USDA Agricultural Research Service

Predicting moisture content and bulk density of various grains from their dielectric properties

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Problem Statement

- Moisture content of grains is a critical variable in the buy-sell process to monitor quality production and crop analysis.
- Water's polar nature leads to correlate microwave frequencies and dielectric properties of moisture-containing materials.
- These properties can contribute to calculate moisture content of grains using calibration equations and non-destructive ‘free-space’ transmission techniques.
- Nevertheless, there are errors associated with calibration-based methods - which can be further reduced.

The main objective of this investigation is to use machine learning and AI-based algorithms to predict moisture content from the dielectric properties measured at a given frequency.

Objectives

Here are the three situations that have been explored:

1. Frequency and bulk density are known.
    - *Input*: Dielectric properties, Frequency and **bulk density**
    - *Output*: Moisture content
2. Frequency is known. Bulk density is unknown.
    - *Input*: Dielectric properties, Frequency
    - *Output*: Moisture content and **bulk density**
3. Frequency is known. Bulk density is unknown.
    - *Input*: Dielectric properties and Frequency
    - *Output*: Moisture content

Overview of work done

1. Literature review

2. Selection of ML/AI based algorithm

3. Dataset pre-processing

4. Workstation setup to incorporate GPU usage

5. Implementation

6. Experiments with variants of model

7. Poster preparation

Literature Review

- <u>Measurement Techniques of dielectric properties</u>
  - Free-space method
    - Non-destructive and non-contact method
  - Calibration techniques
    - Useful for microwave frequencies > 3GHz, where ionic conductivity has no effect and there are no bound-water-related relaxations

- <u>Prediction-based approaches</u>
  - ANN (Bartley et al, 1998)
  - PCA-SVR (Julrat, Trabelsi, 2021)
  - DNN with Batch Normalization (Zhang et al, 2020)

Selection of algorithm

- Deep Neural Networks (DNNs)
  - More hidden layers compared to ANNs
  - Existing works have added batch normalization after each hidden layer
  - Our findings: Results were better **without** it

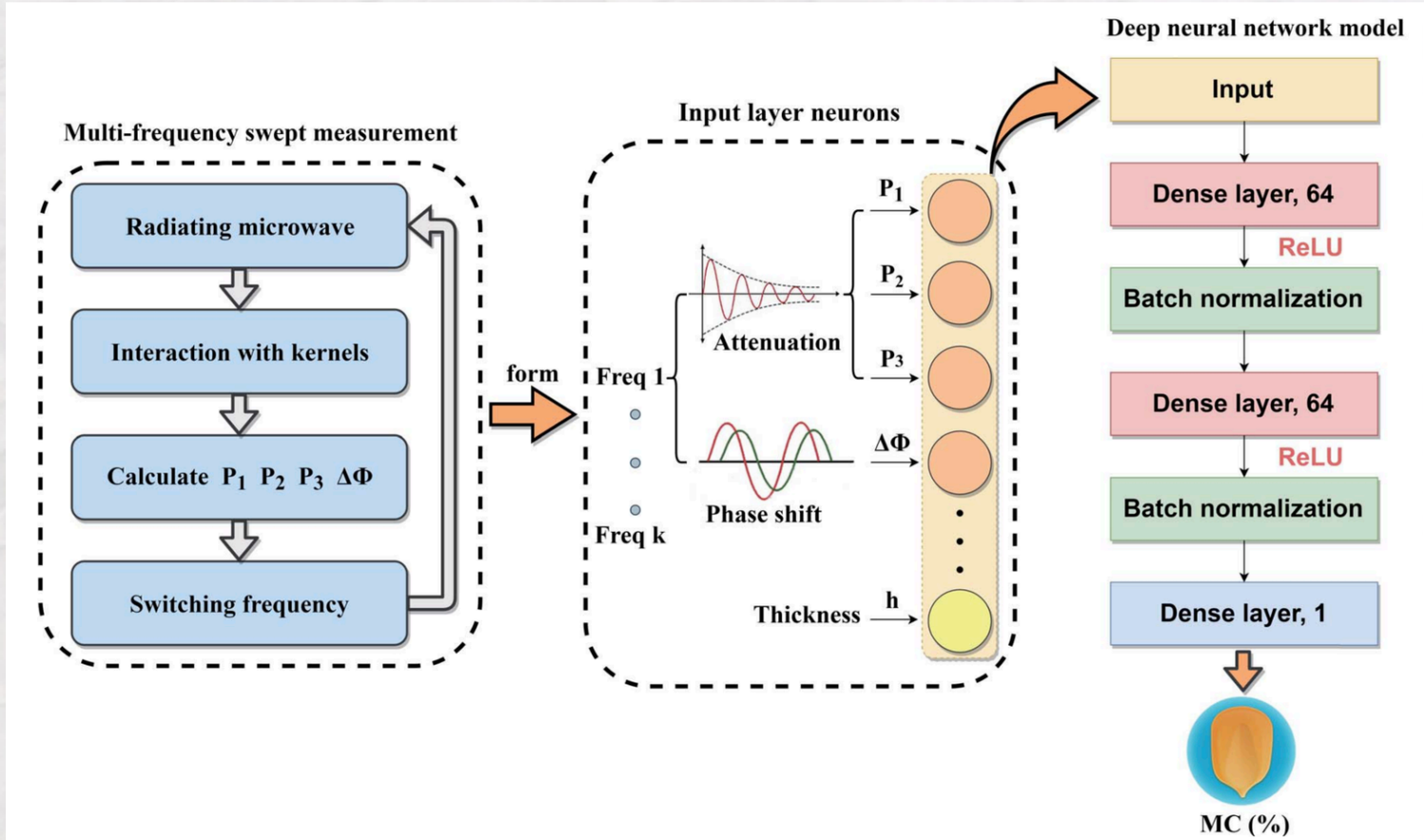

Fig: Schematic used in [1]

[1] Zhang, J., Du, D., Bao, Y., Wang, J., & Wei, Z. (2020). Development of multifrequency-swept microwave sensing system for moisture measurement of sweet corn with deep neural network. *IEEE Transactions on Instrumentation and Measurement*, *69*(9), 6446-6454.

Dataset preprocessing

- Missing data handled, e.g.

	14	7.7	13.42	0.7704	24.0132	-154.487	-874.487	2.794	0.41
	14	7.7	13.42	0.7966	24.583	178.003	-901.997	2.865	0.426
	frequencies of 14 GHz and higher were not taken for this sample								
	14	7.7	10.85	0.6918	15.9721	-32.168	-752.168	2.494	0.258
	14	7.7	10.85	0.7717	16.4782	-79.122	-799.122	2.61	0.272
	14	7.7	10.85	0.8085	16.7129	-102.644	-822.644	2.669	0.279
	14	7.7	12.01	0.7144	19.4939	-69.436	-789.436	2.583	0.32
	14	7.7	12.01	0.7722	20	-117.489	-837.489	2.704	0.336
	14	7.7	12.01	0.8069	20.3546	-142.924	-862.924	2.768	0.347

- Dataset converted to one file per grain type
  - Features:
    - Variety
    - Frequency
    - Depth (cm)
    - Moisture Content
    - Density
    - Attenuation
    - Phase
    - Phase (corrected)
    - Permittivity (real)
    - Permittivity (imaginary)

Excel Wheat

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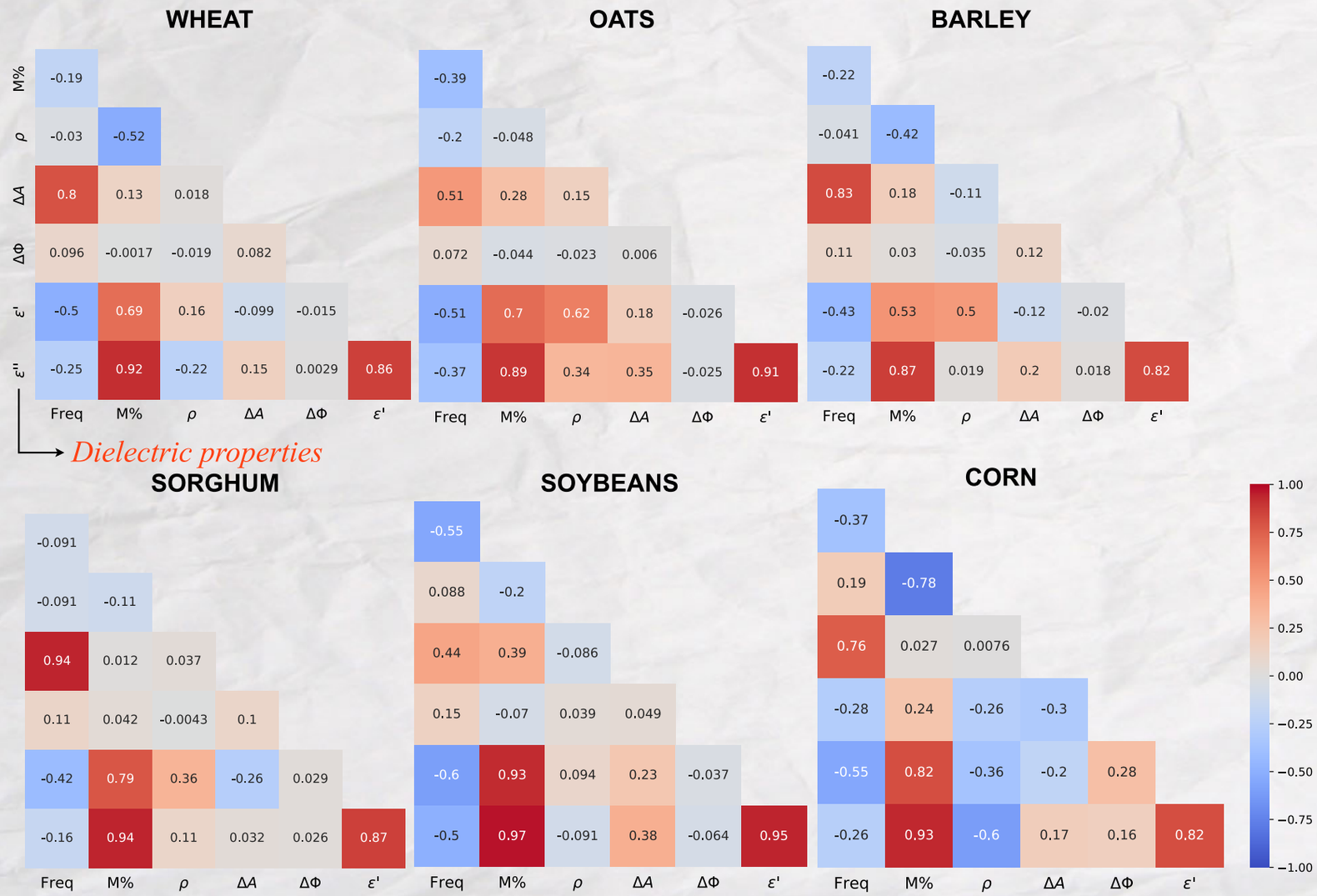
	A	B	C	D	E	F	G	H	I	J	K
		Variety	Freq	d(cm)	M%	Density	Attn	Phase	Phase_Corr	Permittivity_real	Permittivity_imaginary
0		KANSAS	7	8.9	11.3	0.7356	8.8258	-55.973	-415.973	2.416	0.243
1		KANSAS	8	8.9	11.3	0.7356	10.2572	-114.289	-474.289	2.412	0.246
2		KANSAS	9	8.9	11.3	0.7356	11.5679	-168.171	-528.171	2.395	0.246
3		KANSAS	10	8.9	11.3	0.7356	12.8795	134.849	-585.151	2.39	0.246
4		KANSAS	11	8.9	11.3	0.7356	13.7649	83.502	-636.498	2.371	0.238
5		KANSAS	12	8.9	11.3	0.7356	14.4249	27.323	-692.677	2.368	0.229
6		KANSAS	13	8.9	11.3	0.7356	15.0405	-26.224	-746.224	2.359	0.22
7		KANSAS	14	8.9	11.3	0.7356	16.1934	-85.408	-805.408	2.362	0.22
8		KANSAS	15	8.9	11.3	0.7356	17.7211	-139.456	-859.456	2.355	0.225
9		KANSAS	16	8.9	11.3	0.7356	19.5762	164.202	-915.798	2.353	0.232
10		KANSAS	17	8.9	11.3	0.7356	20.9151	113.905	-966.095	2.342	0.232
11		KANSAS	18	8.9	11.3	0.7356	21.31	58.282	-1021.718	2.34	0.224
12		KANSAS	6	8.9	11.3	0.7859	8.0242	-26.205	-386.205	2.562	0.265
13		KANSAS	7	8.9	11.3	0.7859	9.396	-82.811	-442.811	2.529	0.264
14		KANSAS	8	8.9	11.3	0.7859	10.752	-144.973	-504.973	2.524	0.264
15		KANSAS	9	8.9	11.3	0.7859	12.0065	157.545	-562.455	2.506	0.261
16		KANSAS	10	8.9	11.3	0.7859	13.2309	96.589	-623.411	2.501	0.259
17		KANSAS	11	8.9	11.3	0.7859	14.1993	41.997	-678.003	2.481	0.251

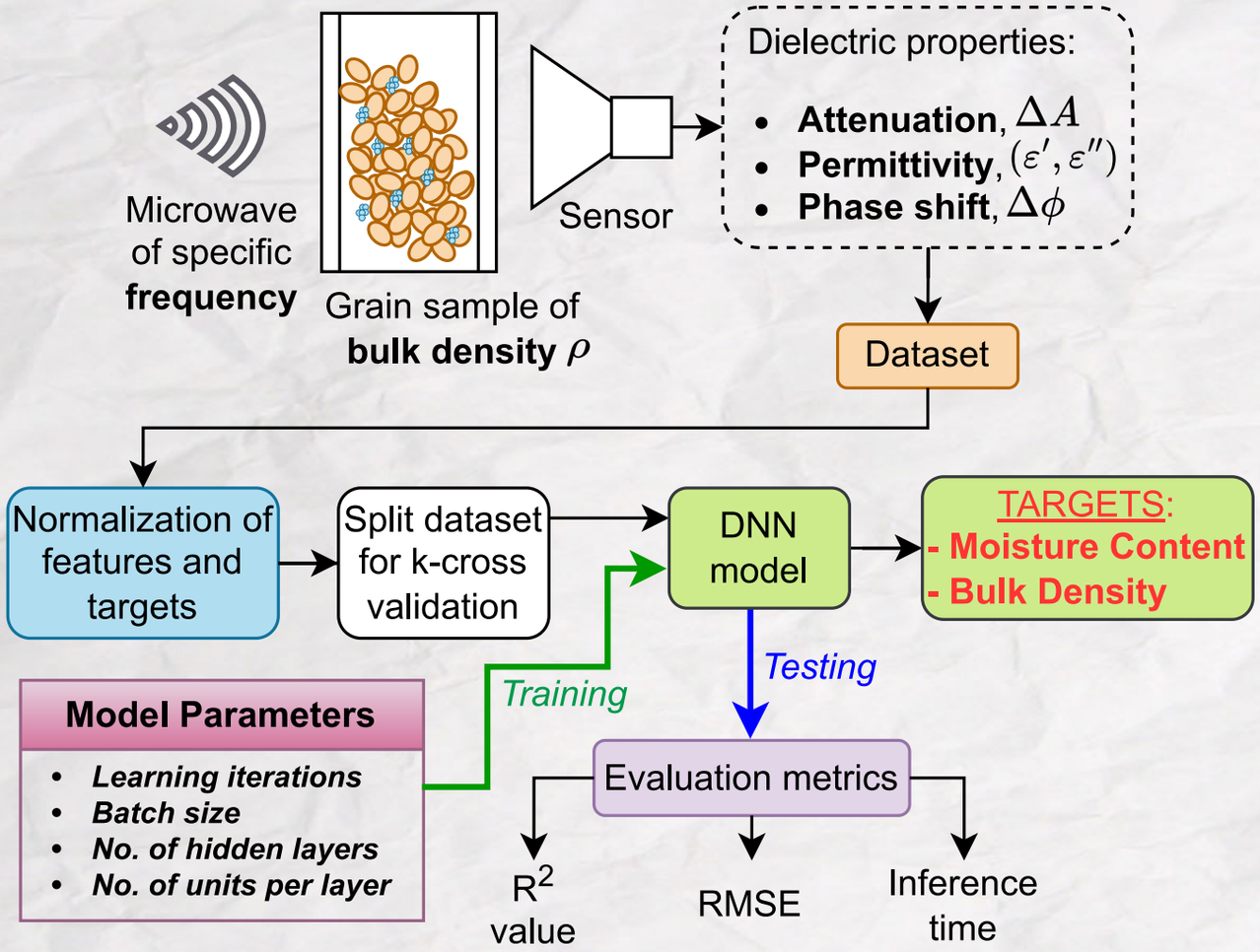
Visualising the dataset

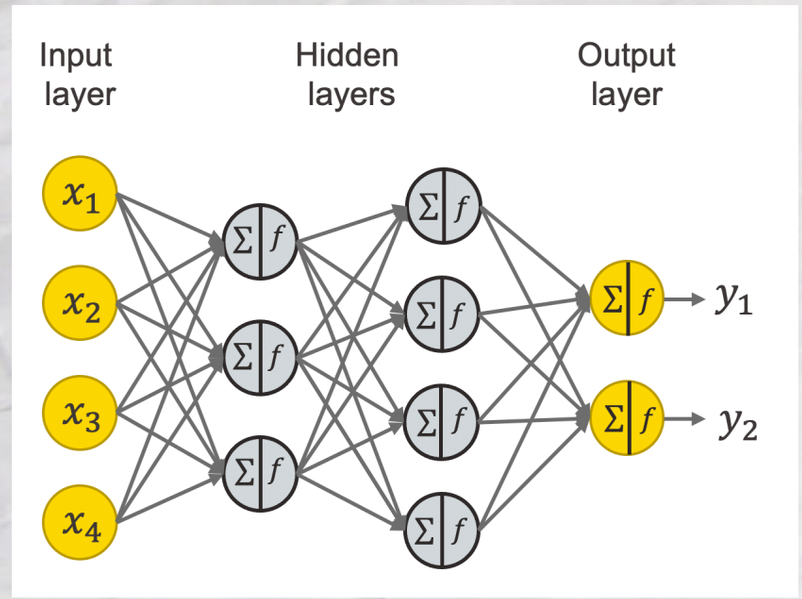
- Wheat (806)
- Oats (485)
- Barley (366)
- Sorghum (399)
- Soybeans (571)
- Corn (1339)

- A larger value indicates stronger correlation
- Observation:
  Weaker correlation of Bulk Density with dielectric properties



Methodology

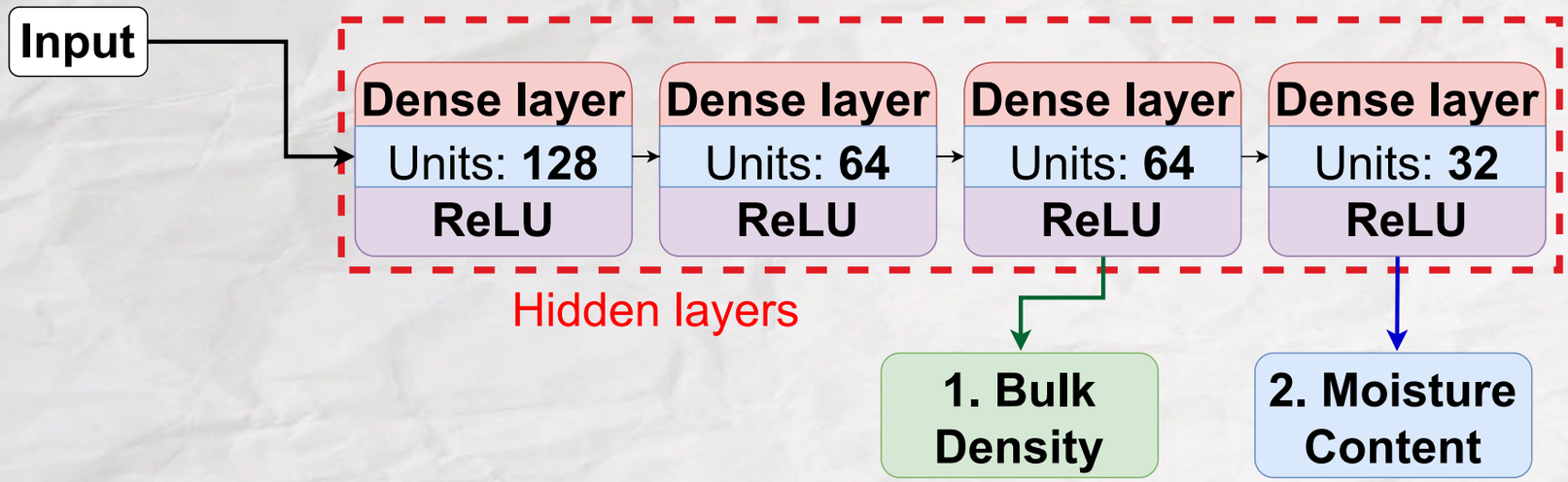




Model Variants explored

I: Prediction of ONE target
(Moisture Content or Bulk Density)

II: Prediction of TWO targets
(Moisture Content + Bulk Density) : Separate Output Layers



III: Prediction of TWO targets
(Moisture Content + Bulk Density) : Single Output Layer

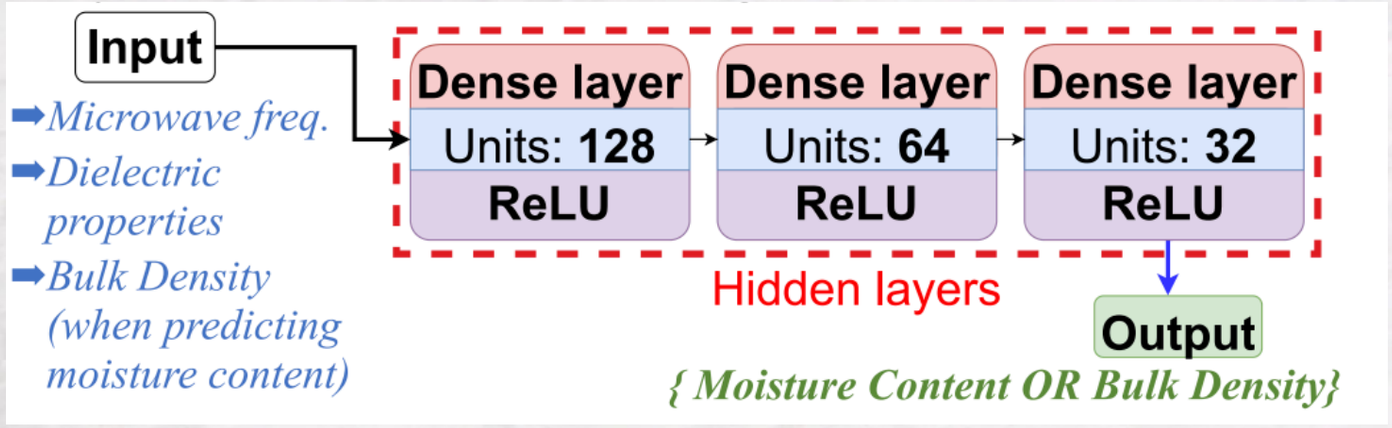
Running models with different parameters

- Train-test ratio
- # of hidden layers
- # of units per hidden layer
- Batch Normalisation
- Optimizer
- Learning Rate
- # of epochs
- Batch size
- Value of k in k-cross validation

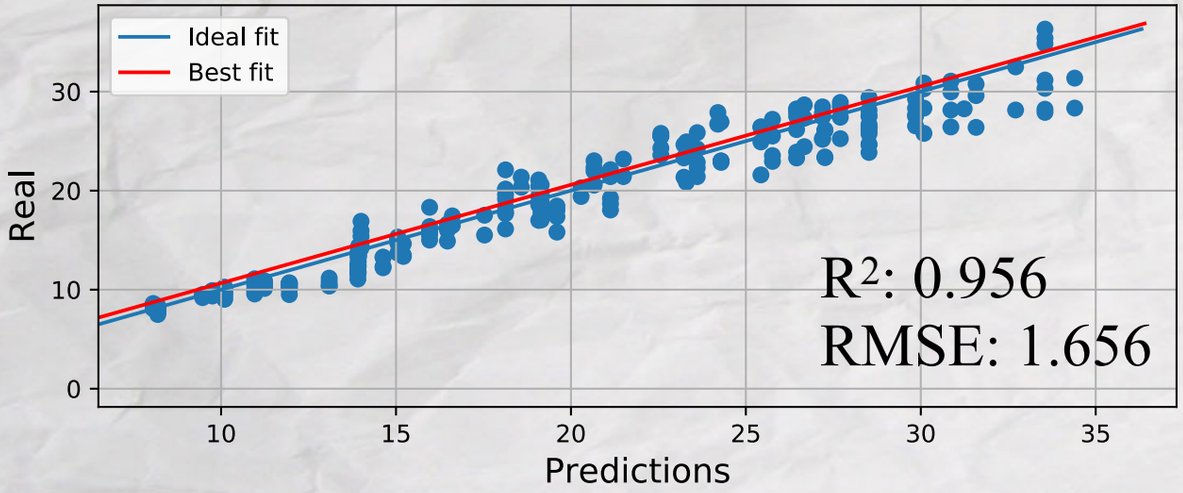
Model variants explored

Objective I: Prediction of ONE target (Moisture Content OR Bulk Density)

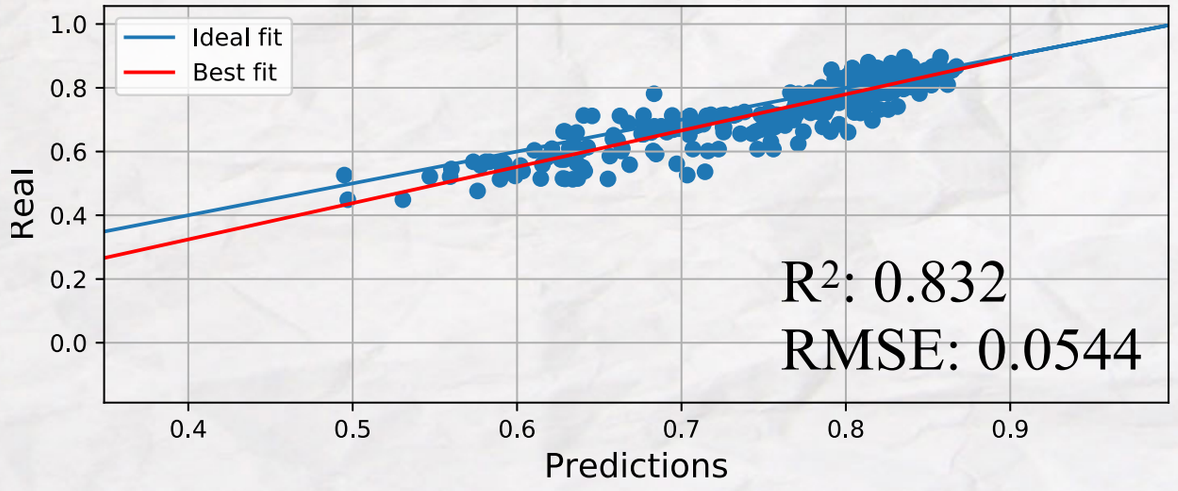
- Different models for each target
- Parameters varied to get model with:
  - Highest R-squared value
  - Lowest RMSE



Moisture Content



Bulk Density

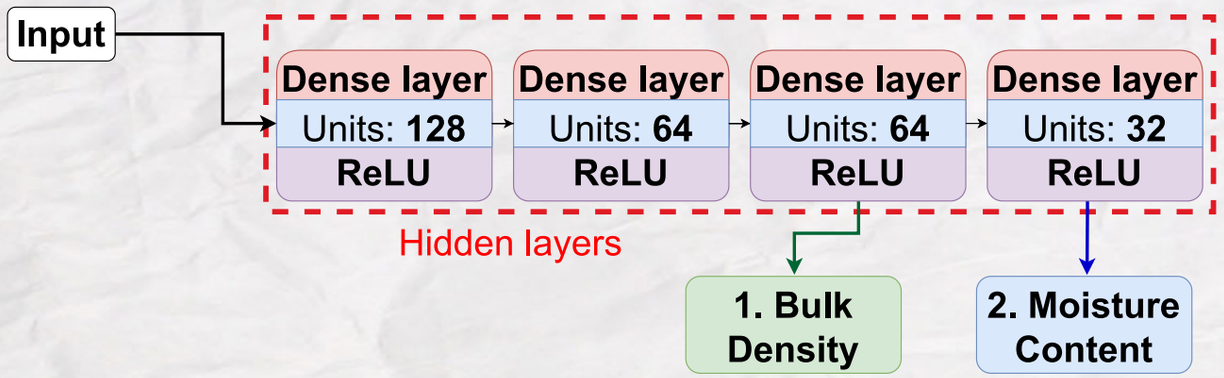


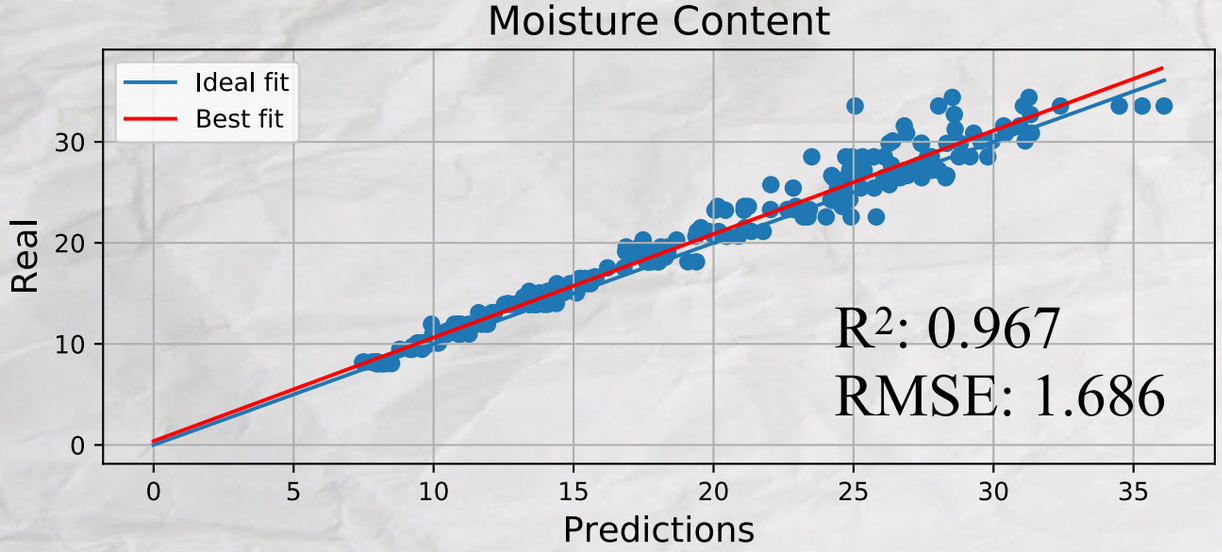
Results of best model for CORN

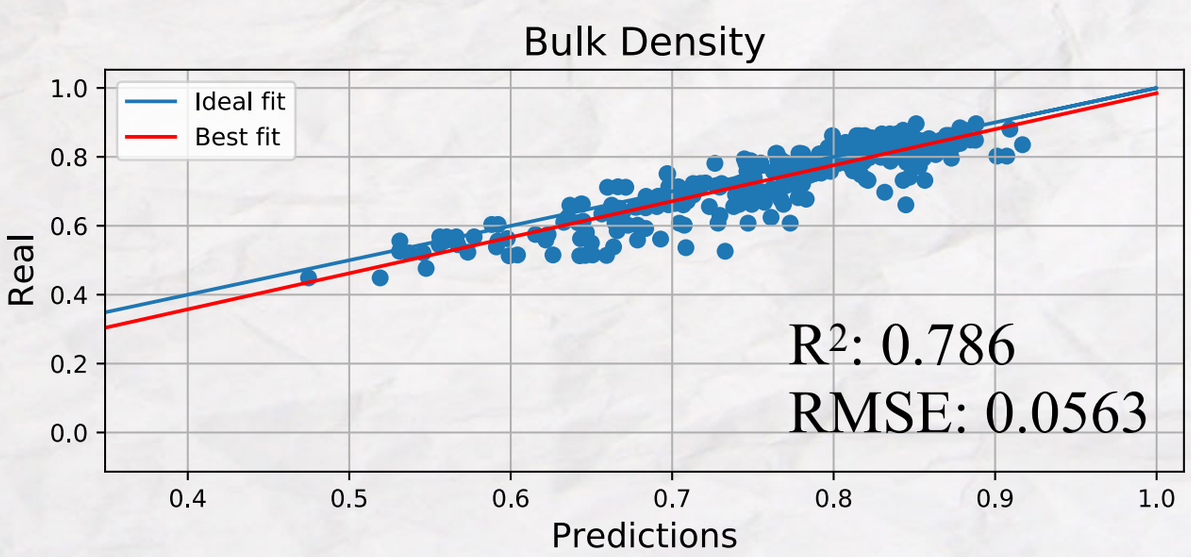
Model variants explored

Objective II: Prediction of TWO targets (Moisture Content + Bulk Density) - SEPARATE output layers

- ONE model for two targets
- Parameters varied to get model with:
  - Highest R-squared value
  - Lowest RMSE





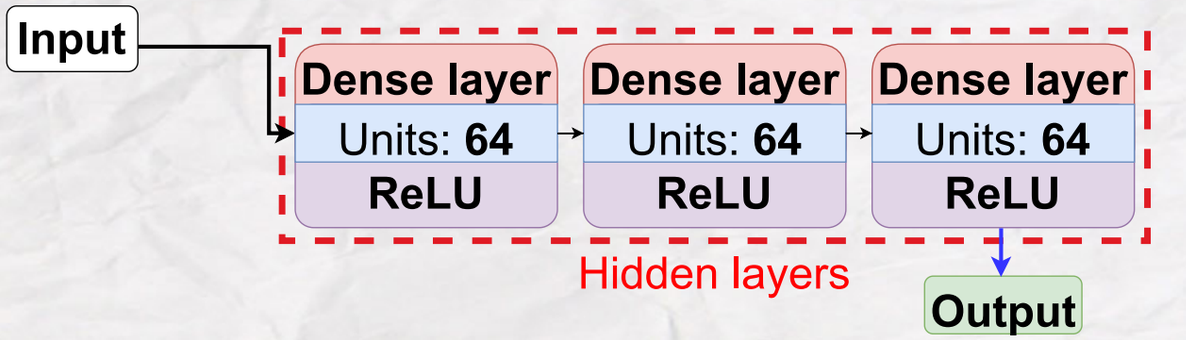


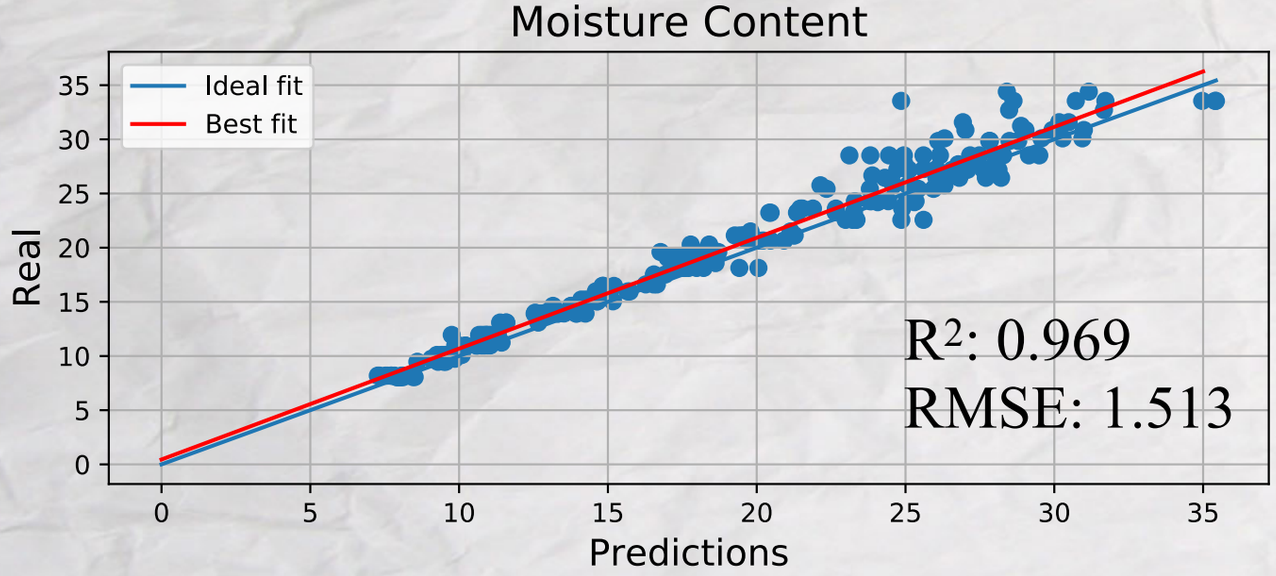
Results of best model for CORN

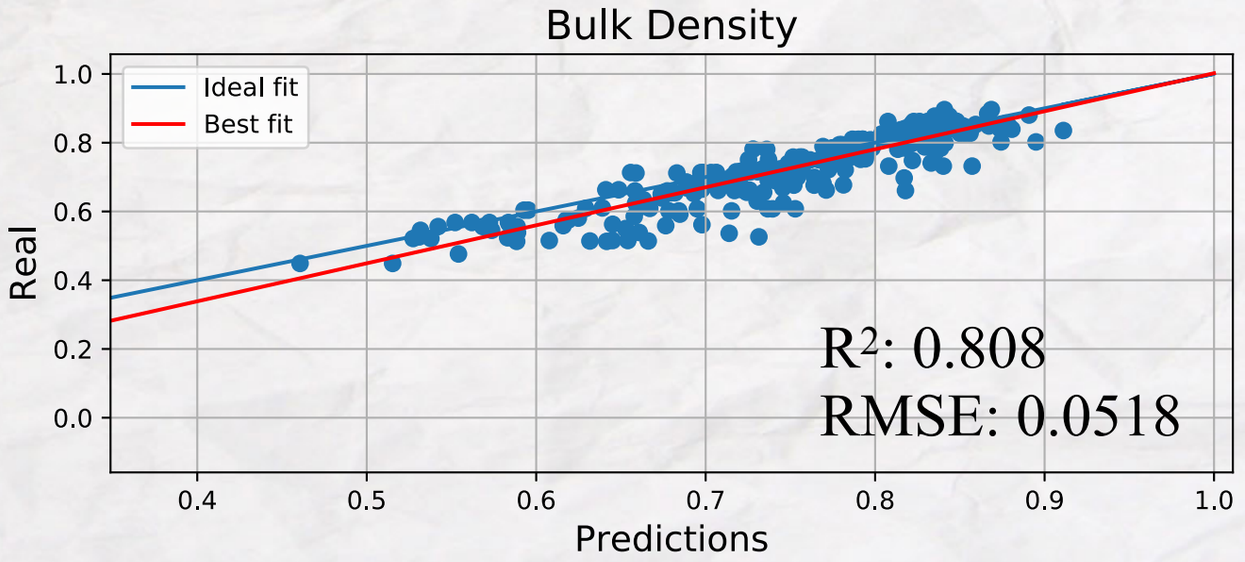
Model variants explored

Objective III: Prediction of TWO targets (Moisture Content + Bulk Density) - SINGLE output layer

- ONE model for two targets
- Parameters varied to get model with:
  - Highest R-squared value
  - Lowest RMSE







Results of best model for CORN

Results

- R^2 values (predicted vs actual values) ranged from:
  - **0.95 to 0.991** for Moisture Content prediction
  - **0.835 to 0.958** for Bulk Density prediction

- RMSE ranged from:
  - **0.739 to 1.875** for Moisture Content prediction
  - **0.0192 to 0.0693** for Bulk Density prediction

- Inference time ranged from **24ms** to **59ms**
- OATS performed best in terms of both outputs
- SORGHUM performed worst for both outputs

Future Work

- For future work, we will compare our DNN models' performance against SVR and Random Forests.

- We have planned to publish this research work as a journal paper.

Thank You