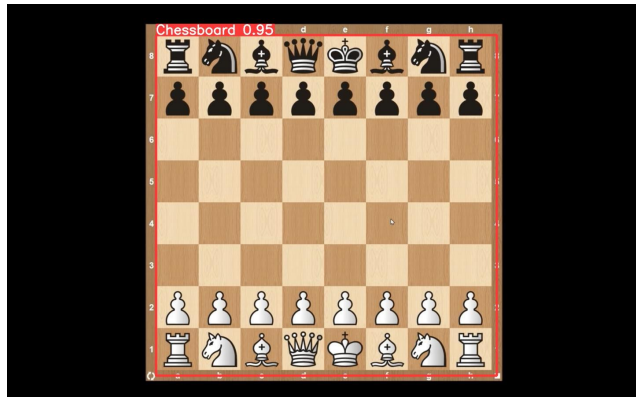
Stopping training early as no improvement observed in last 100 epochs. Best results observed at epoch 498, best model saved as best.pt. To update EarlyStopping(patience=100) pass a new patience value, i.e. `python train.py --patience 300` or use `--patience 0` to disable EarlyStopping. 599 epochs completed in 39.422 hours.

*<https://github.com/ultralytics/yolov5>

**<https://pjreddie.com/media/files/papers/yolo.pdf>

Steps: Board Detection - Prediction on Test Set

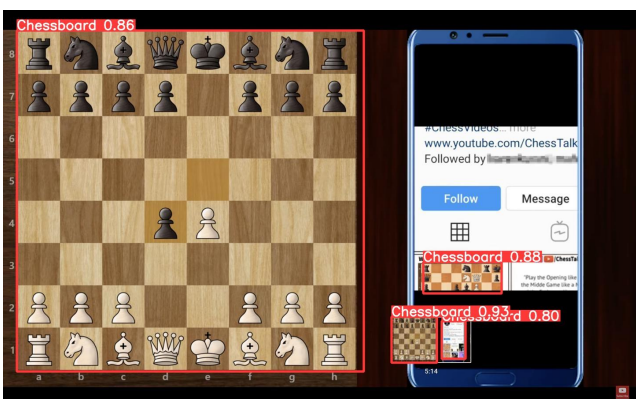
Correct Classification



Correct Classification



False Positive

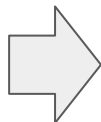


False Negative



Steps: Convert Board to Squares

Split the output from Board Prediction step into 64 squares



Steps: Piece Identification - Goal and Problem Notes

-Uses a CNN in Tensorflow with two Convolution&MaxPooling layers followed by two dense layers (one SoftMax). Similar to MNIST.

-Goal: Classify a square as empty (EE) and if not state the piece.

13 Classes: EE, WP, WR, WN, WB, WQ, WK, BP, BR, BN, BB, BQ, BK.

-Notes:

Solution has to generalize well across several dimensions:

- Difference in shapes across sets**
- Variation in chess square colors**
- Pieces looking alike (e.g. kings and queens)**
- Imbalance in multiclass data in favor of empty**
- Improperly captured squares**

A naive calculation for 3% board error rate: $(0.97)^{(1/64)} = 0.995$

Steps: Piece Identification - Training

-Training

- 4231 squares for training, 1128 for validation at 80x80 during model input
- No pretrained weights (training from scratch)
- Callback function to save “the best” model: validation metric used if validation exists
- Final metric used: Cohen’s Kappa which has some adjustment for class imbalance. The other was ‘loss’.

Results:

-Best epoch as follows:

Epoch 00031: val_cohen_kappa improved from 0.97573 to 0.97573, saving model to data/model/piece-train/exp/cnn_pieces.h5
133/133 - 5s - loss: 3.3121e-06 - accuracy: 1.0000 - cohen_kappa: 1.0000 - val_loss: 0.2934 -
val_accuracy: 0.9858 - val_cohen_kappa: 0.9757- 5s/epoch - 40ms/step

-Model ran for 40 epochs - ~5 seconds each.

Steps: Piece Identification - Training Analysis

Confusion Matrix for the Training Set – _pred stands for model prediction

	EE	WP	WR	WN	WB	WQ	WK	BP	BR	BN	BB	BQ	BK
EE_pred	2658	0	0	0	0	0	0	0	0	0	0	0	0
WP_pred	0	389	0	0	0	0	0	0	0	0	0	0	0
WR_pred	0	0	108	0	0	0	0	0	0	0	0	0	0
WN_pred	0	0	0	83	0	0	0	0	0	0	0	0	0
WB_pred	0	0	0	0	91	0	0	0	0	0	0	0	0
WQ_pred	0	0	0	0	0	50	0	0	0	0	0	0	0
WK_pred	0	0	0	0	0	0	70	0	0	0	0	0	0
BP_pred	0	0	0	0	0	0	0	392	0	0	0	0	0
BR_pred	0	0	0	0	0	0	0	0	106	0	0	0	0
BN_pred	0	0	0	0	0	0	0	0	0	80	0	0	0
BB_pred	0	0	0	0	0	0	0	0	0	0	91	0	0
BQ_pred	0	0	0	0	0	0	0	0	0	0	0	50	0
BK_pred	0	0	0	0	0	0	0	0	0	0	0	0	63

400 Randomly Chosen Correct Classifications [Training Set - 4231 Images]



-For correct classifications, most of the data seems to come from 'clean cut' squares.

-Model seems robust to the color of chessboard square.

Steps: Piece Identification - Prediction on Validation Set

Confusion Matrix for the Validation Set – _pred stands for model prediction All Incorrect Classifications [Validation Set - 1128 Images]

	EE	WP	WR	WN	WB	WQ	WK	BP	BR	BN	BB	BQ	BK
EE_pred	707	0	0	1	0	0	0	0	0	0	0	0	0
WP_pred	0	109	1	0	0	0	0	0	0	0	0	0	0
WR_pred	0	1	28	0	0	0	0	0	0	0	0	0	0
WN_pred	0	0	0	24	0	2	1	0	0	0	0	0	0
WB_pred	0	0	0	0	19	0	0	1	0	0	0	0	0
WQ_pred	0	0	0	0	0	10	0	0	0	0	0	0	0
WK_pred	0	0	0	1	0	0	13	0	0	0	0	0	0
BP_pred	0	2	0	0	0	0	0	103	0	0	0	0	1
BR_pred	0	0	0	0	0	0	0	1	27	0	0	0	0
BN_pred	0	0	0	0	0	0	0	0	0	22	0	0	0
BB_pred	0	0	0	0	1	0	0	1	0	0	20	0	0
BQ_pred	0	0	0	0	0	1	0	0	0	0	0	11	0
BK_pred	0	1	0	0	0	0	0	0	0	0	0	0	19



-For correct classifications, most of the data seems to come from 'clean cut' squares.

-Model seems robust to the color of chessboard square.

Steps: Create Piece Placement & Build URL - Placement

Use FEN Piece Placement String notation and insert the remaining 5 strings (Active Player, Castling Availability, En Passant Target, Half Move, Full Move) so that any mistakes can be fixed quickly in the engine.



```
r . b . k . . r
p p . . p p b p
. . n . . . p .
q . . . . . . .
. . B P P . . .
. . . . . B . . .
P . . . N P P P
R . . Q K . . R
```

FEN Piece Placement String: r1b1k2r/pp2ppbp/2n3p1/q7/2BPP3/4B3/P3NPPP/R2QK2R

Full FEN String: r1b1k2r/pp2ppbp/2n3p1/q7/2BPP3/4B3/P3NPPP/R2QK2R w KQkq - 0 1

Steps: Create Piece Placement & Build URL - Build URL

Final step for this project - observe Lichess API and create a URL. Could be extended to other sites/engines.

<https://lichess.org/editor?fen=r1b1k2r%2Fpp2ppbp%2F2n3p1%2Fq7%2F2BPP3%2F4B3%2FP3NPPP%2FR2QK2R+w+KQkq+-+0+1>



Conclusion + Next Steps

Project has achieved what it has set out to do:

Take in a screenshot of a chess game on a video platform and return a string the represents the piece placement.

Some next steps could be:

Add-ons:

Write a new class wraps the end-to-end process

Make model available in Docker for widespread use

Deploy on the cloud for even wider adoption

Model Improvements:

Experiments to judge relative impact of board detection vs piece classification for appropriate prioritization

Test to see if classification would improve by a hierarchical classification

Generate more training and validation data

Test to see if a model could be estimated the direction of play

Thank you + Open Floor for Discussion

Goal: Decrease the friction to study a chess game played on a video platform

Project Objective: Take in a screenshot of a chess game on a video platform and return a string that represents the piece placement.

Contributions:

- End-to-end neural network based piece placement generation from a screenshot.
- Transfer learning from an object detection model (via PyTorch)
- Bottom up training of a fully connected classifier (Tensorflow)
- Creation of chess specific (& easily extendable) platform independent GUI.

