Herbert Wertheim College of Engineering
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Histogram Layer for Texture Classification

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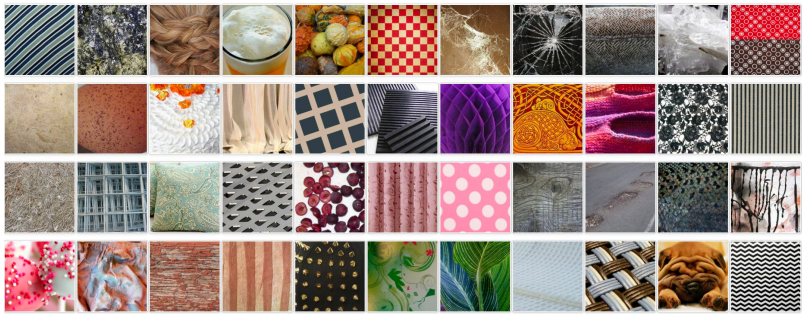
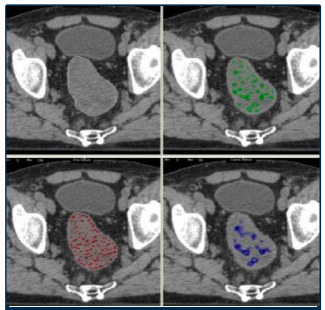
POWERING THE NEW ENGINEER TO TRANSFORM THE FUTURE

Texture Classification

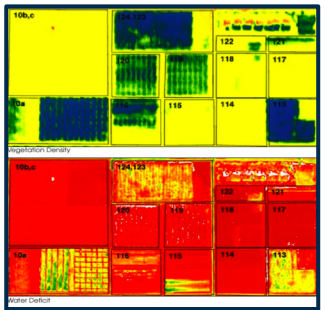
- **Definition**: an area of texture analysis that focuses on assigning images into a texture classes.



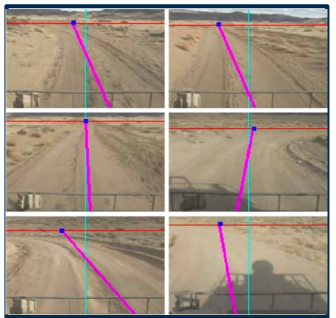
Applications



Medical Imaging



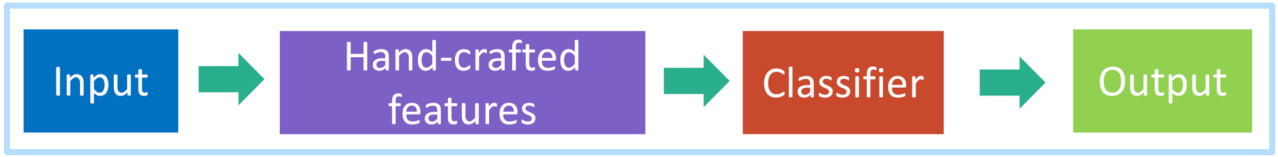
Agriculture



Autonomous Vehicles

Previous Approaches

Traditional Approach



Does not necessarily need a lot of data;
The features are more explainable;

Very laborious; often needed to determine features empirically

Deep Learning Approach

Automated feature learning;
not very laborious

Requires copious amount of labeled data along with immense amount of computational power

Goal of Research

Traditional Approach + Deep Learning Approach

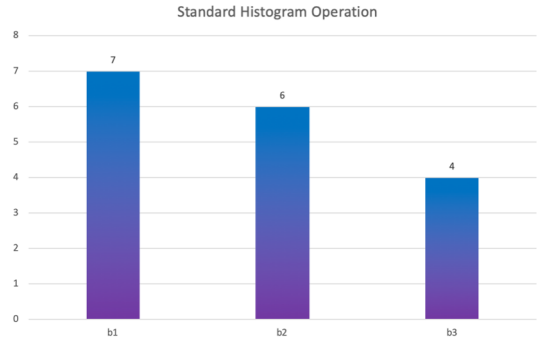
We propose a novel model that incorporates a localized histogram layer to convolutional neural networks for texture classification.

Standard Histogram Operation

$$y_k = \begin{cases} 1, B_k - w \leq x_k < B_k + w \\ 0, otherwise \end{cases}$$

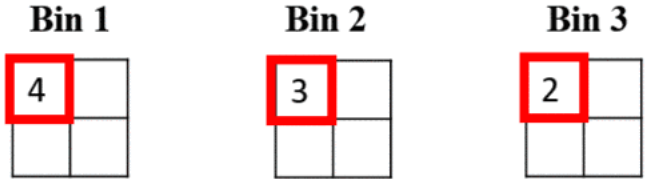
Standard Operation

$$B_k(bin\ center) = \{1, 2, 3\}$$
$$\omega(bin\ width) = \{0, 0, 0\}$$



1	3	2	2
3	1	2	1
1	2	1	3
2	2	1	1

4 x 4 Image



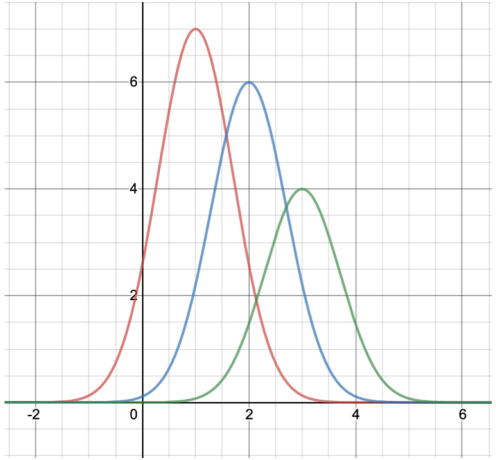
2 x 2 x 3 Feature Maps

Radial Basis Functions (RBFs)

$$y_k = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} e^{-\frac{(x_{ij}-\mu_k)^2}{\sigma_k^2}}.$$

Radial Basis Function

$\mu_k(bin\ center) = \{1,2,3\}$
$\sigma_k(bin\ width) = \{1,1,1\}$
x_{ij} (feature map value)

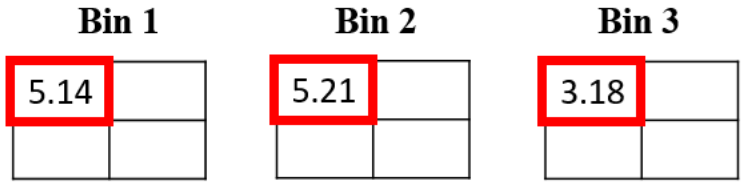


What's different?

1. Soft binning assignments
2. Differentiable

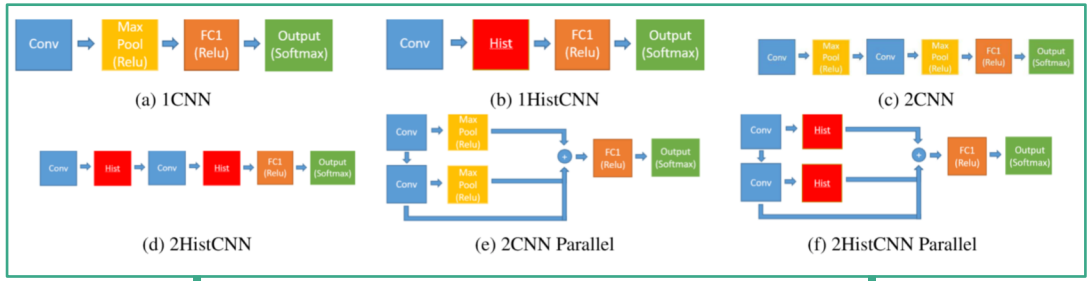
1	3	2	2
3	1	2	1
1	2	1	3
2	2	1	1

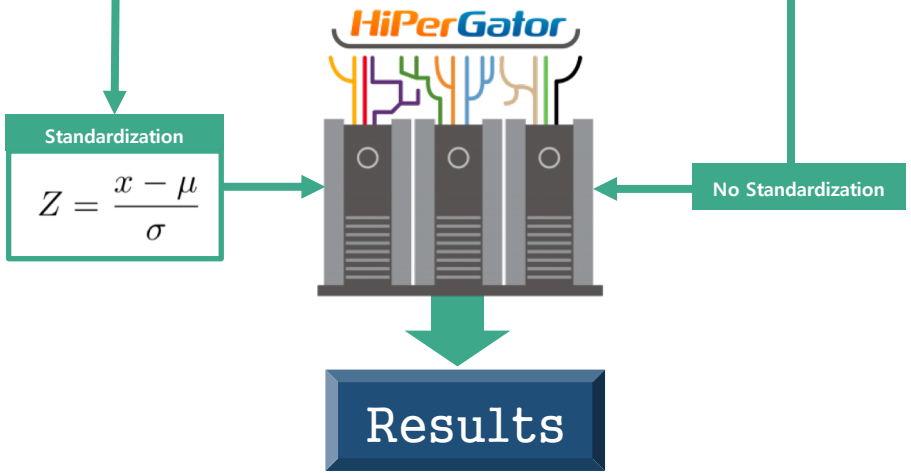
4 x 4 Image



2 x 2 x 3 Feature Maps

Experiment Setup





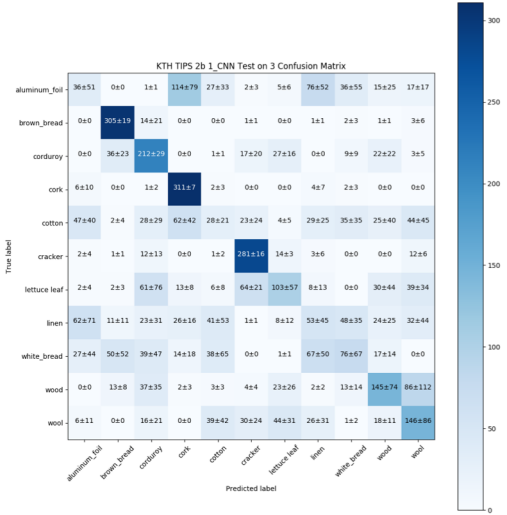
Result: Standardized vs Non-Standardized

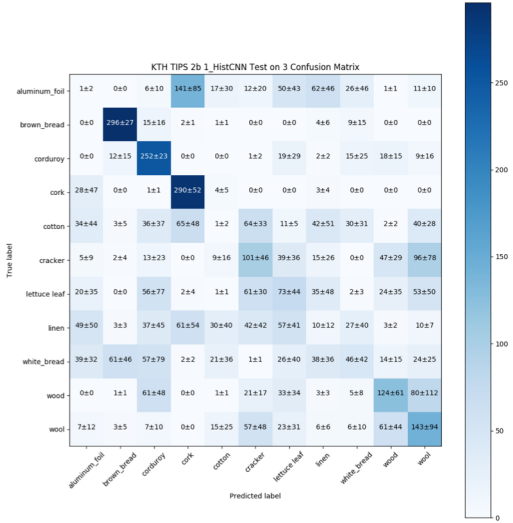
Average Overall Accuracy

Network	Average Overall Accuracy	
	Non-Standardized	Standardized
1_CNN	38.87 ± 4.05	47.48 ± 0.97
1_HistCNN	34.90 ± 4.09	37.43 ± 3.33
2_CNN	29.51 ± 5.14	44.35 ± 1.07
2_HistCNN	36.75 ± 2.58	40.14 ± 1.49
2_CNN_parallel	40.31 ± 3.79	47.66 ± 1.22
2_HistCNN_parallel	35.91 ± 4.15	38.20 ± 2.85

Every network improved performance significantly with standardization, averaging about 6.50% increase in average overall accuracy

Result: 1CNN vs 1HistCNN

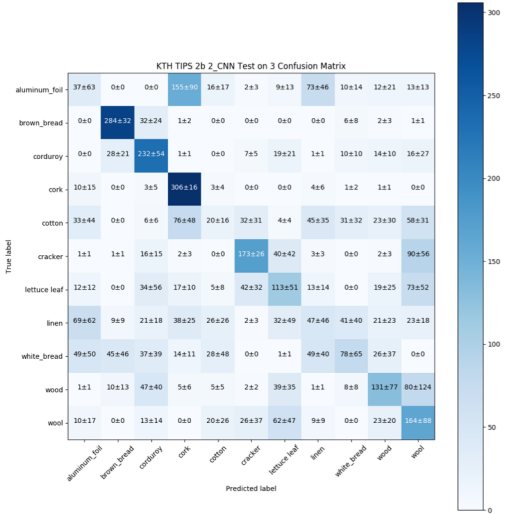


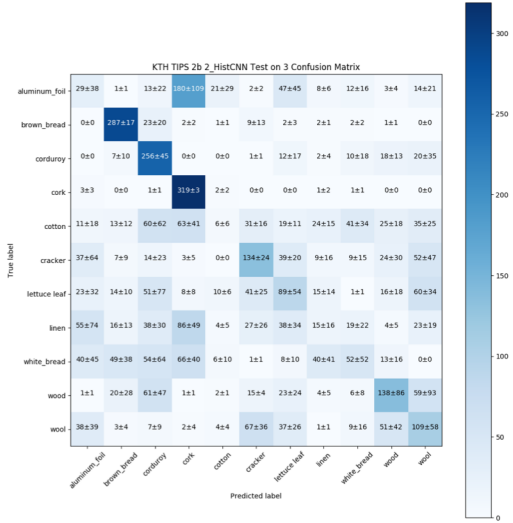


1_CNN & 1_HistCNN

	1_CNN Avg. F1-score	1_HistCNN Avg. F1-score	1_CNN Avg. Precision	1_HistCNN Avg. Precision	1_CNN Avg. Recall	1_HistCNN Avg. Recall
Sample A	0.45 ± 0.24	0.31 ± 0.28	0.47 ± 0.22	0.30 ± 0.27	0.48 ± 0.29	0.36 ± 0.32
Sample B	0.43 ± 0.22	0.35 ± 0.29	0.43 ± 0.21	0.33 ± 0.30	0.47 ± 0.27	0.40 ± 0.32
Sample C	0.44 ± 0.25	0.28 ± 0.28	0.43 ± 0.24	0.29 ± 0.31	0.49 ± 0.28	0.33 ± 0.33
Sample D	0.40 ± 0.23	0.35 ± 0.30	0.42 ± 0.22	0.35 ± 0.29	0.46 ± 0.29	0.41 ± 0.32

Result: 2CNN vs 2HistCNN

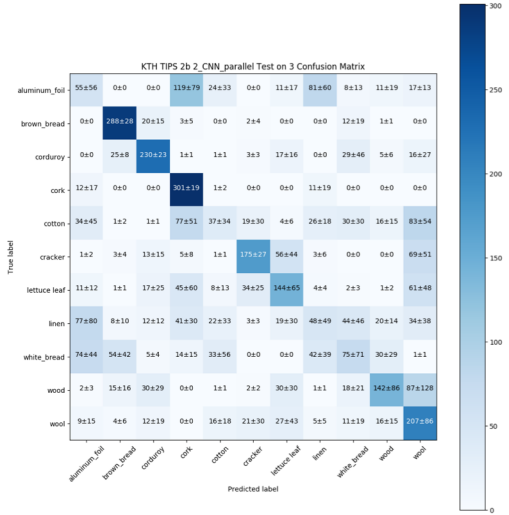


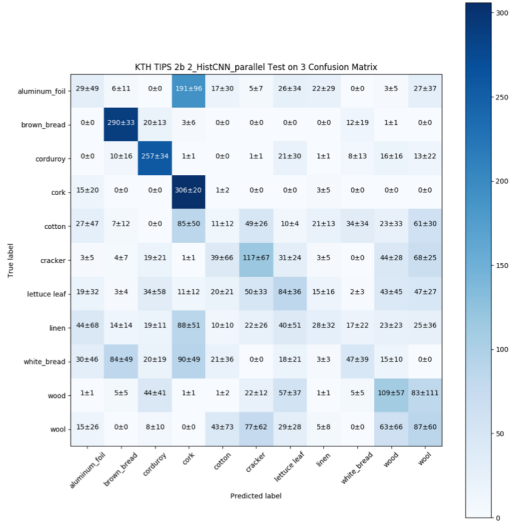


2_CNN & 2_HistCNN

	2_CNN Avg. F1-score	2_HistCNN Avg. F1-score	2_CNN Avg. Precision	2_HistCNN Avg. Precision	2_CNN Avg. Recall	2_HistCNN Avg. Recall
Sample A	0.40 ± 0.23	0.33 ± 0.25	0.41 ± 0.22	0.31 ± 0.21	0.44 ± 0.28	0.41 ± 0.33
Sample B	0.40 ± 0.23	0.37 ± 0.24	0.40 ± 0.21	0.37 ± 0.24	0.44 ± 0.26	0.42 ± 0.31
Sample C	0.42 ± 0.22	0.34 ± 0.25	0.44 ± 0.22	0.34 ± 0.22	0.46 ± 0.29	0.40 ± 0.34
Sample D	0.38 ± 0.24	0.32 ± 0.24	0.40 ± 0.24	0.31 ± 0.22	0.43 ± 0.27	0.38 ± 0.32

Result: 2CNN_parallel vs 2HistCNN_parallel





2_CNN_parallel & 2_HistCNN_parallel

	2_CNN_par Avg. F1-score	2_HistCNN_par Avg. F1-score	2_CNN_par Avg. Precision	2_HistCNN_par Avg. Precision	2_CNN_par Avg. Recall	2_HistCNN_par Avg. Recall
Sample A	0.44 ± 0.26	0.31 ± 0.26	0.45 ± 0.24	0.31 ± 0.31	0.48 ± 0.31	0.36 ± 0.31
Sample B	0.44 ± 0.24	0.31 ± 0.27	0.48 ± 0.23	0.31 ± 0.30	0.46 ± 0.30	0.36 ± 0.30
Sample C	0.45 ± 0.24	0.38 ± 0.25	0.46 ± 0.24	0.39 ± 0.30	0.49 ± 0.32	0.43 ± 0.30
Sample D	0.42 ± 0.28	0.31 ± 0.26	0.43 ± 0.24	0.35 ± 0.31	0.48 ± 0.33	0.38 ± 0.30

Conclusion

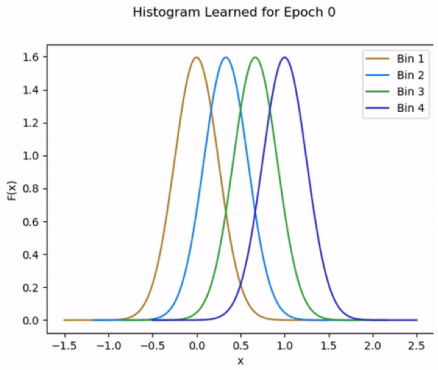
Contributions

1. Learned standardization improves performance significantly.
2. Histogram layer did not necessarily have a better performance overall, but they performed better than the standard CNNs on some classes

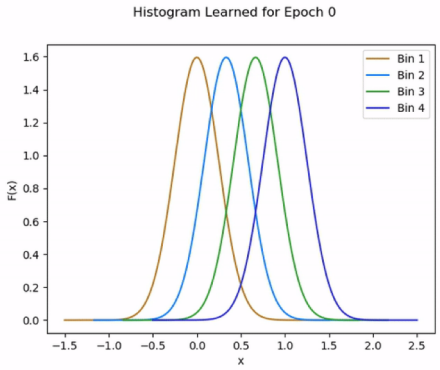
Future Works

1. Different initialization techniques for histogram layer can be used
2. Tuning of parameters (i.e. window size, number of bins, kernel size)

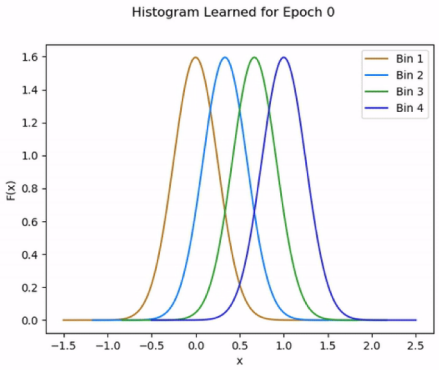
Histogram Learned for 1_HistCNN (Non-standardized, 0-50 epochs)



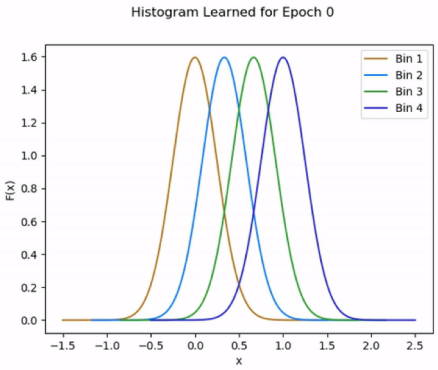
Sample A



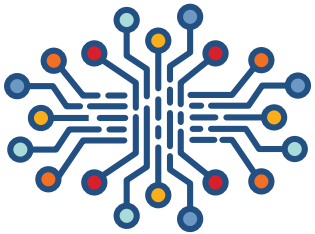
Sample B



Sample C



Sample D



THE MACHINE LEARNING AND SENSING LABORATORY

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STUDENT SCIENCE TRAINING PROGRAM Est. SSTP 1959

References

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- Agriculture: https://images.app.goo.gl/kAPFDa7q7jVcsvMn9
- Autonomous Vehicles: https://www.mdpi.com/1424-8220/19/9/2064/htm
- HiPerGator: https://www.rc.ufl.edu/services/hipergator/
- SSTP Logo: https://www.facebook.com/StudentScienceTrainingProgram/photos/a.468134324467/10152955929819468/?type=1&theater