WWU MÜNSTER

DA2 Case Study: Forest Height

Data Exploration

Reflection Values

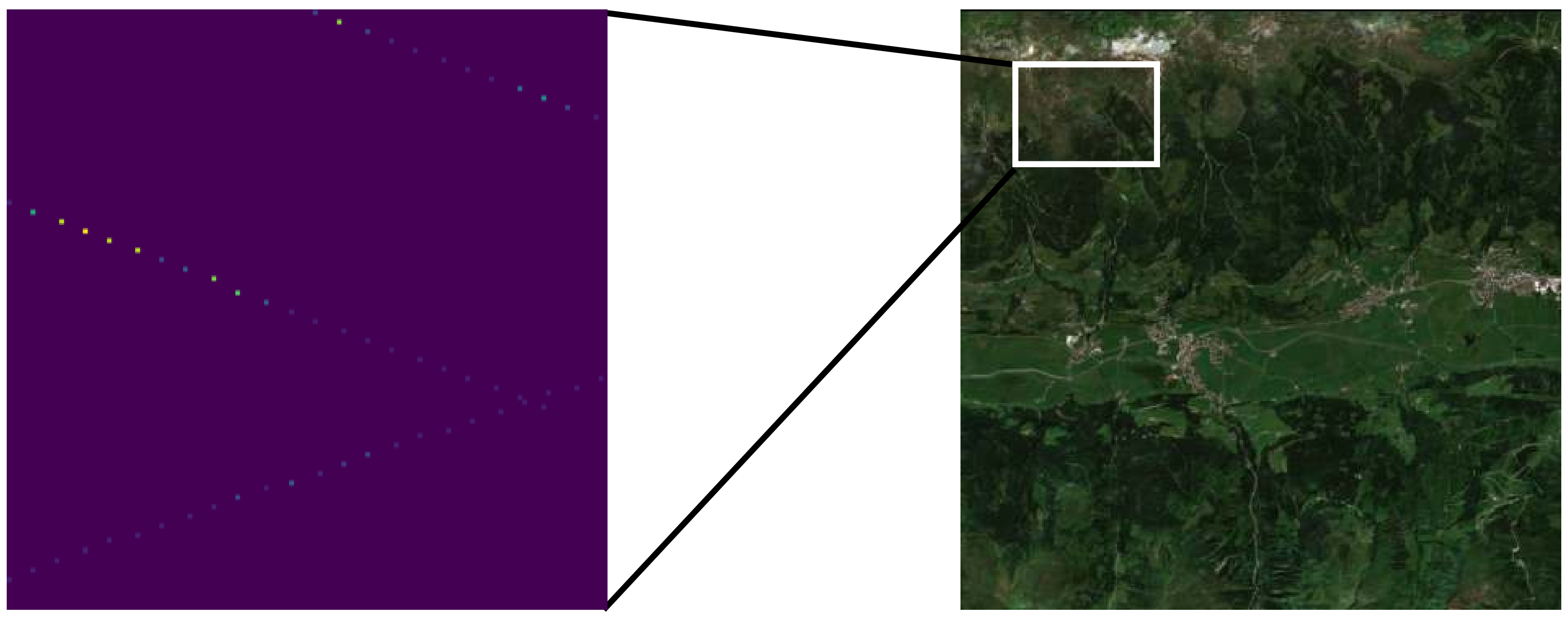
- Images have a reflection value and not image values from 0-265.
- Clouds have a much higher reflection value.
- If used raw, the models might not be able to detect the subtle differences between the lower values.

Imbalanced Dataset

- Tree height: many smaller trees and few larger ones.
- Models tend to predict around the median tree height.

Labels

- Sparse labels (38.863 in all 40 1024x1024px images).
- Insufficient for complete training.



Model Selection and Training

Boosted Trees, Decision Trees, Random Forest

- Grid and Random Search is used to identify best hyperparameters and yield the best possible models.
- Explored performance of models with additional features as Vegetation Indices NDVI, EVI, SAVI, IRECI, S2REP.
- B3 is the most significant feature.

Boosted Trees

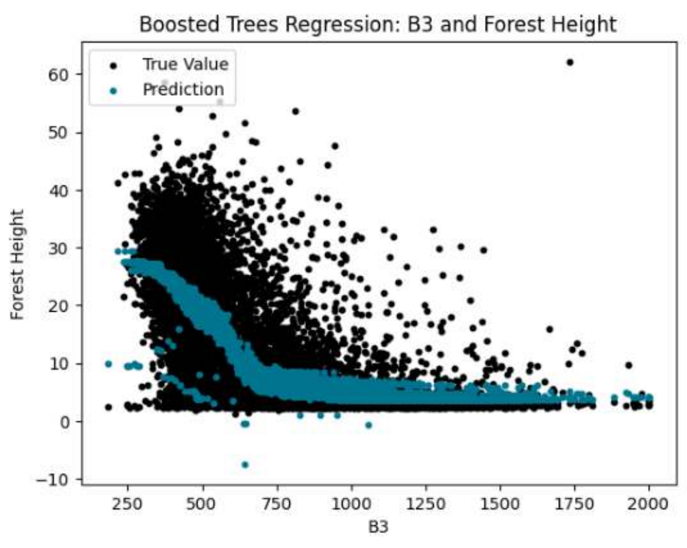
- Not brave enough to predict too far off mean.
- MAE = 4.8852

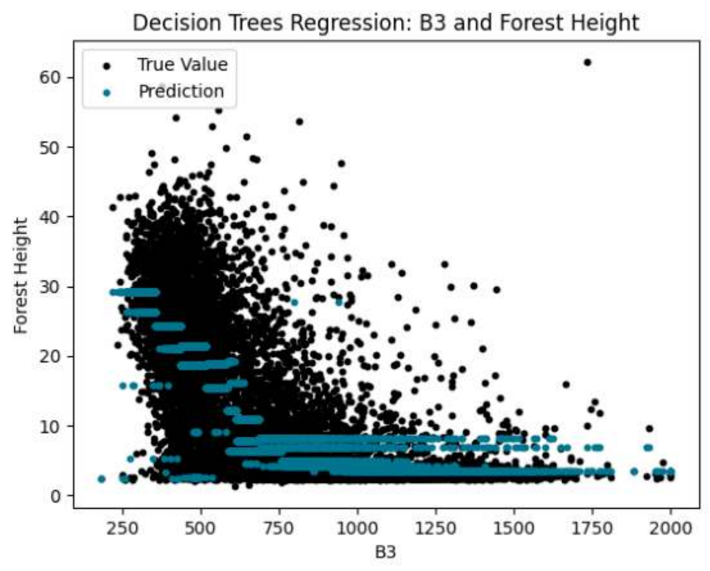
Decision Trees

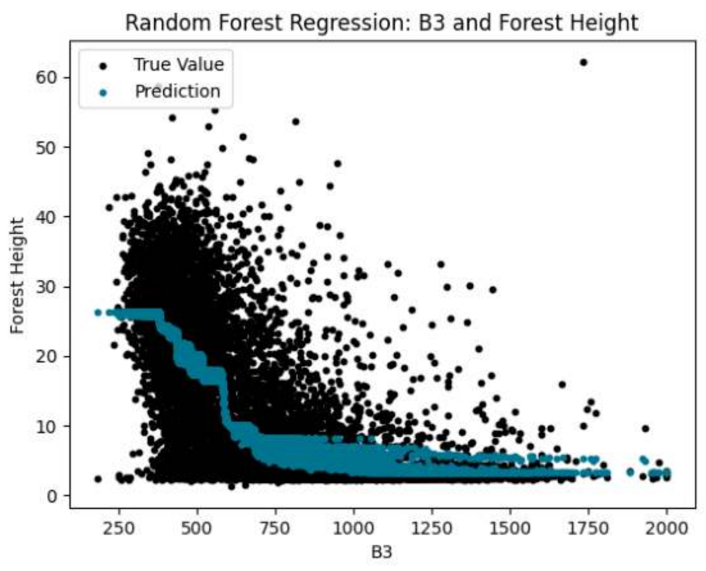
- Predicts whole spectrum of tree heights.
- MAE = 4.7857

Random Forest

- Predicts whole spectrum of tree heights.
- MAE = 4.9591





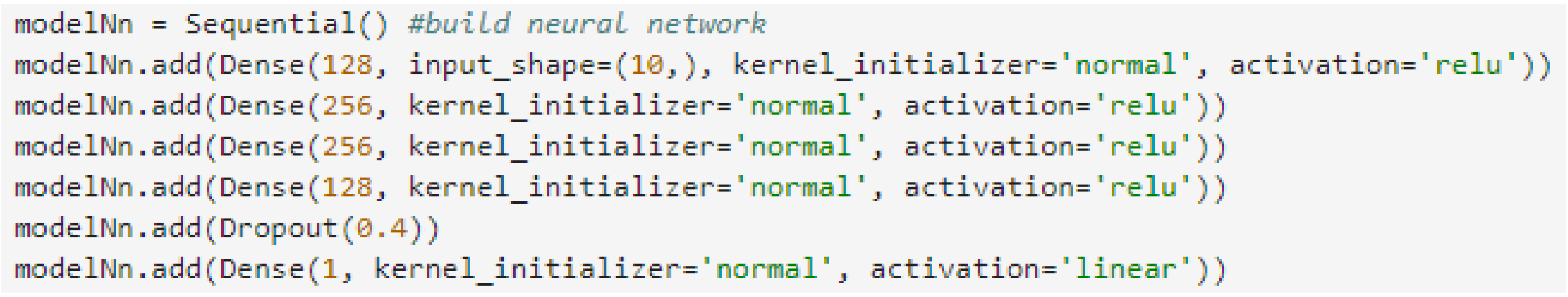


Neural Network, Convolutional Neural Network

- Preprocessing results in 38.531 patches.
- Sliding window: Computationally challenging.

Neural Network

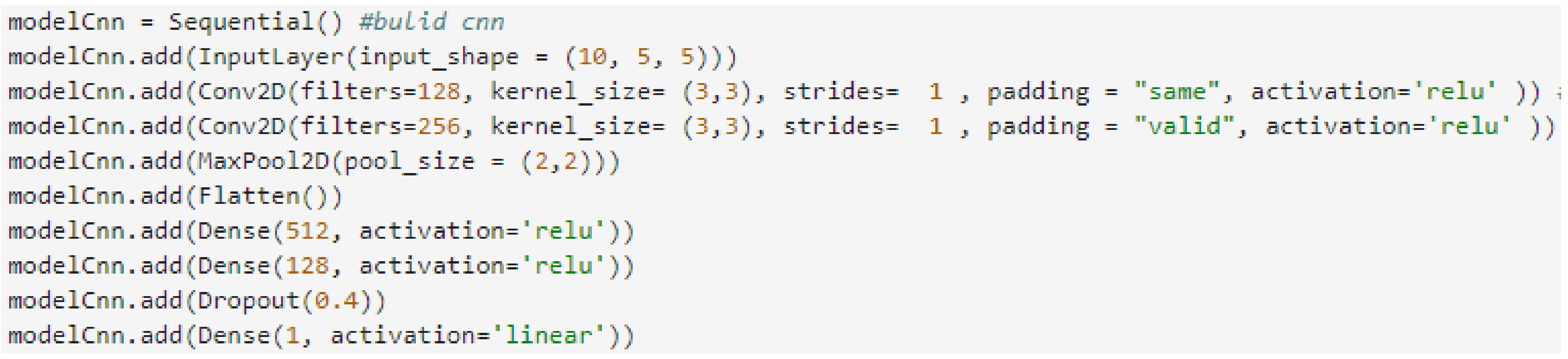
- MAE = 4.43, MAPE = 0.49



```
modelNn = Sequential() #build neural network
modelNn.add(Dense(128, input_shape=(10,), kernel_initializer='normal', activation='relu'))
modelNn.add(Dense(256, kernel_initializer='normal', activation='relu'))
modelNn.add(Dense(256, kernel_initializer='normal', activation='relu'))
modelNn.add(Dense(128, kernel_initializer='normal', activation='relu'))
modelNn.add(Dropout(0.4))
modelNn.add(Dense(1, kernel_initializer='normal', activation='linear'))
```

Convolutional Neural Network

- MAE = 4.145, MAPE = 0.473



```
modelCnn = Sequential() #bulid cnn
modelCnn.add(InputLayer(input_shape = (10, 5, 5)))
modelCnn.add(Conv2D(filters=128, kernel_size= (3,3), strides=  1 , padding = "same", activation='relu' ))
modelCnn.add(Conv2D(filters=256, kernel_size= (3,3), strides=  1 , padding = "valid", activation='relu' ))
modelCnn.add(MaxPool2D(pool_size = (2,2)))
modelCnn.add(Flatten())
modelCnn.add(Dense(512, activation='relu'))
modelCnn.add(Dense(128, activation='relu'))
modelCnn.add(Dropout(0.4))
modelCnn.add(Dense(1, activation='linear'))
```

Data Preparation

Group

Reflection Values

- Not relevant for us → ceiling irrelevant values off at 2000.

Labels

- Extracting all the labels and corresponding features.
- Training multiple models on given labels.
- Comparing approaches (observing what values do the models predict).

Cropping

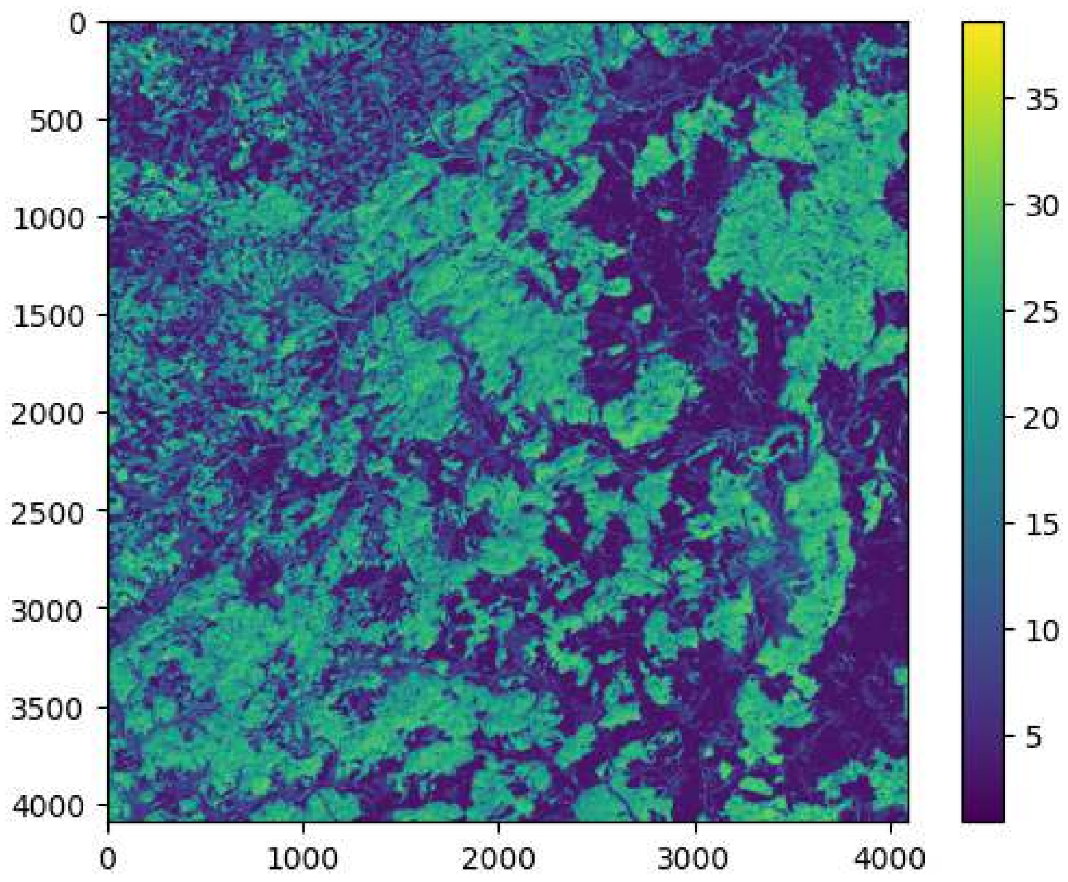
- Cropping to smaller sub-images (1024 x 1024 px).
- Cropping (10, 5, 5) feature patches where the label is in the middle → used for training of CNN.
- Computing the mean of every feature in one patch → used for training NN.

Evaluation

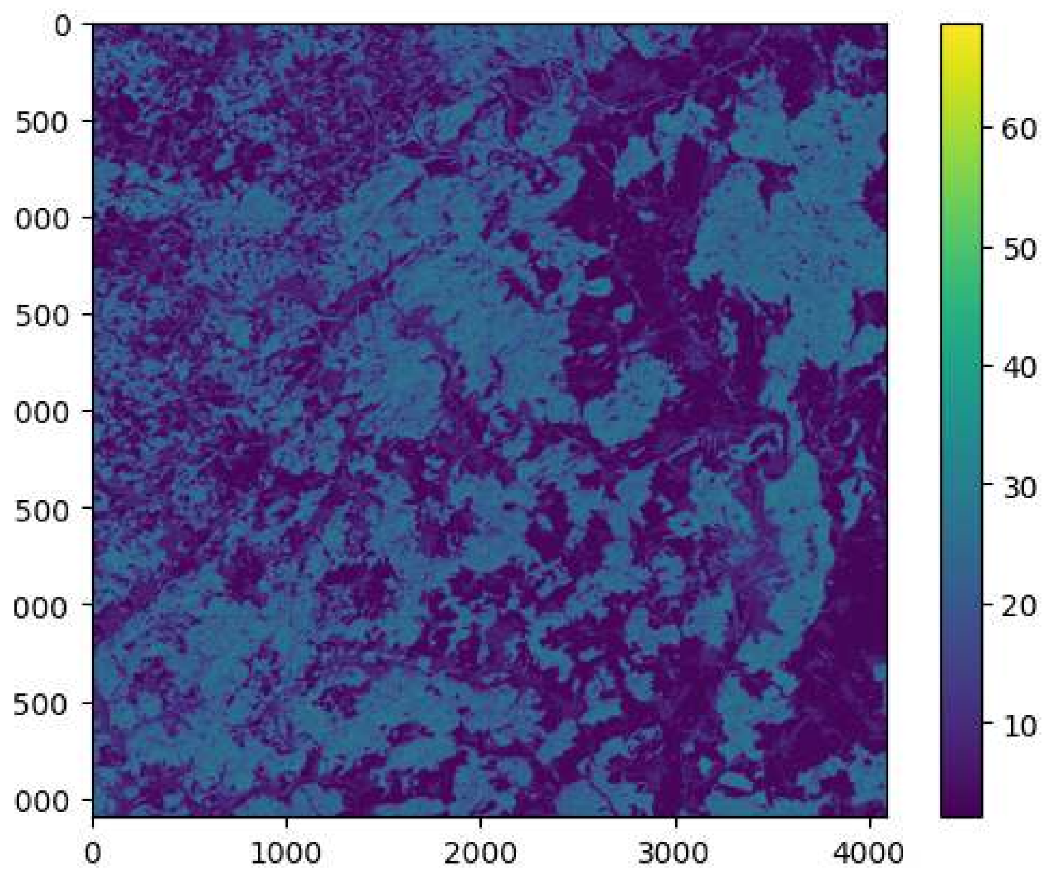
Comparing Convolutional Neural Network to Neural Network:

- Both models can identify canopy properly and can distinguish between canopy and other landscape;
- Both models have a clear lower limit (both ~ 2.8m);
- CNN can predict higher values (CNN: 68m, NN: 38m);
- CNN has higher median.

Neural Network



Convolutional Neural Network



Percentiles	Neural Network	Convolutional Neural Network
0.01	2.7815	2.8542
0.25	3.0449	2.9289
0.50	10.8947	12.2923
0.75	23.8498	23.5796
0.99	31.0686	30.5754

Summary & Outlook

CNN works best ! → Used for supplementing sparse labels by predicting all pixels.

Stacking

Considering all models by combining their predictions. Ensemble a model and weight each prediction based on the model's overall accuracy relative to the accuracy of the other models. Leveraging the strength of each model would potentially result in higher level of accuracy.

Data Augmentation

Giving CNN model more data to learn from (random flipping and rotation).

Equally Distributed Dataset

Grouping tree heights by a 3m interval → down- and upsampling over- and under-represented groups to create equally distributed training data.

Standardization of features

living.knowledge

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