Mass Estimation From Images Using Deep Neural Network and Sparse Ground Truth

Muhammad Hamdan
Department of Electrical and Computer Engineering
Iowa State University

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Motivation

Literature Review

Sugarcane mass flow estimation methods

- Mass measurement through **load cell** **[1, 2, 3, 4, 5, 6]**
- Volume measurement through roller displacement **[7]**
- Volume measurement via optical sensor **[8, 9]**
  - Inexpensive, simple, and relatively accurate ( )
  - Depends on ambient light (night time and early morning)
  - Requires calibration and highly affected by changes in material density

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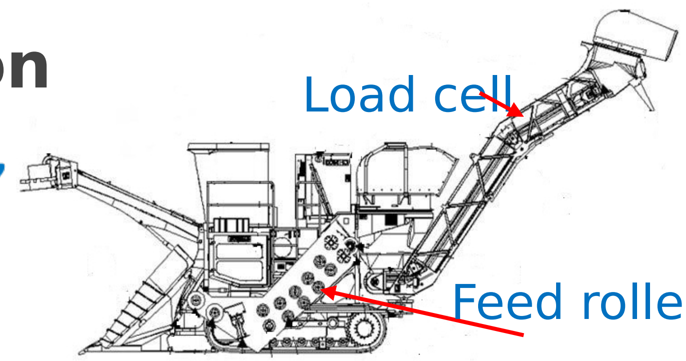


- **Mass measurement through images from stereo camera**

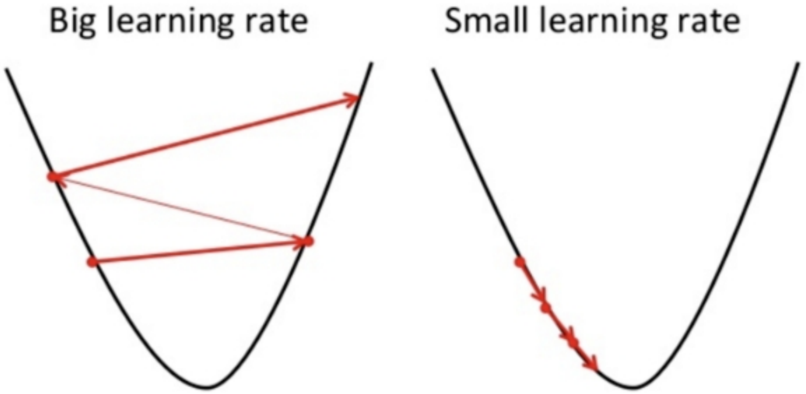
Problem Complexity

- **Factors**
  - Angle of capture
  - Mass flow rate
  - Frame overlap
  - Variable elevator spe
  - Different run sizes
  - Different lighting con
  - Sparse ground truth

Deep Learning Basics

What to consider when deciding on using a DNN?

- CNN architecture
  - AlexNet, VGG, GoogleNet, ResNet, Your own?
- Activation function
  - Sigmoid, Tanh, ReLU, ELU
- Choice of hyper-parameters:
  - Learning rate
- Loss function
  - Classification: Softmax
  - Regression: MSE



$$\mathbf{MSE} = \quad L(y;\hat{y}) = \sum_{i=1}^{k} \frac{1}{n}\Big(y_i - \hat{y}_i\Big)^2$$

Loss Function

$$L_i(x, y; w) = \frac{1}{n_i}\left\{y_i - \boxed{\sum_{j=1}^{n_i}(f(x_{ij}; w) \times v_{ij} \times t})\right\}^2$$

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that we handled frame overlap, we need to figure out to obtain correct predictions per frame

Gradient Update

- Our loss function
- Gradient update occurs at every end of a run
- We keep a running sum of gradients and predictions
- Compute the derivative of the loss function to apply loss

$$\frac{\partial L_i}{\partial w} \leftarrow -\frac{2}{n_i}\left[y_i - \sum_{j=1}^{n_i} \hat{y}_{ij}\right] \times \sum_{j=1}^{n_i} \frac{\partial \hat{y}_{ij}}{\partial w}$$

DNN Architecture Summary

- DNN Architecture
  - Input image size: 96 x 144 (5th original size)
  - Parameters: 4K and Size of parameters: 0.17 MB
  - Training time: ~11 hours
  - Testing average error: 4.5%

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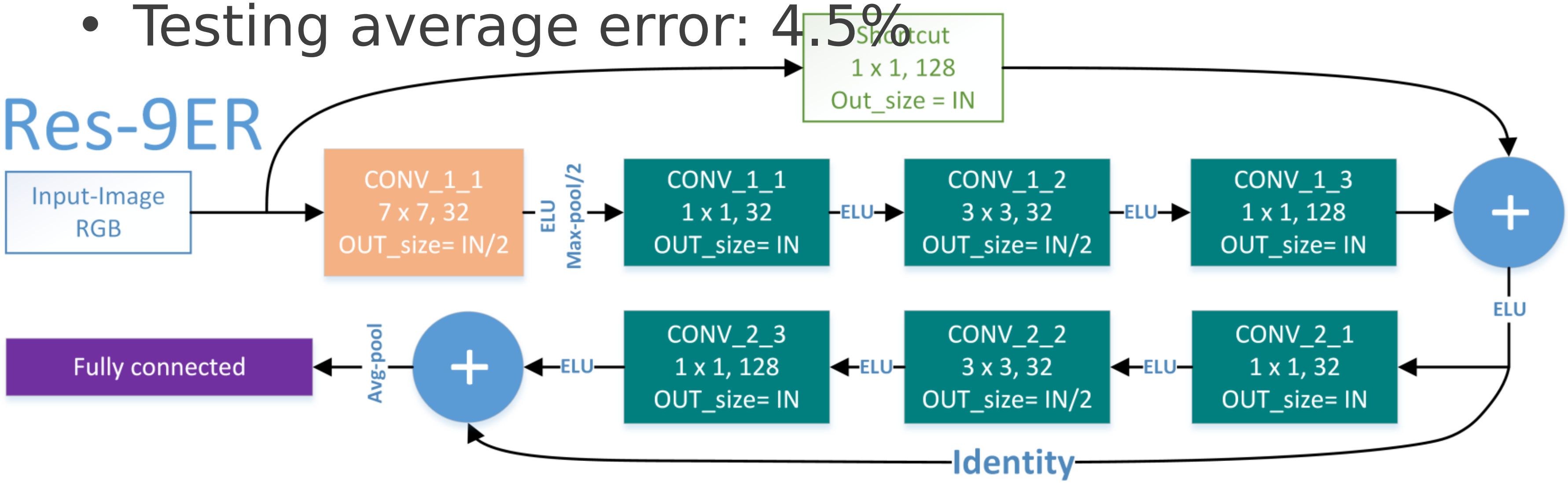
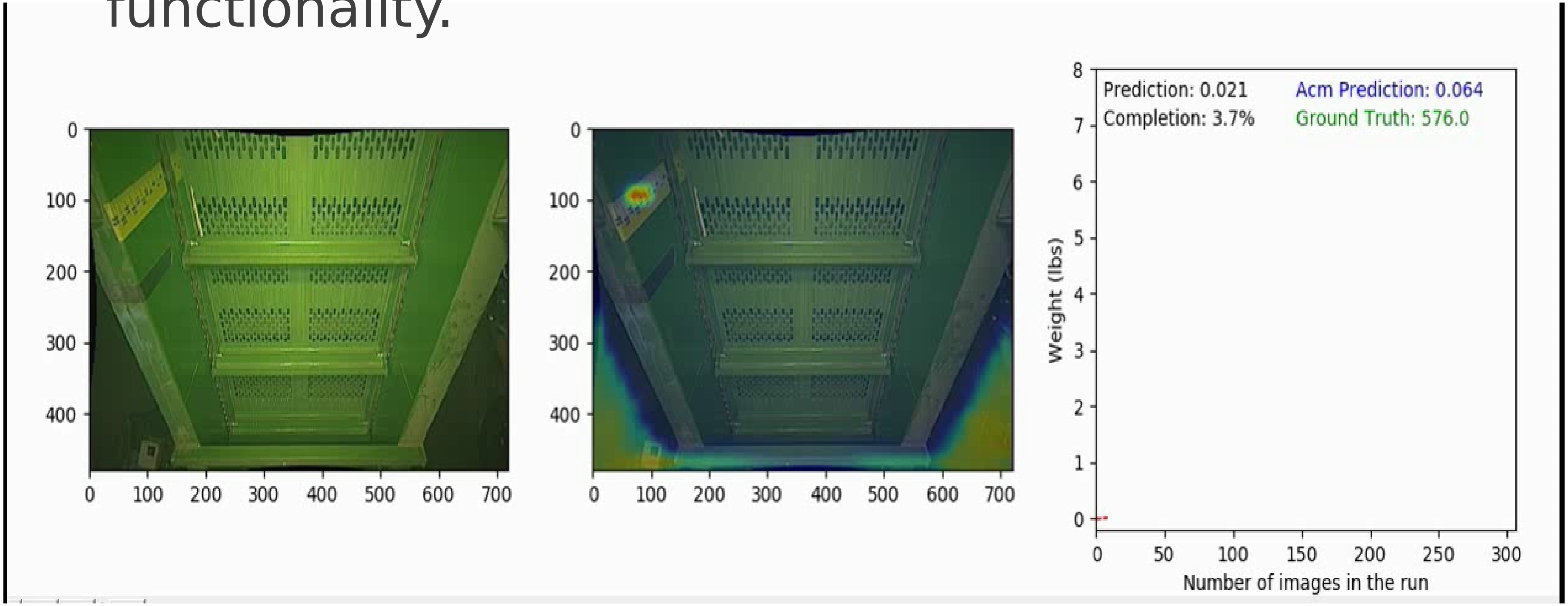
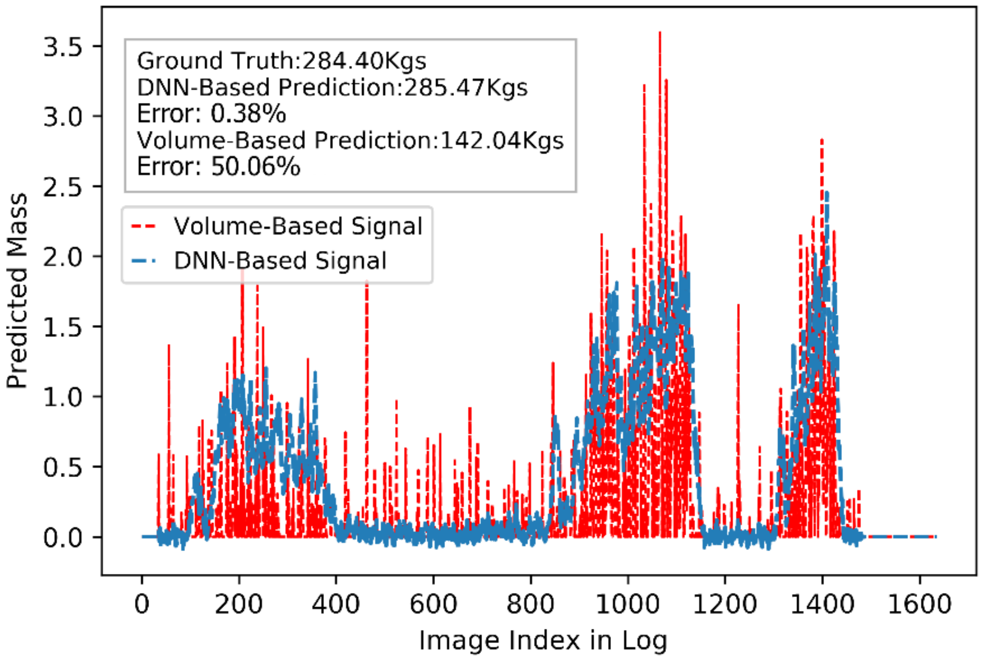


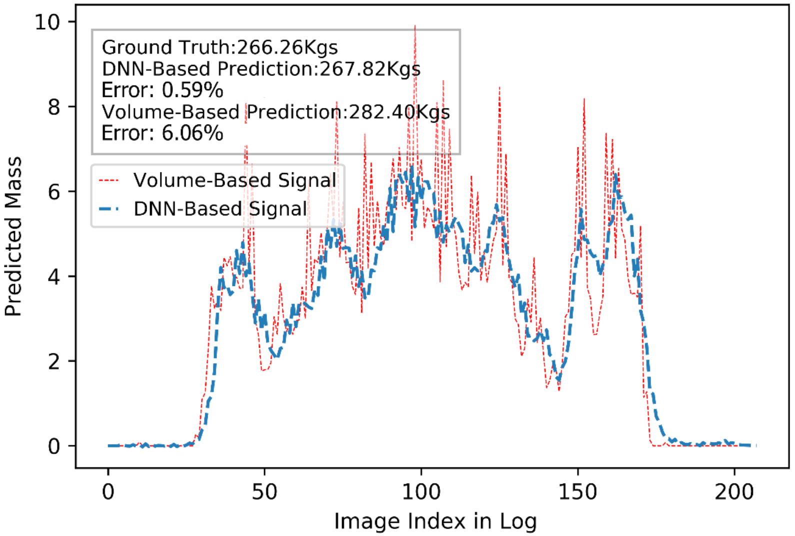
What is Going on Behind the Scenes?

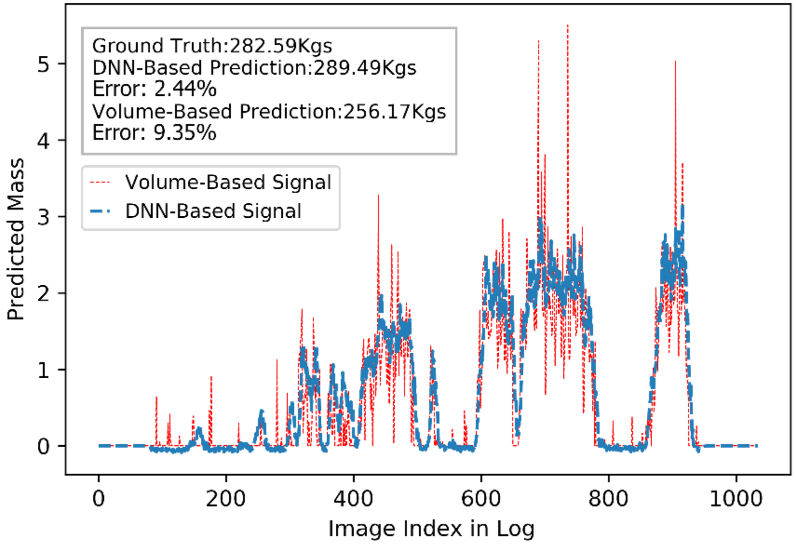
- Proper visualization techniques can support the investigation of DNN functionality.



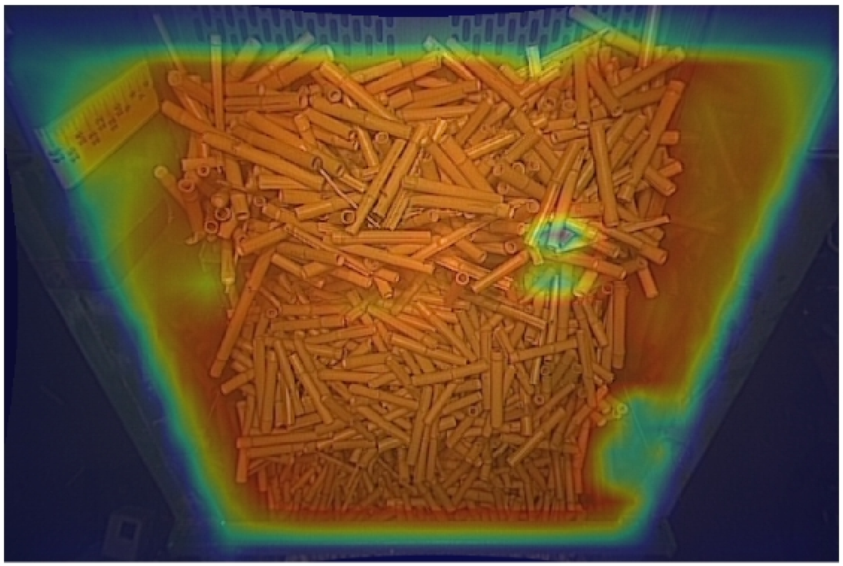
Robustness

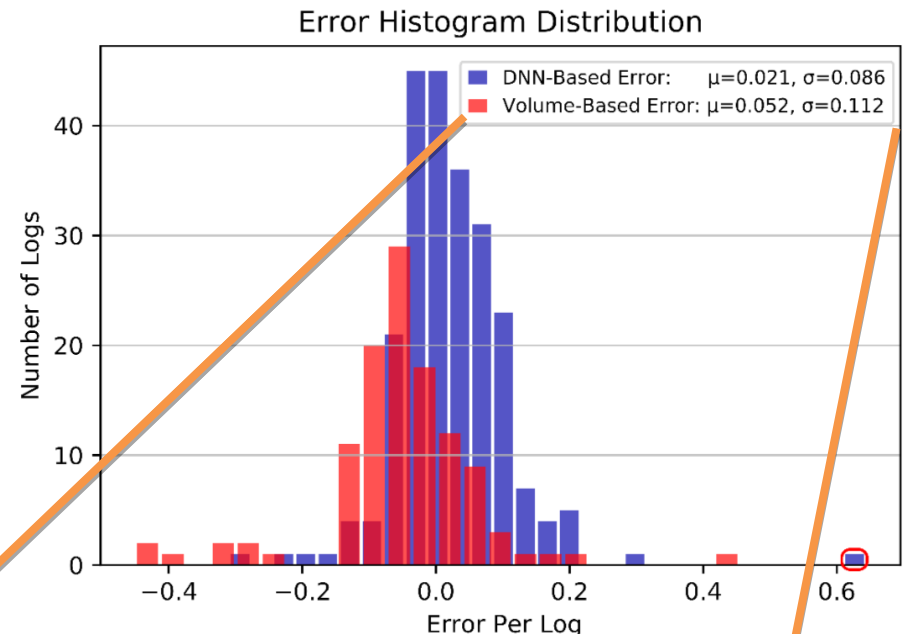

Ground Truth:284.40Kgs
DNN-Based Prediction:285.47Kgs
Error: 0.38%
Volume-Based Prediction:142.04Kgs
Error: 50.06%
Volume-Based Signal
DNN-Based Signal
Predicted Mass
Image Index in Log
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0
200
400
600
800
1000
1200
1400
1600

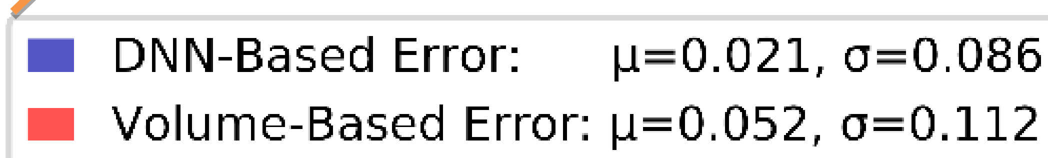

Ground Truth:266.26Kgs
DNN-Based Prediction:267.82Kgs
Error: 0.59%
Volume-Based Prediction:282.40Kgs
Error: 6.06%
Volume-Based Signal
DNN-Based Signal
Predicted Mass
Image Index in Log
0
2
4
6
8
10
0
50
100
150
200


Ground Truth:282.59Kgs
DNN-Based Prediction:289.49Kgs
Error: 2.44%
Volume-Based Prediction:256.17Kgs
Error: 9.35%
Volume-Based Signal
DNN-Based Signal
Predicted Mass
Image Index in Log
0
1
2
3
4
5
0
200
400
600
800
1000

Histogram Distribution of Error and Outliers







Questions

Questions?

References

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[7] Cox, Graeme J. "A yield mapping system for sugar cane chopper harvesters." PhD diss., University of Southern Queensland, 2002.
[8] Mike Mailander, Caryn Benjamin, Randy Price, and Steven Hall. Sugar cane yield monitoring system. Applied engineering in agriculture, 26(6):965{969, 2010
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Volumetric-Based Approach to Mass estimation

- Instant volume measurement is available
- Ground truth (true mass) is only available by run

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$$\frac{\text{MASS}}{\text{sec}} = \frac{\text{Volume}}{\text{sec}} \times \text{DENSITY}$$

$$Mass = f(max(V-\beta,0);\theta) \times max(V-\beta,0) \times v_{elev} \times t$$

Where "f" is a 2-layer neural network parameterized by "θ" that outputs a prediction of density based on the volume (V), scaled by elevator speed (V_{elev}) and capture time (t), with tanh activation

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$Percent\ error_{avg}$ using neural network **including** low ligh runs: $\mathbf{12.58}\%$

$Percent\ error_{avg}$ using neural network **without** low ligh runs: $\mathbf{8.65}\%$

Data Summary

Laboratory data summary

Location	Runs	Samples	Material	Representation	Environment
ISU	239	>120K	Bamboo	Images and point cloud	Controlled

Laboratory etup

Temporal Smoothness

- Images near in time should have more similarity in mass than images further away in time
- Hyper-parameter λ (chosen empirically 0.05)
- This term is added to the loss function

$$L_i(x, y; w) = \frac{1}{n_i}\left\{y_i - \sum_{j=1}^{n_i}(f(x_{ij}; w) \times v_{ij} \times t)\right\}^2 +$$

$$\frac{\lambda}{n_i}\sum_{j=1}^{n_i}\left\{f(x_{ij}; w) - f(x_{i(j-1)}; w)\right\}^2$$