# Music Score Image Guitar Pro (GPX)

# converter

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COURSE: ARTIFICIAL INTELLIGENCE

Chungbuk National University

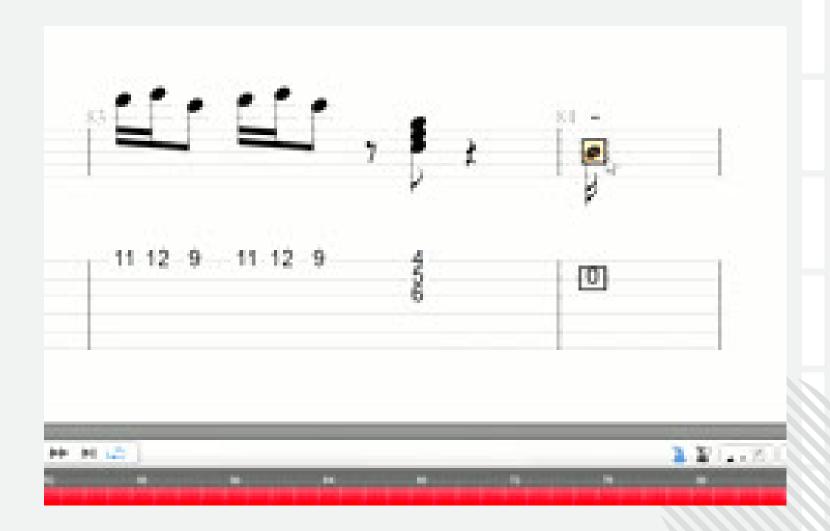
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#### MOTIVATION







Identifying music symbols and entering them into a guitar pro program

→ Music Scores Image Guitar Pro converter

#### RESEARCH OBJECT











Music Scores Image

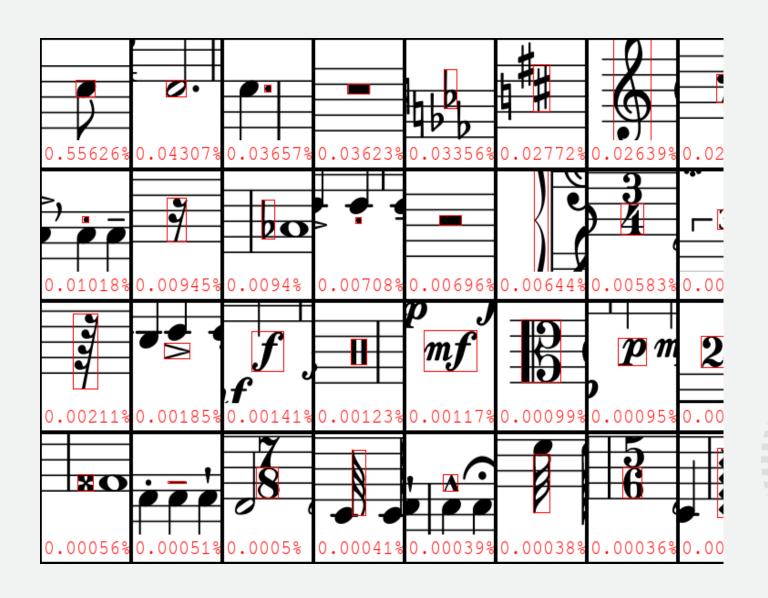
Object Detection

Create Guitar Pro file (.gpx)

# MATERIAL (DATASET)

What is DeepScoresV2?





Music score image dataset Symbols of various shapes and sizes in Coco data format (clef, key signature, note, rest, beat, scale) included

## MATERIAL (DATASET)

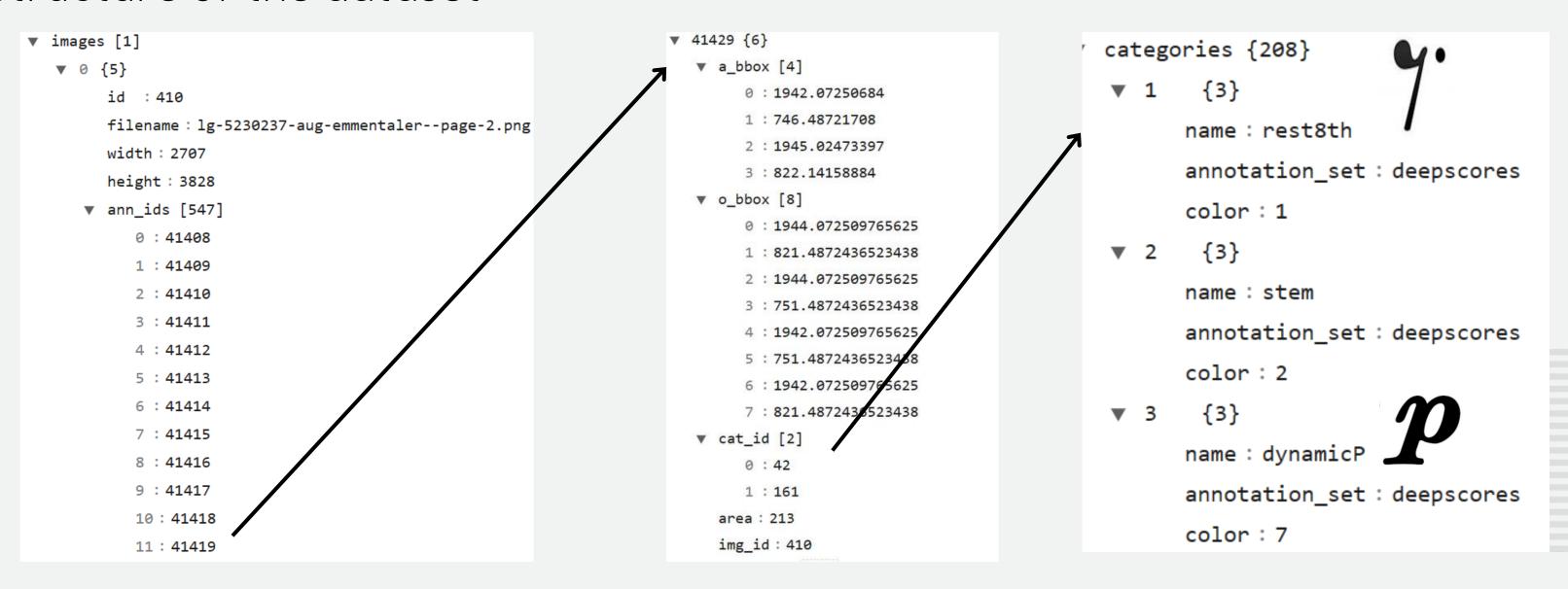
Why DeepScoresV2?

Dataset	Classes	Images	Object Inst.	Avg. Inst. per Image
PASCAL VOC [19] COCO 2014 [20] ImageNet [21] DOTA [22] MUSCIMA++V2 [23]	20 80 200 15 163	21,503 $123,287$ $349,379$ $2,806$ $140$	62, 199 886, 266 478, 806 188, 282 102, 914	2.89 7.19 1.37 67.10 735
$\begin{array}{c} {\rm DeepScoresV2} \\ \hookrightarrow {\rm dense} \end{array}$	136 136	$255,385 \\ 1,714$	151M 1.1M	592 660

Select a dataset that fits the topic of recognizing music symbols through music score images DeepScoresV2 dataset has a larger number of images and instances than MUSCIMA++V2

# MATERIAL (DATASET)

#### Structure of the dataset



Deepscores V2 is in Coco data format and includes information about image, annotation (object), and category.

Consists of images, 'train.json' for learning and 'test.json' for testing.

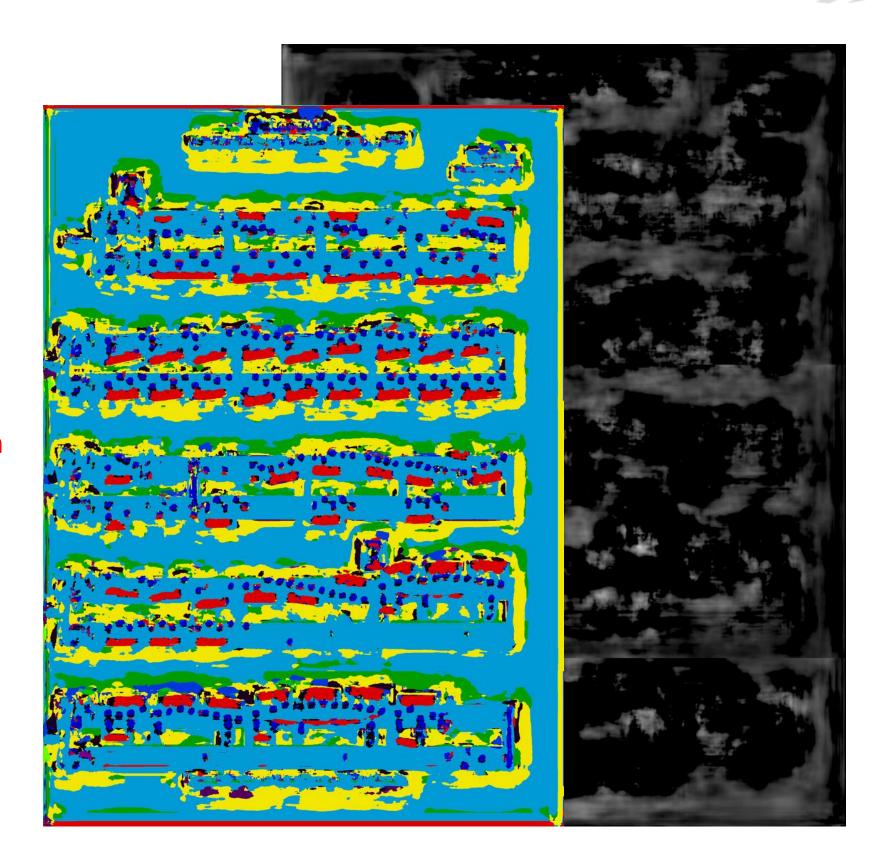
#### MODEL

#### DEEP WATERSHED DETECTION

Watershed algorithm, one of the image segmentation algorithms, combined with deep learning network

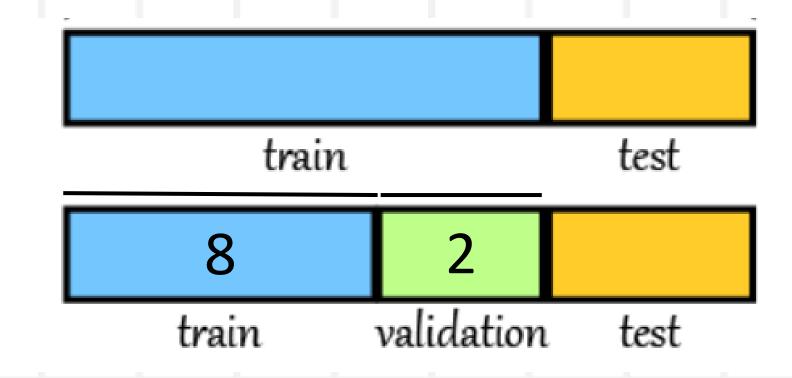
Deep learning network identifies object boundaries in images

→ Apply watershed transformation to **perform segmentation** 



Ref. https://github.com/tuggeluk/DeepWatershedDetection

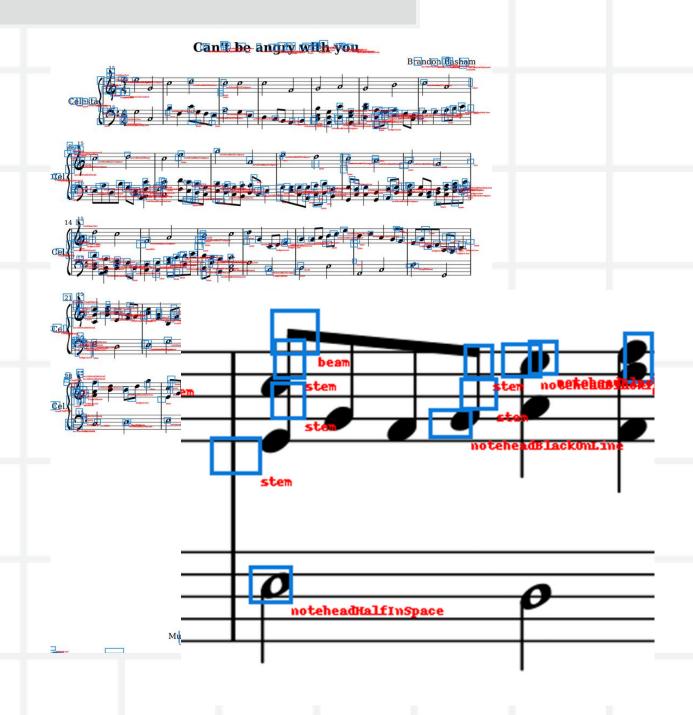
## TRAINING



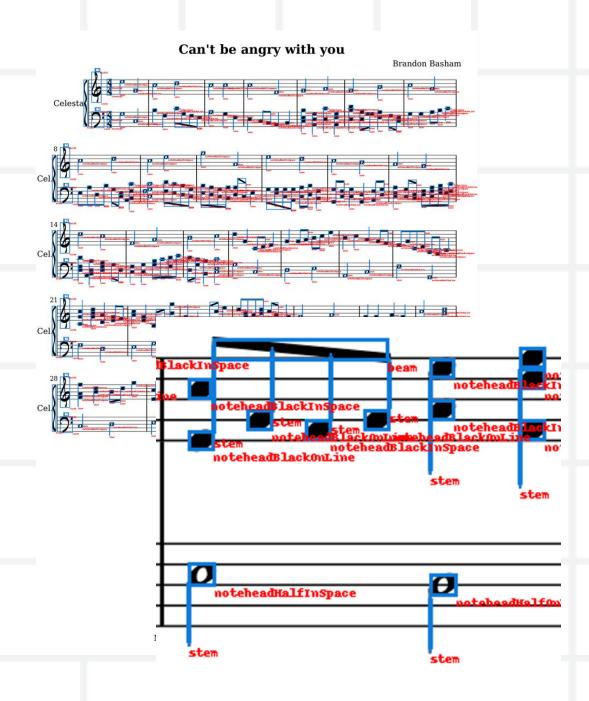
학습 횟수	iteration1	iteration2	iteration3	iteration4	iteration combine
1	10	10	10	20	30
2	10	10	10	20	30
3	50	50	50	40	60
4	70	70	70	60	100

5 steps per learning batch size 1

## RESULT



prediction



ground truth

#### RESULT

∷Nr	:::	class	No. Occurences	mAP	AP at 0.5
0		ledgerLine	8857	0	0
1		clefG	820	2.51965e-07	2.51965e-06
2		clefF	534	0.000706414	0.00373715
3		noteheadBlackOnLine	13845	0.000264698	0.00211199
4		noteheadBlackInSpace	13635	0.0001671	0.00142662
5		noteheadHalfOnLine	957	0.000318644	0.00214455
6	noteheadHalfInSpace		1045	0.000158156	0.000834523
7		noteheadWholeOnLine	389	0	0
8		noteheadWholeInSpace	391	0	0
9		augmentationDot	1859	0	0
				0	0
		_		5.79406e-05	0.000320882
				0	0
				1.12023e-07	1.12023e-06
	Area of Overlap			0	0
l = .	——————————————————————————————————————			0	0
	Area o	f Union			

		_		
20	restWhole	753	7.22017e-05	0.000657758
21	restQuarter	736	0.000106242	0.000954252
22	rest8th	818	0.000129629	0.00087739
23	rest32nd	30	0	0
24	dynamicP	289	0.000110467	0.000941411
25	dynamicM	265	0	0
26	dynamicF	622	8.471e-05	0.000568641
27	dynamicS	37	0	0
28	stringsDownBow	29	0	0
29	slur	956	0	0
30	beam	7716	2.21617e-05	4.63631e-06
31	tie	1058	0	0
32	dynamicDiminuendoHairpin	53	0	0

mAP: Mean Average Precision

AP at 0.5: Average precision when IoU is 0.5

#### DISCUSSION

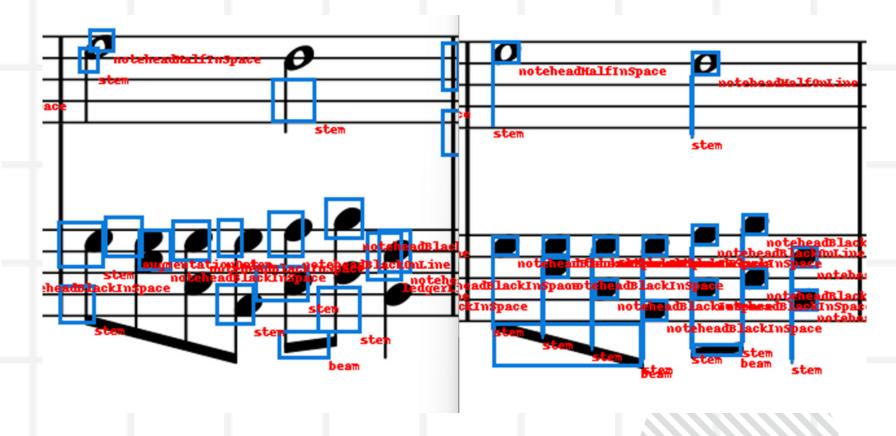
1. Improved performance

Can't be angry with you Can't be angry with you

prediction

ground truth

Recognize the title of the score as a musical symbol



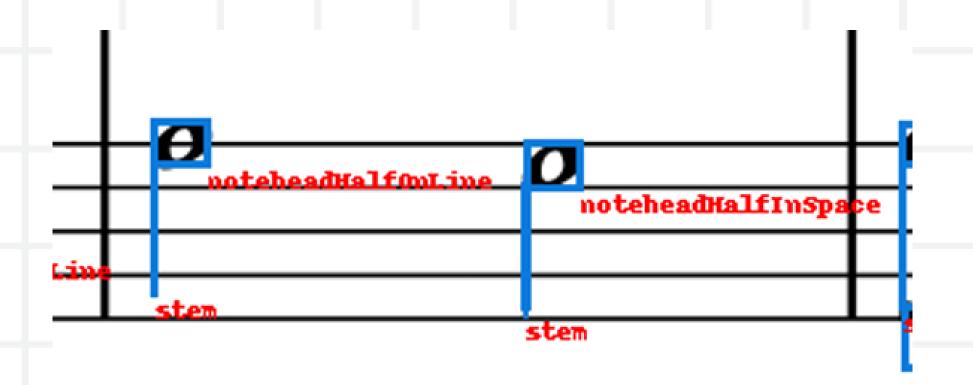
prediction

ground truth

Incorrect Bounding Box

#### DISCUSSION

2. Identifying of syllable name



#### noteheadHalfInSpace

What can be confirmed with prediction?

- Beat of notes
- Whether the note spans a line
- Syllable name of note
   → not yet

