Classifying Paintings by Artistic Genre with Deep Learning







Team #72

Problem

- The artistic style of a painting describes the visual and historical information about a painting
- Correctly identifying the artistic style of paintings is necessary to index large artistic databases
- Detect artistic style of a painting using the Wikiart database







Data



WikiArt Dataset (Primary)

- 20+ distinct artistic styles
- 80 000+ fine art paintings
- 1 000+ artists
- 1500s to Present

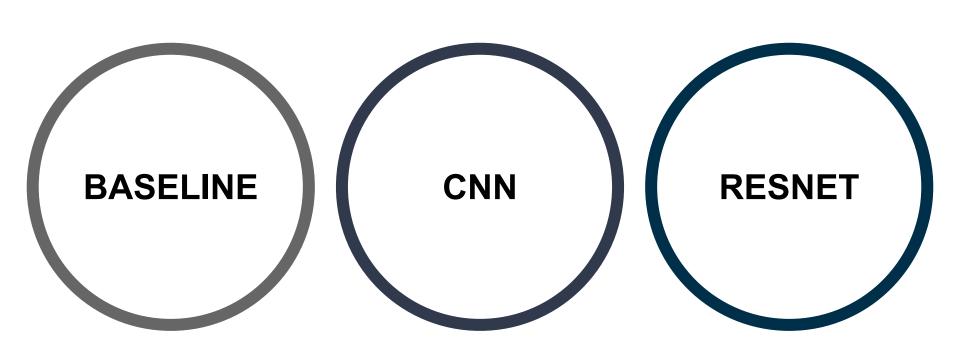
Supplementary Data

- Pedro Torres' Kaggle Dataset
- BryanB's Abstract Art Gallery Dataset

Data Processing

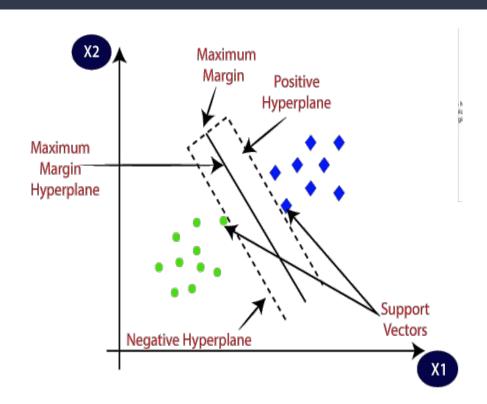
- Aggregate images from different datasets into labelled folders which express their associated classifications
- Use python script to shuffle images in folders and select the number of datapoints we want
- 3. Resize images to 128x128 pixels
- 4. Split the data into training, validation, and testing sets
- 5. Compute mean of all pixel values of training set, and then subtract the mean from the pixel values in all the sets

Models

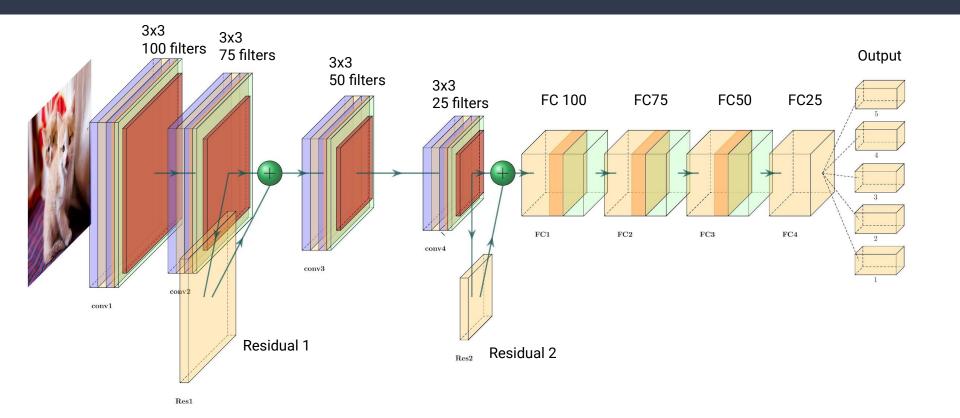


Baseline: Support Vector Machine

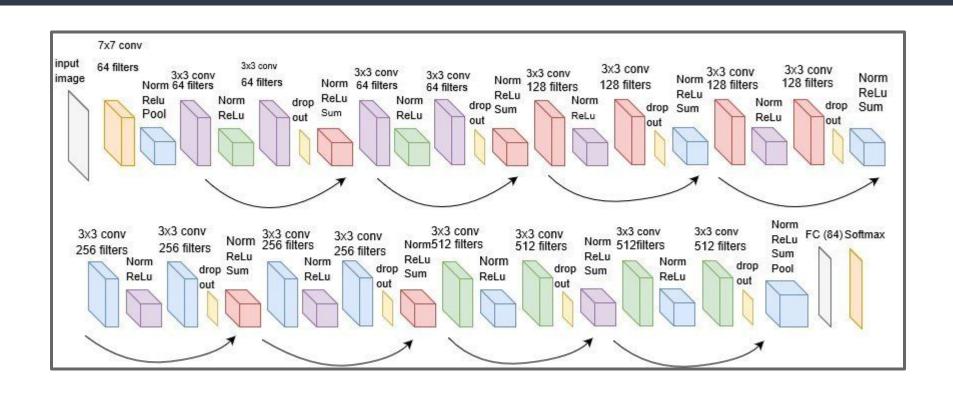
- Linear Kernel
- L2 penalty
- Squared-Hinge loss
- Dual optimization
- One-vs-Rest multi-class classification



CNN Architecture



ResNet-18 Architecture



Baseline Qualitative and Quantitative Results

Baseline Testing 5 Styles Confusion Matrix

	a_Rom	anticism_2000	a_Cubism_2000 a_	Expressionism_2000	a_Symbolism_2000	a_Impressionism_2000
p_Romanticis	sm_2000	104.0	54.0	62.0	52.0	55.0
p_Cubism_	_2000	54.0	52.0	62.0	51.0	53.0
p_Expressioni	sm_2000	37.0	61.0	69.0	42.0	43.0
p_Symbolisr	n_2000	47.0	45.0	43.0	73.0	51.0
p_Impressioni	sm_2000	68.0	76.0	60.0	75.0	111.0
Recall	0.335484	0.180556	0.233108		Impressionism_2000 0.354633	
Recall	0.335484	0.180556	0.233108	0.249147	0.354633	
Precision	0.318043	0.191176	0.273810	0.281853	0.284615	
	0.326531	0.185714	0.251825	0.264493	0.315789	
F1-Score						

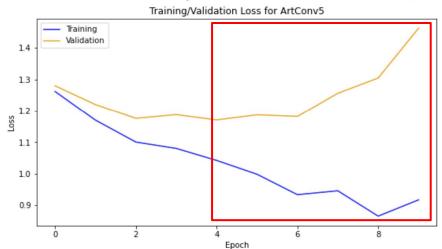
Baseline Qualitative and Quantitative Results

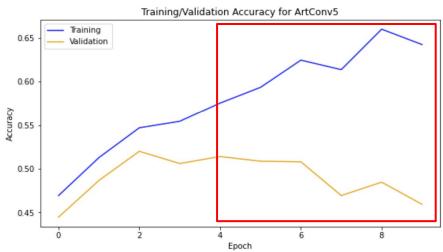
Baseline Testing 5 Styles Confusion Matrix

p_Romanticis	m 2000	104.0	54.0	62.0	52.0	55.0
p_Cubism_		54.0	52.0	62.0	51.0	53.0
p_Expressioni	sm_2000	37.0	61.0	69.0	42.0	43.0
p_Symbolism	n_2000	47.0	45.0	43.0	73.0	51.0
p_Impressioni	sm_2000	68.0	76.0	60.0	75.0	111.0
Recall	0.335484	0.180556	0.233108	0.249147	0.354633	
	0.335484		3 - 3,		Impressionism_2000	
Precision	0.318043	0.191176	0.273810	0.281853	0.284615	
	0.326531	0.185714	0.251825	0.264493	0.315789	
F1-Score						

CNN For 5 Styles Training Results

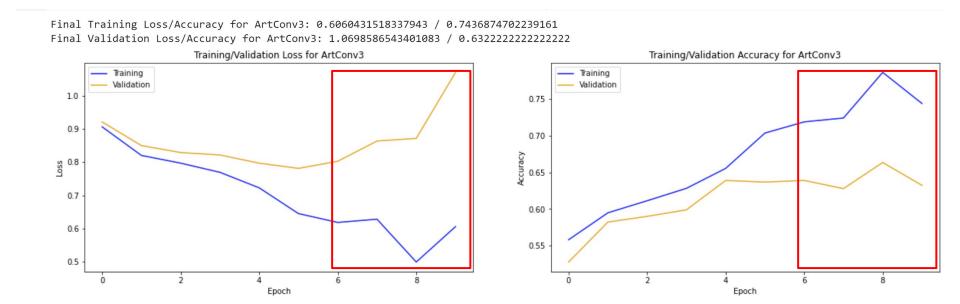
Final Training Loss/Accuracy for ArtConv5: 0.9171773252162067 / 0.6424796457648907 Final Validation Loss/Accuracy for ArtConv5: 1.4625743329524994 / 0.459333333333333333





Noticeable overfitting occurs at epoch 4

CNN For 3 Styles Training Results



Noticeable overfitting occurs at epoch 6

CNN Qualitative and Quantitative Results

CNN 5 Styles Testing Confusion Matrix

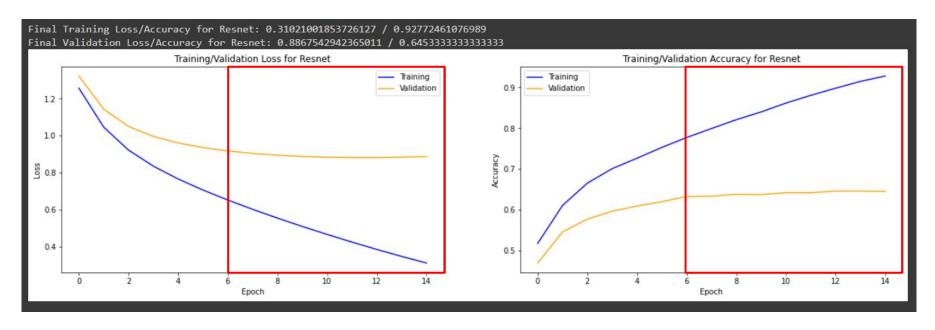
	sm 2000	194.0	9.0	62.0	15.0	5.0
p_Symb	olism_2000	22.0	92.0	32.0	33.0	17.0
p_Express	ionism_2000	101.0	40.0	109.0	34.0	18.0
p_Impress	ionism_2000	13.0	34.0	29.0	156.0	43.0
p_Romanticism_2000		6.0	90.0	47.0	92.0	207.0
Class Metr	ic Scores	Testing:				
Class Metr			Expressionism_2000	Impressionism_2000	Romanticism_2000	
Class Metr						
	Cubism_2000	Symbolism_2000 0.347170	0.390681	0.472727	0.713793	

CNN Qualitative and Quantitative Results

CNN 5 Styles Testing Confusion Matrix

n Cub	ism 2000	194.0	9.0	62.0	15.0	5.
p_cub	15111_2000	194.0	9.0	02.0	15.0	J.
p_Symb	olism_2000	22.0	92.0	32.0	33.0	17.
p_Express	ionism_2000	101.0	40.0	109.0	34.0	18.
p_Impress	ionism_2000	13.0	34.0	29.0	156.0	43.
p_Roman	ticism_2000	6.0	90.0	47.0	92.0	207.
Class Metr	ic Scores	1				
Class Metr	ic Scores Cubism_2000	1	Expressionism_2000	0 Impressionism_2000	Romanticism_2000	
Class Metr Recall		1	Expressionism_2006	_	_	
	Cubism_2000	Symbolism_2000 0.347170	_	1 0.472727	0.713793	
Recall	Cubism_2000 0.577381	Symbolism_2000 0.347170 0.469388	0.39068	0.472727 0.567273	0.713793 0.468326	

ResNet-18 For 5 Styles Results



ResNet-18 5 Styles Test Results

ResNet-18 5 Styles Testing Confusion Matrix

Confusion M	Matrix Testing:							
		actual_Impressionism_2	000 actual_E	pressionism_2	000 actual_Symb	olism_2000	actual_Cubism_2000	actual_Romanticism_2000
predicted_l	Impressionism_2000	25	39.0	1	7.0	46.0	3.0	37.0
predicted_E	Expressionism_2000	:	26.0	16	1.0	56.0	46.0	18.0
predicted	l_Symbolism_2000	:	22.0	2	0.0	153.0	8.0	28.0
predicte	ed_Cubism_2000		6.0	4	7.0	12.0	228.0	1.0
predicted_	_Romanticism_2000	:	28.0	3	3.0	60.0	0.0	205.0
Class Metri	ic Scores Testing							
	Impressionism_2000	Expressionism_2000 S	ymbolism_2000	Cubism_2000	Romanticism_200	ө		
Recall	0.744548	0.579137	0.467890	0.800000	0.70934	3 Tes		
Precision	0.698830	0.524430	0.662338	0.775510	0.62883			
F1-Score	0.720965	0.550427	0.548387	0.787565	0.66666	7		
Test Accura	acy: 0.658	- Woods						

ResNet-18 5 Styles Test Results

ResNet-18 5 Styles Testing Confusion Matrix

	x Testing:			12 12 12000		. 121222		1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
		actual_Impressionism	_2000 actual_Ex	(pressionism_200	00 actual_Symbol	ism_2000	actual_Cubism_2000	actual_Romanticism_2000
predicted_Impre	ssionism_2000		239.0	17	.0	46.0	3.0	37.0
predicted_Expre	ssionism_2000		26.0	161	.0	56.0	46.0	18.0
predicted_Sym	nbolism_2000		22.0	20	.0	153.0	8.0	28.0
predicted_Cι	ubism_2000		6.0	47	.0	12.0	228.0	1.0
predicted_Roma	anticism_2000		28.0	33	.0	60.0	0.0	205.0
Class Metric Sc	ores Testing							
		: Expressionism_2000	Symbolism_2000	Cubism_2000 R	omanticism_2000			
			Symbolism_2000 0.467890	Cubism_2000 R	Comanticism_ 2000 0.709343			
Impr	essionism_2000	Expressionism_2000	_	-1.1013-0.00	120000000000000000000000000000000000000			
Recall	essionism _2000 0.744548	Expressionism_2000 0.579137	0.467890	0.800000	0.709343			

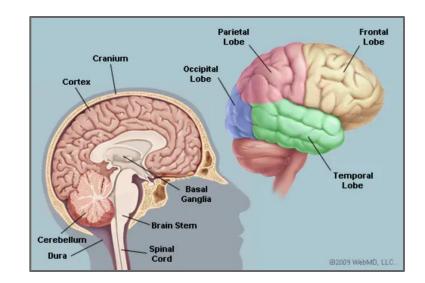
ResNet-18 5 Styles Test Results

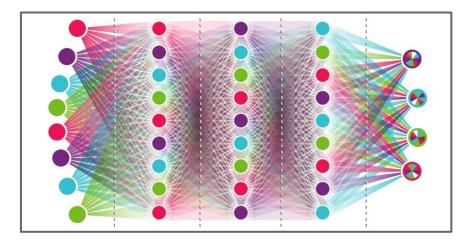
ResNet-18 5 Styles Testing Confusion Matrix

Confusion Ma	atrix Testing:	as the last		20 100		W		THE REAL PROPERTY AND ADDRESS OF THE PERSON
		actual_Impressionism	_2000 actual_Ex	pressionism_2	000 actual_Symb	olism_2000	actual_Cubism_2000	actual_Romanticism_2000
predicted_In	npressionism_2000		239.0		17.0	46.0	3.0	37.0
predicted_E	xpressionism_2000		26.0	10	61.0	56.0	46.0	18.0
predicted_	Symbolism_2000		22.0	;	20.0	153.0	8.0	28.0
predicted	d_Cubism_2000		6.0	ž	47.0	12.0	228.0	1.0
predicted_F	Romanticism_2000		28.0	;	33.0	60.0	0.0	205.0
Class Metric	: Scores Testing	:						
1	[mpressionism_2000	Expressionism_2000	Symbolism_2000	Cubism_2000	Romanticism_2000			
Recall	0.744548	0.579137	0.467890	0.800000	0.709343			
Precision	0.698830	0.524430	0.662338	0.775510	0.628834	4 V		
F1-Score	0.720965	0.550427	0.548387	0.787565	0.666667	7		

Takeaways

- Learning art styles is an intrinsically difficult problem to solve
- Resources can limit how well of a model one can train in a reasonable amount of time
- Neural networks have a long way to go





Demonstration



Symbolism



Cubism



Impressionism



Expressionism



Romanticism

References

- 1. H. Halle and H. Halle, "The most famous paintings of all time," Time Out New York. [Online]. Available: https://www.timeout.com/newyork/art/top-famous-paintings-in-art-history-ranked. [Accessed: 05-Apr-2021].
- 2. "File:Mona Lisa, by Leonardo da Vinci, from C2RMF retouched.jpg," Wikipedia, 25-Jun-2020. [Online]. Available: https://en.wikipedia.org/wiki/Painting#/media/File:Mona_Lisa,_by_Leonardo_da_Vinci,_from_C2RMF_retouched.jpg. [Accessed: 05-Apr-2021].
- 3. Subscribe, "Best destinations to see the most famous paintings in Europe," Europe's Best Destinations. [Online]. Available: https://www.europeanbestdestinations.com/best-of-europe/best-destinations-to-see-the-most-famous-paintings-in-europe/. [Accessed: 05-Apr-2021].
- 4. "Side View Portrait Of Young African-american Man Looking At Paintings And Thinking At Art Gallery Or Museum Exhibition," Freepik, 19-Jan-2021. [Online]. Available:

 https://www.freepik.com/premium-photo/side-view-portrait-young-african-american-man-looking-paintings-thinking-art-gallery-museum-exhibition, 12199978.
 - https://www.freepik.com/premium-photo/side-view-portrait-young-african-american-man-looking-paintings-thinking-art-gallery-museum-exhibition_12199978.ht m. [Accessed: 05-Apr-2021].
- 5. A. Sooke, "It is time to reopen our galleries and museums," The Telegraph, 01-May-2020. [Online]. Available: https://www.telegraph.co.uk/art/what-to-see/time-reopen-galleries-museums/. [Accessed: 05-Apr-2021].
- 6. "Support Vector Machine (SVM) Algorithm Javatpoint," www.javatpoint.com. [Online]. Available: https://www.javatpoint.com/machine-learning-support-vector-machine-algorithm. [Accessed: 05-Apr-2021].
- 7. M. A. Hasan, *ResearchGate*. [Online]. Available: https://www.researchgate.net/figure/Proposed-Modified-ResNet-18-architecture-for-Bangla-HCR-In-the-diagram-conv-stands-for_fig1_323063171. [Accessed: 04-Apr-2021].
- 8. M. Hoffman, "Brain (Human Anatomy): Picture, Function, Parts, Conditions, and More," WebMD. [Online]. Available: https://www.webmd.com/brain/picture-of-the-brain. [Accessed: 04-Apr-2021].
- 9. K. Hauptfleisch, "This Is How Artificial Intelligence Will Shape eLearning For Good," eLearning Industry, 31-Oct-2017. [Online]. Available: https://elearningindustry.com/artificial-intelligence-will-shape-elearning. [Accessed: 04-Apr-2021].