CISC3024 Machine Learning Final Project

- Title: Wound Detection
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```
In [157... # Basics
         import os
         import random
         import cv2
         import copy
         import time
         from itertools import product
         from typing import List, Callable, Any, Union
         # Pre-processing
         import matplotlib.pyplot as plt
         import matplotlib.patches as mpatches
         import matplotlib.lines as mlines
         from PIL import Image
         import numpy as np
         from sklearn.metrics import mean_squared_error
         import pandas as pd
         # Model Training
         import pickle
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.svm import SVR
         from sklearn.model_selection import KFold
 In [2]: model_path = "./models"
```

1. Dataset

1.1 Data Retrieval

```
In [3]: def get_labels(data_type: str) -> np.ndarray:
             Get ground truth labels from .csv file.
             :param data_type: Type of data: Training or Testing.
             df = pd.read_csv(f"./Wound/{data_type}/myData.csv", delimiter=";")
             return df.to_numpy()
In [46]: def get images(data_type: str,
                        image_names: np.ndarray,
                        augmentation: Union[Callable[[np.ndarray, Any], np.ndarray], None] = None,
                        flatten=True,
                        resize=True,
                        **kwargs) -> np.ndarray:
             Get the images from directory.
             :param data_type: Type of data: Training or Testing.
             :param image_names: Names of images from ground truth.
             :param augmentation: Augmentation function.
             :param flatten: Whether to flatten the images.
             :param kwargs: Other arguments to pass to augmentation function.
             images = []
             for i name in image names:
                 img = Image.open(os.path.join(f"./Wound/{data_type}/", i_name))
                 if resize:
                    img = img.resize((32, 32), Image.BICUBIC)
                 img = np.array(img)
                 if augmentation:
                     img = augmentation(img, **kwargs)
                 images.append(img.flatten() if flatten else img)
             images = np.array(images)
             return images
```

1.2 Image Augmentation

```
In [5]: def add black edge(img: np.array, w: int = 4) -> np.array:
            Image augmentation. Add an inner black edge to an image.
            :param img: Image to be processed.
            :param w: Width of the edge.
            if w > min(img.shape[0:2]) // 2:
                raise ValueError("Width of the edge must be smaller than half of the shorter side of an image.")
            new_img = np.zeros_like(img)
            new_img[w:-w, w:-w, :] = img[w:-w, w:-w, :]
            return new_img
In [6]: def stretch(img: np.ndarray, f: List[float]) -> np.ndarray:
            Image augmentation. Stretch an image on the width and height side.
            :param img: Image to be augmented.
            :param f: Factor tuple. Width and Height.
            fw. fh = f
            if fw < 1 or fh < 1:
                raise ValueError("Width and height factors should be greater than or equal to 1.")
            # New widths
            new width = int(img.shape[1] * fw)
            new_height = int(img.shape[0] * fh)
            # Adjust image
            img pil = Image.fromarray(img)
            img_resized = img_pil.resize((new_width, new_height), Image.BICUBIC)
            # Crop regions
            # Keep 32x32 size
            left = (new\_width - 32) // 2
            top = (new height - 32) // 2
            right = left + 32
            bottom = top + 32
            # Crop image
            img_cropped = img_resized.crop((left, top, right, bottom))
            # Convert to numpy array
            img_stretched = np.array(img_cropped)
            return img_stretched
```

2. Train Model

One trainig of model would result in the following structure:

```
"x": {
    "Best MSE": smallest_mse,
    "Best Fold": best_fold_idx,
    "Avg MSE": avg mse,
    "model": ModelInstance,
    "Best MSE": smallest mse,
    "Best Fold": best fold idx,
    "Avg MSE": avg mse,
    "model": ModelInstance,
    "Best MSE": smallest mse,
    "Best Fold": best fold idx,
    "Avg MSE": avg_mse,
    "model": ModelInstance,
},
"h": {
    "Best MSE": smallest mse,
    "Best Fold": best fold idx,
    "Avg MSE": avg_mse,
    "model": ModelInstance,
},
```

This is named as an "experiment object".

```
In [195... def train(ModelInstance, X, Y, desc: str = "DESC", n_fold: int = 3, save: bool = False):
             Train the model. Output would be of shape:
             :param ModelInstance: Instance of a model class.
             :param X: Image data.
             :param Y: Image file name, x, y, w, h.
             :param desc: Description of the saved file.
             :param n fold: Number of folds for cross-validation.
             :param save: Whether to save the experiment object.
             model_name = ModelInstance.__class__.
             semantic_y = ["File Name", "x", "y", "w", "h"]
             # Print Model configurations
             print(f"Training model {model name}. Description: {desc}\nStarted at: {time.time()}")
             # Predict all for x, y, w, h
             exp = \{\}
             for i in range(1, Y.shape[1]):
                 # Totally 4 labels to predict.
                 # Select one of them.
                 y = Y[:, i]
                 # Split original data into 3 parts
                 # to perform cross-validation
                 kf = KFold(n splits=n fold, shuffle=True, random state=1919810)
                 splits = kf.split(X)
                 # Record MSE of each fold.
                 # Keep the model with the smallest MSE
                 mse scores = []
                 cur best model = None
                 cur_smallest_MSE = np.inf
                 for train_index, val_index in splits:
                     X_train, X_val = X[train_index], X[val_index]
                     y train, y val = y[train index], y[val index]
                     model = copy.deepcopy(ModelInstance)
                     model.fit(X_train, y_train)
                     y_pred = model.predict(X_val)
                     mse = mean_squared_error(y_val, y_pred)
                     mse scores.append(mse)
                     if cur_smallest_MSE > mse_scores[-1]:
                         cur best model = copy.deepcopy(model)
                 exp[semantic_y[i]] = {
                      "Best MSE": cur_smallest_MSE,
                     "Best Fold": np.argmin(mse_scores),
                     "Avg MSE": np.mean(mse_scores),
                     "model": copy.deepcopy(cur_best_model)
                 del cur_best_model
                 print(f"{semantic_y[i]} - Avg MSE={np.mean(mse_scores):.4f}, "
                       f"Best MSE={np.min(mse scores):.4f} at index {np.argmin(mse scores)}")
             # Save models
             print(f"Ended at {time.time()}\n\n")
             if save:
                 time_str = str(time.time()).replace(".", "")
                 pickle.dump(exp, open(f"./save models/{model name} {desc} {time_str}.sav", "wb"))
             return exp
In [22]: def grid search(ModelClass, hyper params, hyper param names, kwarg names, **kwargs):
             Perform grid search for the given model class and hyperparameters.
             :param ModelClass: The class to instantiate the model.
             :param hyper params: The product of two lists of candidate hyperparameters.
             :hyper param names: The display name of two hyperparameters.
             :kwarg names: Names of keyword arguments to be passed into the model.
             :returns: A list of dictionaries containing hyperparameters and experiment objects.
             param exps = []
             n1, n2 = hyper param names
             kw1, kw2 = kwarg_names
             model name = ModelClass. name
             # Data Augmentation
             # Change some useless information
```

Y_ori = get_labels(data_type="Training")

```
# Add black edge
              Y be = get labels(data type="Training")
               X\_be = \texttt{get\_images}(\texttt{data\_type="Training"}, \texttt{image\_names=Y\_be[:, 0]}, \texttt{augmentation=add\_black\_edge}, \texttt{w=4}) 
              # Stretch height
              Y sh = get labels(data type="Training")
               X\_sh = \texttt{get\_images}(\texttt{data\_type="Training"}, \texttt{image\_names=Y\_sh[:, 0]}, \texttt{augmentation=stretch}, \texttt{f=[1.0, 1.05]}) 
              Y_{sh}[:, 4] *= 1.05
              # Stretch Width
              Y sw = get labels(data type="Training")
              X_sw = get_images(data_type="Training", image_names=Y_sw[:, 0], augmentation=stretch, f=[1.05, 1.0])
              Y sw[:, 3] *= 1.05
              X = np.concatenate((X ori, X be, X sh, X sw))
              Y = np.concatenate((Y ori, Y be, Y sh, Y sw))
              for param1, param2 in hyper_params:
                   # Dynamically add the hyperparameters to kwargs
                   model_kwargs = {
                       kw1: param1,
                       kw2: param2
                   model kwargs.update(kwargs)
                   model instance = ModelClass(**model kwargs)
                   \label{eq:continuous} \texttt{exp} = \texttt{train}(\texttt{model\_instance}, \ X, \ Y, \ \texttt{desc=f"\{n1\}-\{param1\}--\{n2\}-\{param2\}", \ n\_fold=3, \ save=\textbf{False})}
                   param_exps.append({
                       n1: param1,
                       n2: param2,
                       "exp": exp
                   })
              time str = str(time.time()).replace(".", "")
              pickle.dump(param\_exps, open(os.path.join(model\_path, f"\{model\_name\}_{n1}-\{n2\}_{time\_str}.sav"), "wb"))
              return param_exps
In [189... def test(exp_list, Y_test, X_test):
              Test the model's performance with test dataset.
              \hbox{:param exp\_list: List of experiment objects loaded from local files.}
              :param Y test: Image file name, x, y, w, h.
              :param X_test: Image data.
              # Y test = get labels(data_type="Test")
              # X test = get images(data type="Test", image names=Y test[:,0])
              results = []
              for i, exp in enumerate(exp_list):
                   param_name1, param_name2, _ = exp.keys()
                   param1, param2, models = list(exp.values())
                   model_x, model_y, model_w, model_h = (models["x"]["model"],
                                                             models["y"]["model"],
                                                             models["w"]["model"],
                                                             models["h"]["model"])
                   y_x, y_y, y_w, y_h = Y_test[:, 1], Y_test[:, 2], Y_test[:, 3], Y_test[:, 4]
                   y_pred_x, y_pred_y, y_pred_w, y_pred_h = (model_x.predict(X_test),
                                                                 model_y.predict(X_test),
                                                                 model w.predict(X test),
                                                                 model h.predict(X test))
                   mse_x, mse_y, mse_w, mse_h = (mean_squared_error(y_x, y_pred_x),
                                                    mean_squared_error(y_y, y_pred_y),
                                                    mean_squared_error(y_w, y_pred_w),
                                                    mean_squared_error(y_h, y_pred_h))
                   weighted_avg_mse = (mse_x + mse_y) * 0.3 + (mse_w + mse_h) * 0.2
                   results.append({
                       param_name1: param1,
                       param name2: param2,
                        "weighted avg mse": weighted avg mse
                   })
              return results
In [190... def inference(model_dict, X):
```

X_ori = get_images(data_type="Training", image_names=Y_ori[:, 0])

[190... def inference(model_dict, X):
 """
 Model inference on a single data.

3. Grid Search

3.1 Grid Search: RandomForestRegressor

minl: min_samples_leaf, Minimum sample number a leaf requires.

Hyper parameters for Random Forest Regressor:

```
    nest: n_estimators, Number of estimators.
    maxd: max_depth, Maximum Depth of the tree.
    mins: min_samples_split, Minimum sample number that allows a leaf to be split again.
```

```
In [175...
    rfr_nest = [10, 20, 30, 40, 50]
    rfr_maxd = [11, 13, 15, 17, 19]
    rfr_mins = [4, 6, 8, 10, 12]
    rfr_minl = [6, 8, 10, 12, 14]
    rfr_grid0 = product(rfr_nest, rfr_maxd)
    rfr grid1 = product(rfr mins, rfr minl)
```

3.1.1 Grid Search 0: Num Estimators + Max Deapth

```
In [9]: rfr grid0 exp = grid search(ModelClass=RandomForestRegressor,
                                     hyper_params=rfr_grid0,
                                     hyper param names=["nest", "maxd"],
                                     kwarg names=["n estimators", "max depth"])
       Training model RandomForestRegressor. Description: nest-10--maxd-11
       Started at: 1732799242.455379
       x - Avg MSE=265.0281, Best MSE=226.6704 at index 1 \,
       y - Avg MSE=319.6748, Best MSE=206.1377 at index 1
       w - Avg MSE=981.5292, Best MSE=914.7635 at index 0 \,
       h - Avg MSE=1024.7640, Best MSE=774.9044 at index 0
       Ended at 1732799277.573622
       Training model RandomForestRegressor. Description: nest-10--maxd-13
       Started at: 1732799303.3531008
       x - Avg MSE=303.6308, Best MSE=264.3288 at index 2
       y - Avg MSE=330.7782, Best MSE=254.7151 at index 1
       w - Avg MSE=1046.2773, Best MSE=935.1649 at index 0 \,
       h - Avg MSE=1015.2763, Best MSE=801.2331 at index 1
       Ended at 1732799339.3567605
       Training model RandomForestRegressor. Description: nest-10--maxd-15
       Started at: 1732799364.6094503
       x - Avg MSE=300.3605, Best MSE=246.8027 at index 2
       y - Avg MSE=316.6453, Best MSE=246.9491 at index 1
       w - Avg MSE=1039.2064, Best MSE=971.3801 at index 0 \,
       h - Avg MSE=1130.1478, Best MSE=980.0463 at index 1
       Ended at 1732799401.170166
       Training model RandomForestRegressor. Description: nest-10--maxd-17
       Started at: 1732799426.1358972
       x - Avg MSE=300.4805, Best MSE=221.9252 at index 2
       y - Avg MSE=338.9396, Best MSE=276.1063 at index 1
       w - Avg MSE=1021.4995, Best MSE=950.0199 at index \theta
       h - Avg MSE=1006.8791, Best MSE=919.2143 at index 2
       Ended at 1732799462.3547573
       Training model RandomForestRegressor. Description: nest-10--maxd-19
       Started at: 1732799486.7901278
       x - Avg MSE=302.8487, Best MSE=288.1919 at index 1
```

```
y - Avg MSE=328.5022, Best MSE=271.5901 at index 1
w - Avg MSE=1002.2346, Best MSE=857.0157 at index 0
h - Avg MSE=958.0220, Best MSE=848.5257 at index 1
Ended at 1732799523.2739859
Training model RandomForestRegressor. Description: nest-20--maxd-11
Started at: 1732799548.2014005
x - Avg MSE=285.0670, Best MSE=266.7257 at index 1
y - Avg MSE=309.2617, Best MSE=230.4450 at index 1
w - Avg MSE=812.8412, Best MSE=782.5403 at index 0 \,
h - Avg MSE=876.8053, Best MSE=744.5018 at index 0
Ended at 1732799618.3518734
Training model RandomForestRegressor. Description: nest-20--maxd-13
Started at: 1732799642.5200229
x - Avg MSE=252.7599, Best MSE=221.1697 at index 2
y - Avg MSE=298.5948, Best MSE=219.2555 at index 1
w - Avg MSE=881.0838, Best MSE=758.1520 at index 2
h - Avg MSE=787.2464, Best MSE=742.0857 at index 0
Ended at 1732799715.4098089
Training model RandomForestRegressor. Description: nest-20--maxd-15
Started at: 1732799739.9309459
x - Avg MSE=253.8009, Best MSE=203.6632 at index 2
y - Avg MSE=289.7559, Best MSE=216.9240 at index 1
w - Avg MSE=936.1498, Best MSE=894.1271 at index 0 \,
h - Avg MSE=913.3963, Best MSE=819.3239 at index 1
Ended at 1732799813.0232718
Training model RandomForestRegressor. Description: nest-20--maxd-17
Started at: 1732799838.0781047
x - Avg MSE=253.8418, Best MSE=222.3508 at index 2
y - Avg MSE=329.0912, Best MSE=246.1059 at index 1
w - Avg MSE=884.3192, Best MSE=718.6947 at index \theta
h - Avg MSE=902.8129, Best MSE=831.9966 at index 2
Ended at 1732799910.988647
Training model RandomForestRegressor. Description: nest-20--maxd-19
Started at: 1732799935.958038
x - Avg MSE=268.1530, Best MSE=228.2566 at index 2
y - Avg MSE=329.3778, Best MSE=236.9652 at index 1
w - Avg MSE=849.3705, Best MSE=713.9744 at index 0 \,
h - Avg MSE=901.6856, Best MSE=797.9166 at index 0
Ended at 1732800008.8168418
Training model RandomForestRegressor. Description: nest-30--maxd-11
Started at: 1732800033.754099
x - Avg MSE=272.9434, Best MSE=214.3267 at index 2
y - Avg MSE=309.8040, Best MSE=244.9138 at index 1
w - Avg MSE=874.0065, Best MSE=786.2825 at index 0 \,
h - Avg MSE=892.1854, Best MSE=776.4926 at index 0
Ended at 1732800138.805168
Training model RandomForestRegressor. Description: nest-30--maxd-13
Started at: 1732800162.8637316
x - Avg MSE=274.6289, Best MSE=240.6389 at index 2
y - Avg MSE=293.3156, Best MSE=201.7539 at index 1
w - Avg MSE=831.7885, Best MSE=747.1287 at index 0 \,
h - Avg MSE=793.4268, Best MSE=752.4546 at index 0
Ended at 1732800271.1492708
Training model RandomForestRegressor. Description: nest-30--maxd-15
Started at: 1732800295.3863888
x - Avg MSE=253.0778, Best MSE=208.0780 at index 1
y - Avg MSE=301.5480, Best MSE=218.6238 at index 1
w - Avg MSE=940.0108, Best MSE=835.9889 at index 0
h - Avg MSE=874.5578, Best MSE=814.1522 at index 1
Ended at 1732800404.3143518
Training model RandomForestRegressor. Description: nest-30--maxd-17
Started at: 1732800428.4378633
x - Avg MSE=278.1840, Best MSE=251.4836 at index 2
y - Avg MSE=300.7216, Best MSE=214.8380 at index 1 \,
w - Avg MSE=855.0443, Best MSE=826.7070 at index 0
h - Avg MSE=792.9134, Best MSE=750.9542 at index 0 \,
Ended at 1732800538.099123
Training model RandomForestRegressor. Description: nest-30--maxd-19
Started at: 1732800562.0520394
x - Avg MSE=220.2197, Best MSE=207.4006 at index 2
y - Avg MSE=284.1861, Best MSE=210.9069 at index 1
w - Avg MSE=854.7060, Best MSE=785.5057 at index 0
h - Avg MSE=814.5918, Best MSE=776.2419 at index 2
```

```
Training model RandomForestRegressor. Description: nest-40--maxd-11
Started at: 1732800695.766269
x - Avg MSE=251.8448, Best MSE=215.4979 at index 1
y - Avg MSE=289.9733, Best MSE=226.2858 at index 1
w - Avg MSE=896.8800, Best MSE=767.0302 at index 0
h - Avg MSE=869.4700, Best MSE=844.8714 at index 0
Ended at 1732800835.5782795
Training model RandomForestRegressor. Description: nest-40--maxd-13
Started at: 1732800860.1936045
x - Avg MSE=259.2456, Best MSE=233.5999 at index 2
y - Avg MSE=292.2659, Best MSE=208.6475 at index 1
w - Avg MSE=824.1160, Best MSE=760.9130 at index 0
h - Avg MSE=806.5849, Best MSE=778.1615 at index 0
Ended at 1732801004.565523
Training model RandomForestRegressor. Description: nest-40--maxd-15
Started at: 1732801029.0618072
x - Avg MSE=244.2120, Best MSE=226.4907 at index 1
y - Avg MSE=291.8532, Best MSE=225.0804 at index 1
w - Avg MSE=868.4658, Best MSE=724.4030 at index 0
h - Avg MSE=781.5694, Best MSE=727.7959 at index 1
Ended at 1732801210.976922
Training model RandomForestRegressor. Description: nest-40--maxd-17
Started at: 1732801254.3320477
x - Avg MSE=234.3425, Best MSE=200.5500 at index 2
y - Avg MSE=286.3102, Best MSE=221.9404 at index 1 \,
w - Avg MSE=862.7032, Best MSE=726.3788 at index 0
h - Avg MSE=865.5574, Best MSE=813.9664 at index 0
Ended at 1732801497.655775
Training model RandomForestRegressor. Description: nest-40--maxd-19
Started at: 1732801539.3561637
x - Avg MSE=242.0519, Best MSE=206.8850 at index 2
y - Avg MSE=293.3265, Best MSE=227.6444 at index 1
w - Avg MSE=868.8398, Best MSE=772.2479 at index 0
h - Avg MSE=881.9131, Best MSE=807.3104 at index 0
Ended at 1732801778.9195538
Training model RandomForestRegressor. Description: nest-50--maxd-11
Started at: 1732801819.7143903
x - Avg MSE=270.1062, Best MSE=244.6453 at index 1
y - Avg MSE=284.4660, Best MSE=222.7727 at index \boldsymbol{1}
w - Avg MSE=889.8490, Best MSE=768.3454 at index 0
h - Avg MSE=836.6008, Best MSE=804.7312 at index 0
Ended at 1732802107.0316658
Training model RandomForestRegressor. Description: nest-50--maxd-13
Started at: 1732802147.970842
x - Avg MSE=241.5700, Best MSE=213.1301 at index 2
y - Avg MSE=270.0202, Best MSE=190.1522 at index 1 \,
w - Avg MSE=847.1258, Best MSE=703.7665 at index 0
h - Avg MSE=842.7185, Best MSE=816.7929 at index 0
Ended at 1732802444.4113607
Training model RandomForestRegressor. Description: nest-50--maxd-15
Started at: 1732802485.3644946
x - Avg MSE=253.3668, Best MSE=212.1847 at index 2
y - Avg MSE=285.6002, Best MSE=196.1240 at index 1
w - Avg MSE=826.6384, Best MSE=753.8100 at index 2
h - Avg MSE=823.7715, Best MSE=784.7041 at index 1
Ended at 1732802781.4783213
Training model RandomForestRegressor. Description: nest-50--maxd-17
Started at: 1732802823.8504105
x - Avg MSE=255.9907, Best MSE=225.8875 at index 2
y - Avg MSE=285.5330, Best MSE=213.0238 at index 1
w - Avg MSE=865.0635, Best MSE=841.2231 at index 0
h - Avg MSE=821.2326, Best MSE=761.4187 at index 2
Ended at 1732803122.3551664
Training model RandomForestRegressor. Description: nest-50--maxd-19
Started at: 1732803163.495206
x - Avg MSE=253.7331, Best MSE=223.8237 at index 1
y - Avg MSE=275.0223, Best MSE=196.7816 at index 1
w - Avg MSE=862.6752, Best MSE=767.1612 at index 0
h - Avg MSE=864.4260, Best MSE=791.0012 at index 0
Ended at 1732803463.0916922
```

```
rfr grid0 exp loaded = pickle.load(rfr grid0 exp f)
In [103... Y test = get labels(data type="Test")
            X_test = get_images(data_type="Test", image_names=Y_test[:,0])
            rfr grid0 results = test(exp list=rfr grid0 exp loaded, Y test=Y test, X test=X test)
In [104... rfr grid0 results
Out[104... [{'nest': 10, 'maxd': 11, 'weighted avg mse': np.float64(1037.866711863164)},
             {'nest': 10, 'maxd': 19, 'weighted avg mse': np.float64(1210.9086421250008)},
              {'nest': 20, 'maxd': 11, 'weighted_avg_mse': np.float64(1041.9624518709904)}, 
{'nest': 20, 'maxd': 13, 'weighted_avg_mse': np.float64(1131.6653485552738)}, 
{'nest': 20, 'maxd': 15, 'weighted_avg_mse': np.float64(1081.842526424827)},
              {'nest': 20, 'maxd': 17, 'weighted_avg_mse': np.float64(1022.9588525584991)},
              {'nest': 20, 'maxd': 19, 'weighted_avg_mse': np.float64(1022.3114634687497)}, {'nest': 30, 'maxd': 11, 'weighted_avg_mse': np.float64(1002.6387328184359)}, {'nest': 30, 'maxd': 13, 'weighted_avg_mse': np.float64(978.7584204580128)},
              {'nest': 30, 'maxd': 15, 'weighted avg mse': np.float64(1027.4104595490564)},
              {'nest': 30, 'maxd': 17, 'weighted_avg_mse': np.float64(997.9180385277775)}, 
{'nest': 30, 'maxd': 17, 'weighted_avg_mse': np.float64(977.6827556527779)}, 
{'nest': 40, 'maxd': 11, 'weighted_avg_mse': np.float64(979.8591202866849)},
              {'nest': 40, 'maxd': 15, 'weighted_avg_mse': np.float64(995.2617179147078)}, 
{'nest': 40, 'maxd': 17, 'weighted_avg_mse': np.float64(1008.430395293182)}, 
{'nest': 40, 'maxd': 19, 'weighted_avg_mse': np.float64(1009.1554874687499)},
              {'nest': 50, 'maxd': 11, 'weighted_avg_mse': np.float64(1003.441016700693)},
              {'nest': 50, 'maxd': 13, 'weighted_avg_mse': np.float64(1026.1017976872838)}, {'nest': 50, 'maxd': 15, 'weighted_avg_mse': np.float64(990.8895085709411)}, {'nest': 50, 'maxd': 17, 'weighted_avg_mse': np.float64(979.7050705067662)},
              {'nest': 50, 'maxd': 19, 'weighted avg mse': np.float64(1065.0097557450013)}]
In [105... rfr grid0 mean = np.mean([res["weighted avg mse"] for res in rfr grid0 results])
            rfr grid0 best = min(rfr grid0 results, key=lambda x: x["weighted avg mse"])
            print(f"Best:{rfr_grid0_best}\nDiff:{rfr_grid0_best["weighted_avg_mse"]-rfr_grid0_mean}")
           Best:{'nest': 30, 'maxd': 19, 'weighted avg mse': np.float64(977.6827556527779)}
           Diff: -66.33404769846572
            3.1.2 Grid Search 1: Min Samples Split, Min Samples Leaf
In [63]: rfr grid1 exp = grid search(ModelClass=RandomForestRegressor,
                                                 hyper_params=rfr_grid1,
                                                 hyper param names=["mins", "minl"],
                                                 kwarg_names=["min_samples_split", "min_samples leaf"],
                                                 # Settled Parameters
                                                 n estimators=30,
                                                 max_depth=19)
```

Training model RandomForestRegressor. Description: mins-4--minl-6 Started at: 1732856800.760463 x - Avg MSE=326.0675, Best MSE=280.6331 at index 1 y - Avg MSE=327.7088, Best MSE=258.5277 at index 1 w - Avg MSE=1074.9534, Best MSE=991.6896 at index 0 h - Avg MSE=1065.0379, Best MSE=880.3963 at index 0 Ended at 1732856888.760798

Training model RandomForestRegressor. Description: mins-4--minl-8 Started at: 1732856888.760947 x - Avg MSE=338.8816, Best MSE=293.7372 at index 2 y - Avg MSE=363.2080, Best MSE=275.7450 at index 1w - Avg MSE=1130.0578, Best MSE=1012.6302 at index 0 h - Avg MSE=1093.0109, Best MSE=1006.7138 at index 2 Ended at 1732856968.4516952

Training model RandomForestRegressor. Description: mins-4--minl-10 Started at: 1732856968.451767 x - Avg MSE=362.3157, Best MSE=326.9200 at index 1 y - Avg MSE=390.4445, Best MSE=299.2935 at index 1

w - Avg MSE=1202.0076, Best MSE=1027.7504 at index 0 $\,$ h - Avg MSE=1182.0632, Best MSE=1125.1176 at index 0 Ended at 1732857042.551244

Training model RandomForestRegressor. Description: mins-4--minl-12 Started at: 1732857042.551657 x - Avg MSE=387.2047, Best MSE=347.7490 at index 2 y - Avg MSE=457.0623, Best MSE=380.3171 at index 1 $\,$

w - Avg MSE=1349.5902, Best MSE=1210.3508 at index 0

Started at: 1732857110.712325

Training model RandomForestRegressor. Description: mins-4--minl-14

```
x - Avg MSE=414.6892, Best MSE=378.5784 at index 1 y - Avg MSE=448.2827, Best MSE=374.3078 at index 1
w - Avg MSE=1494.3689, Best MSE=1260.2119 at index 0
h - Avg MSE=1376.1246, Best MSE=1088.9423 at index 0
Ended at 1732857174.1005042
Training model RandomForestRegressor. Description: mins-6--minl-6
Started at: 1732857174.100596
x - Avg MSE=308.1539, Best MSE=277.8514 at index 1
y - Avg MSE=333.9432, Best MSE=255.1904 at index 1
w - Avg MSE=999.9675, Best MSE=882.3105 at index 0
h - Avg MSE=1008.4652, Best MSE=964.5096 at index 2
Ended at 1732857262.3876858
Training model RandomForestRegressor. Description: mins-6--minl-8
Started at: 1732857262.388395
x - Avg MSE=335.1505, Best MSE=309.3420 at index 2
y - Avg MSE=357.5733, Best MSE=282.5742 at index 1
w - Avg MSE=1131.7024, Best MSE=1015.0260 at index 0
h - Avg MSE=1110.7058, Best MSE=1039.7166 at index 0
Ended at 1732857343.509079
Training model RandomForestRegressor. Description: mins-6--minl-10
Started at: 1732857343.50933
x - Avg MSE=384.0030, Best MSE=352.8803 at index 2
y - Avg MSE=399.1749, Best MSE=328.0118 at index 1
w - Avg MSE=1229.0135, Best MSE=1135.7809 at index 0 \,
h - Avg MSE=1225.1177, Best MSE=1127.3294 at index 0
Ended at 1732857417.773901
Training model RandomForestRegressor. Description: mins-6--minl-12
Started at: 1732857417.774088
x - Avg MSE=382.8800, Best MSE=363.1657 at index 1
y - Avg MSE=432.5145, Best MSE=354.1876 at index 1
w - Avg MSE=1313.8871, Best MSE=1160.9318 at index 0
h - Avg MSE=1277.1958, Best MSE=1226.2863 at index 2
Ended at 1732857485.851247
Training model RandomForestRegressor. Description: mins-6--minl-14
Started at: 1732857485.851352
x - Avg MSE=428.1227, Best MSE=385.7580 at index 1
y - Avg MSE=452.1929, Best MSE=377.2100 at index 1
w - Avg MSE=1428.0822, Best MSE=1288.4722 at index 0 \,
h - Avg MSE=1358.7429, Best MSE=1216.5172 at index 0
Ended at 1732857549.002858
Training model RandomForestRegressor. Description: mins-8--minl-6
Started at: 1732857549.002997
x - Avg MSE=306.8516, Best MSE=292.9354 at index 2
y - Avg MSE=327.1679, Best MSE=252.7554 at index 1
w - Avg MSE=1046.2740, Best MSE=917.5920 at index 0
h - Avg MSE=960.6163, Best MSE=889.5745 at index 0
Ended at 1732857637.7303722
Training model RandomForestRegressor. Description: mins-8--minl-8
Started at: 1732857637.730516
x - Avg MSE=360.6055, Best MSE=298.0623 at index 1
y - Avg MSE=366.3725, Best MSE=271.5181 at index 1
w - Avg MSE=1169.0414, Best MSE=1074.6156 at index 2
h - Avg MSE=1104.9641, Best MSE=1032.8115 at index 2
Ended at 1732857719.070292
Training model RandomForestRegressor. Description: mins-8--minl-10
Started at: 1732857719.070383
x - Avg MSE=355.6136, Best MSE=318.7152 at index 2
y - Avg MSE=394.2206, Best MSE=300.6892 at index 1
w - Avg MSE=1264.0395, Best MSE=1032.7116 at index 0
h - Avg MSE=1225.3672, Best MSE=1126.8638 at index 0
Ended at 1732857793.819081
```

```
Started at: 1732857793.819297
x - Avg MSE=389.9695, Best MSE=354.9138 at index 1
y - Avg MSE=430.5395, Best MSE=364.4108 at index 1
w - Avg MSE=1366.1019, Best MSE=1225.0655 at index 0
h - Avg MSE=1260.9887, Best MSE=1031.0237 at index 0
Ended at 1732857862.781905
Training model RandomForestRegressor. Description: mins-8--minl-14
Started at: 1732857862.782188
x - Avg MSE=430.4666, Best MSE=392.7796 at index 1 \,
y - Avg MSE=466.1909, Best MSE=358.7826 at index 1
w - Avg MSE=1477.8265, Best MSE=1271.8621 at index 0
h - Avg MSE=1375.9559, Best MSE=1204.4168 at index 0
Ended at 1732857926.73861
Training model RandomForestRegressor. Description: mins-10--minl-6
Started at: 1732857926.738683
x - Avg MSE=299.8077, Best MSE=277.9532 at index 2
y - Avg MSE=340.3186, Best MSE=256.9503 at index 1
w - Avg MSE=1105.3671, Best MSE=987.2962 at index 2
h - Avg MSE=1047.4830, Best MSE=938.0438 at index 0
Ended at 1732858015.5977721
Training model RandomForestRegressor. Description: mins-10--minl-8
Started at: 1732858015.597964
x - Avg MSE=331.7604, Best MSE=303.7267 at index 2
y - Avg MSE=368.8866, Best MSE=270.4076 at index 1
w - Avg MSE=1190.1597, Best MSE=1055.7868 at index 0
h - Avg MSE=1051.5489, Best MSE=1004.2388 at index 0
Ended at 1732858094.962867
Training model RandomForestRegressor. Description: mins-10--minl-10
Started at: 1732858094.963012
x - Avg MSE=355.7016, Best MSE=322.3980 at index 2
y - Avg MSE=375.9516, Best MSE=307.6887 at index 1
w - Avg MSE=1236.8031, Best MSE=1109.8976 at index 2
h - Avg MSE=1217.0728, Best MSE=1066.2648 at index 0
Ended at 1732858168.1504462
Training model RandomForestRegressor. Description: mins-10--minl-12
Started at: 1732858168.150672
x - Avg MSE=412.5593, Best MSE=359.6623 at index 2
y - Avg MSE=415.5667, Best MSE=349.6455 at index 1
w - Avg MSE=1354.4408, Best MSE=1166.7235 at index 0
h - Avg MSE=1227.3570, Best MSE=1103.0337 at index 0
Ended at 1732858235.984776
Training model RandomForestRegressor. Description: mins-10--minl-14
Started at: 1732858235.98503
x - Avg MSE=410.9545, Best MSE=387.5067 at index 1
y - Avg MSE=456.5057, Best MSE=362.5386 at index 1
w - Avg MSE=1452.3753, Best MSE=1248.6713 at index 0
h - Avg MSE=1384.1886, Best MSE=1149.0275 at index 0
Ended at 1732858299.3219578
Training model RandomForestRegressor. Description: mins-12--minl-6
Started at: 1732858299.322016
x - Avg MSE=326.4791, Best MSE=298.2585 at index 1
y - Avg MSE=322.2471, Best MSE=246.9821 at index 1
w - Avg MSE=1024.0750, Best MSE=875.6955 at index 0
h - Avg MSE=1012.1551, Best MSE=953.1265 at index 0 \,
Ended at 1732858387.542382
Training model RandomForestRegressor. Description: mins-12--minl-8
Started at: 1732858387.542625
x - Avg MSE=348.1009, Best MSE=329.1898 at index 2
y - Avg MSE=372.8824, Best MSE=272.7803 at index 1
w - Avg MSE=1175.6590, Best MSE=985.4241 at index 0
h - Avg MSE=1065.9766, Best MSE=954.0569 at index 0 \,
```

Ended at 1732858467.993131

Training model RandomForestRegressor. Description: mins-8--minl-12

```
Started at: 1732858467.993502
        x - Avg MSE=360.7314, Best MSE=324.7620 at index 2
        y - Avg MSE=397.6804, Best MSE=309.2426 at index 1
        w - Avg MSE=1221.0095, Best MSE=1083.7336 at index 2
        h - Avg MSE=1124.3736, Best MSE=985.6330 at index 0
        Ended at 1732858539.8387918
        Training model RandomForestRegressor. Description: mins-12--minl-12
        Started at: 1732858539.838901
        x - Avg MSE=396.6108, Best MSE=370.1791 at index 1
        y - Avg MSE=423.5424, Best MSE=344.7904 at index 1
        w - Avg MSE=1406.9043, Best MSE=1255.5046 at index 0
        h - Avg MSE=1316.6607, Best MSE=1147.2850 at index 0
        Ended at 1732858606.793222
        Training model RandomForestRegressor. Description: mins-12--minl-14
        Started at: 1732858606.7932742
        x - Avg MSE=400.5662, Best MSE=364.5680 at index 2
        y - Avg MSE=457.6092, Best MSE=360.0932 at index 1
        w - Avg MSE=1432.8053, Best MSE=1209.0362 at index 0
        h - Avg MSE=1351.3050, Best MSE=1192.4676 at index 0
        Ended at 1732858670.543082
In [129... with open(os.path.join(model path, "RandomForestRegressor mins-minl 173285867054318.sav"), "rb") as rfr gridl ex
             rfr grid1 exp loaded = pickle.load(rfr grid1 exp f)
In [130. rfr grid1 exp loaded
Out[130... [{'mins': 4,
            'minl': 6,
            'exp': {'x': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(326.06745338827005),
              'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=4,
                                    n estimators=30)},
             'y': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(327.70875259964413),
              'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=4,
                                    n estimators=30)},
             'w': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(1074.9533748950205),
              'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=4,
                                    n estimators=30)},
             'h': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(1065.0378871162209),
              'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=4,
                                    n_estimators=30)}}},
           {'mins': 4,
            'minl': 8.
            'exp': {'x': {'Best MSE': inf,
              'Best Fold': np.int64(2),
              'Avg MSE': np.float64(338.88161377775975),
              'model': RandomForestRegressor(max_depth=19, min_samples_leaf=8, min_samples_split=4,
                                    n estimators=30)},
             'y': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(363.20795886109227),
              'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=4,
                                    n estimators=30)},
             'w': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(1130.0577615012533),
              'model': RandomForestRegressor(max_depth=19, min_samples_leaf=8, min_samples_split=4,
                                    n estimators=30)},
             'h': {'Best MSE': inf,
              'Best Fold': np.int64(2),
              'Avg MSE': np.float64(1093.0108751455793),
              'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=4,
                                    n estimators=30)}}},
           {'mins': 4,
            'minl': 10,
             exp': {'x': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(362.3157194593953),
              'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=4,
```

Training model RandomForestRegressor. Description: mins-12--minl-10

```
n estimators=30)}.
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(390.4444703648881),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=4,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1202.007618379573),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=10, min_samples_split=4,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1182.0631734605765),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=4,
                         n estimators=30)}}}.
{'mins': 4,
 'minl': 12,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(387.20468317601643),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=12, min_samples_split=4,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(457.0623033138475),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=4,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1349.5902237054179),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=4,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1321.2614176327272),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=4,
                         n_estimators=30)}}},
{'mins': 4,
 'minl': 14,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(414.6892158533924),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=14, min_samples_split=4,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(448.28271511739257),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=4,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1494.3688645655095),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=4,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1376.1245549369203),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=4,
                         n estimators=30)}}},
{'mins': 6,
 'minl': 6,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(308.1539217794009),
   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=6,
                         n_estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(333.9431873164692),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=6,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(999.967472812004),
   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=6,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(1008.4652080089289),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=6,
                         n estimators=30)}}},
{'mins': 6.
```

```
'minl': 8,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(335.15048527944515),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=6,
                         n estimators=30)},
  'v': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(357.57333379527955),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=8, min_samples_split=6,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1131.7023522789088),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=6,
                         n estimators=30)}.
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1110.7058175888708),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=8, min_samples_split=6,
                         n estimators=30)}}},
{'mins': 6,
 'minl': 10,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(384.0030157165013),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=6,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(399.1748523740218),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=6,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1229.0134895620104),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=6,
                         n_estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1225.1177214192164),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=6,
                         n estimators=30)}}},
{'mins': 6,
 'minl': 12,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(382.8800231967921),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=6,
                         n estimators=30)}.
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(432.51449560196966),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=6,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1313.8871474541636),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=6,
                         n estimators=30)}.
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(1277.195780774294),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=6,
                         n_estimators=30)}}},
{'mins': 6,
 'minl': 14,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(428.1226832540919),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=14, min_samples_split=6,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(452.19290342281937),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=6,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0).
   'Avg MSE': np.float64(1428.0822107367776),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=14, min_samples_split=6,
                         n estimators=30)},
  'h': {'Best MSE': inf,
```

```
'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1358.7428695821561),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=6,
                         n_estimators=30)}}},
{'mins': 8,
 'minl': 6,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(306.85158877880417),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=8,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(327.1678643860244),
   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=8,
                         n estimators=30)}.
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1046.273989049578),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=8,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(960.6163423888355),
   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=8,
                         n estimators=30)}}},
{'mins': 8,
 'minl': 8.
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                         n estimators=30)},
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                         n_estimators=30)},
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   'Best Fold': np.int64(2).
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                         n estimators=30)},
  'h': {'Best MSE': inf.
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(1104.964060406972).
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=8,
                         n estimators=30)}}},
{'mins': 8,
 'minl': 10,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
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                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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                         n estimators=30)}.
  'w': {'Best MSE': inf,
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                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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                         n estimators=30)}}},
{'mins': 8,
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 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=8,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(430.539461402906),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=12, min_samples_split=8,
                         n estimators=30)},
  'w': {'Best MSE': inf,
```

```
'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1366.1019401741187),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=8,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1260.9886560840166),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=8,
                         n estimators=30)}}},
{'mins': 8,
 'minl': 14,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(430.4666414007852),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=8,
                         n estimators=30)}.
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(466.1908778836112),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=14, min_samples_split=8,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1477.8264851209715),
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                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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{'mins': 10,
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   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=10,
                         n_estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(340.31863106658733),
   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=10,
                         n estimators=30)},
  'w': {'Best MSE': inf.
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(1105.3671235851016).
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                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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                         n estimators=30)}}},
{'mins': 10,
 'minl': 8,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
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   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=10,
                         n estimators=30)}.
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(368.88656847103715),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=10,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1190.1596522473353),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=8, min_samples_split=10,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1051.5488568602568),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=10,
                         n estimators=30)}}},
{'mins': 10,
 'minl': 10,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
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   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=10, min_samples_split=10,
                         n estimators=30)},
  'y': {'Best MSE': inf,
```

```
'Best Fold': np.int64(1),
   'Avg MSE': np.float64(375.95156000364915),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=10,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(1236.8030800389367),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=10,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1217.0728006534935),
   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=10,
                         n estimators=30)}}},
{'mins': 10,
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   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(412.55929922686414),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=12, min_samples_split=10,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(415.56668552456125),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=10,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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                         n estimators=30)}}},
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 'minl': 14,
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                         n estimators=30)},
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                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=14, min_samples_split=10,
                         n estimators=30)}}},
{'mins': 12,
 'minl': 6,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=12,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(322.24707451908006),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=12,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1024.0749827613665),
   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=12,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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   'model': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=12,
                         n_estimators=30)}}},
{'mins': 12,
 'minl': 8.
 'exp': \{'x': \{'Best MSE': inf,
```

```
'Best Fold': np.int64(2),
   'Avg MSE': np.float64(348.10094378489345),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=12,
                         n estimators=30)},
  'v': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(372.88241966327223),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=12,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1175.6589965587987),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=12,
                         n estimators=30)}.
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1065.9765569131284),
   'model': RandomForestRegressor(max depth=19, min samples leaf=8, min samples split=12,
                         n_estimators=30)}}},
{'mins': 12,
 'minl': 10,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
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   'model': RandomForestRegressor(max depth=19, min samples leaf=10, min samples split=12,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(2),
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                         n_estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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                         n estimators=30)}}},
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                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=12,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1406.9043253441744),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=12, min_samples_split=12,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1316.6607088977933),
   'model': RandomForestRegressor(max depth=19, min samples leaf=12, min samples split=12,
                         n estimators=30)}}},
{'mins': 12,
 'minl': 14,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(2),
   'Avg MSE': np.float64(400.5661553197953),
   'model': RandomForestRegressor(max_depth=19, min_samples_leaf=14, min_samples_split=12,
                         n estimators=30)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(457.6091756036264),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=12,
                         n estimators=30)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1432.805308713826),
   'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=12,
                         n estimators=30)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1351.3050286819214),
```

```
n estimators=30)}}}]
In [131... Y_test = get_labels(data_type="Test")
            X test = get images(data type="Test", image names=Y test[:,0])
            rfr_grid1_results = test(exp_list=rfr_grid1_exp_loaded, Y_test=Y_test, X_test=X_test)
In [132... rfr_grid1_results
Out[132... [{'mins': 4, 'minl': 6, 'weighted_avg_mse': np.float64(1030.0319577545959)},
              {'mins': 4, 'minl': 8, 'weighted_avg_mse': np.float64(1077.343572941986)},
               \{ \verb|'mins': 4, \verb|'minl': 10, \verb|'weighted_avg_mse': np.float64(965.7390259597503) \}, \\
              {'mins': 4, 'minl': 12, 'weighted_avg_mse': np.float64(1001.5366133034171)}, {'mins': 4, 'minl': 14, 'weighted_avg_mse': np.float64(1104.5554561859)},
              {'mins': 6, 'minl': 6, 'weighted avg mse': np.float64(1059.7983548651566)},
              {'mins': 6, 'minl': 8, 'weighted_avg_mse': np.float64(1042.7518063871962)}, {'mins': 6, 'minl': 10, 'weighted_avg_mse': np.float64(968.3559043781738)},
              {'mins': 6, 'minl': 12, 'weighted avg mse': np.float64(1010.3198934567595)},
              {'mins': 6, 'minl': 14, 'weighted avg mse': np.float64(1069.8815027499604)},
              {'mins': 8, 'minl': 6, 'weighted_avg_mse': np.float64(923.2098763833342)},
              {'mins': 8, 'minl': 8, 'weighted_avg_mse': np.float64(1017.9480888058059)},
{'mins': 8, 'minl': 10, 'weighted_avg_mse': np.float64(1001.0090268207798)},
              {'mins': 8, 'minl': 12, 'weighted_avg_mse': np.float64(994.3513751375535)},
              {'mins': 8, 'minl': 14, 'weighted_avg_mse': np.float64(975.0766309208572)}, {'mins': 10, 'minl': 6, 'weighted_avg_mse': np.float64(1013.3827100186105)},
              {'mins': 10, 'minl': 8, 'weighted_avg_mse': np.float64(1025.8023477009074)},
              {'mins': 10, 'minl': 10, 'weighted avg mse': np.float64(1052.0913655828344)},
              {'mins': 10, 'minl': 12, 'weighted_avg_mse': np.float64(1030.5990940395427)}, {'mins': 10, 'minl': 14, 'weighted_avg_mse': np.float64(1025.600643111045)},
              {'mins': 12, 'minl': 6, 'weighted_avg_mse': np.float64(987.2579517063418)},
              {'mins': 12, 'minl': 8, 'weighted_avg_mse': np.float64(995.0606239828946)},
              {'mins': 12, 'minl': 10, 'weighted_avg_mse': np.float64(1096.0163546806302)}, {'mins': 12, 'minl': 12, 'weighted_avg_mse': np.float64(969.2809944903406)},
              {'mins': 12, 'minl': 14, 'weighted_avg_mse': np.float64(981.2242151196722)}]
```

'model': RandomForestRegressor(max depth=19, min samples leaf=14, min samples split=12,

3.1.3 Store Best RandomForestRegressor Model

```
In [133... rfr_grid1_mean = np.mean([res["weighted_avg_mse"] for res in rfr_grid1_results])
        rfr_grid1_best = min(rfr_grid1_results, key=lambda x: x["weighted_avg_mse"])
        rfr grid1 best index = rfr grid1 results.index(rfr grid1 best)
        Best:{'mins': 8, 'minl': 6, 'weighted avg mse': np.float64(923.2098763833342)}
       Diff: -93.51913907602784
       At:10
In [134... time_str = str(time.time()).replace(".", "")
        best_model_rfr_exp = rfr_grid1_exp_loaded[rfr_grid1_best_index] # Experiment object where the best model is stolength.
        best model rfr = {
            "x":best_model_rfr_exp["exp"]["x"]["model"],
           "y":best_model_rfr_exp["exp"]["y"]["model"],
            "w":best_model_rfr_exp["exp"]["w"]["model"],
           "h":best_model_rfr_exp["exp"]["h"]["model"],
        pickle.dump(best model rfr,
                  open(os.path.join(model_path, f"best_model_rfr {time_str}.sav"),"wb"))
```

3.2 Grid Search: Support Vector Regressor

Hyperparameters for Support Vector Regressor:

- krnl: kernel, the kernel of the non-linear SVM.
- C: C, trade of factor between margin and wrong samples.
- epsl: epsilon, margin of tolerance around predicted values.
- gamm: gamma, defines how far the influence of a single training example reaches.

```
In [200_ svr_krnl = ["linear", "poly", "rbf", "sigmoid"]
    svr_C = [1e-2, 1e-1, 1, 10, 100]
    svr_epsl = [1e-2, 5e-2, 1e-1, 5e-1, 1]
    svr_gamm = ["scale", "auto", 1e-2, 1e-1, 1]
    svr_grid2 = product(svr_krnl, svr_C)
    svr_grid3 = product(svr_epsl, svr_gamm)
```

3.2.1 Grid Search 2: Kernel and C

```
Training model SVR. Description: krnl-linear--C-0.01
Started at: 1732885883.7892659
x - Avg MSE=154.3559, Best MSE=144.1069 at index 0
y - Avg MSE=184.7328, Best MSE=175.3178 at index 0
w - Avg MSE=346.2883, Best MSE=312.1882 at index 2
h - Avg MSE=497.9693, Best MSE=429.7424 at index 2
Ended at 1732885887.438577
Training model SVR. Description: krnl-linear--C-0.1
Started at: 1732885887.438615
x - Avg MSE=154.3559, Best MSE=144.1069 at index 0
y - Avg MSE=184.7328, Best MSE=175.3178 at index 0
w - Avg MSE=346.2883, Best MSE=312.1882 at index 2
h - Avg MSE=497.9693, Best MSE=429.7424 at index 2
Ended at 1732885891.076158
Training model SVR. Description: krnl-linear--C-1
Started at: 1732885891.076183
x - Avg MSE=154.3559, Best MSE=144.1069 at index 0
y - Avg MSE=184.7328, Best MSE=175.3178 at index 0
w - Avg MSE=346.2883, Best MSE=312.1882 at index 2
h - Avg MSE=497.9693, Best MSE=429.7424 at index 2
Ended at 1732885894.703306
Training model SVR. Description: krnl-linear--C-10
Started at: 1732885894.703443
x - Avg MSE=154.3559, Best MSE=144.1069 at index 0
y - Avg MSE=184.7328, Best MSE=175.3178 at index 0
w - Avg MSE=346.2883, Best MSE=312.1882 at index 2
h - Avg MSE=497.9693, Best MSE=429.7424 at index 2
Ended at 1732885898.306389
Training model SVR. Description: krnl-linear--C-100
Started at: 1732885898.306508
x - Avg MSE=154.3559, Best MSE=144.1069 at index 0
y - Avg MSE=184.7328, Best MSE=175.3178 at index 0
w - Avg MSE=346.2883, Best MSE=312.1882 at index 2
h - Avg MSE=497.9693, Best MSE=429.7424 at index 2
Ended at 1732885902.000722
Training model SVR. Description: krnl-poly--C-0.01
Started at: 1732885902.000871
x - Avg MSE=900.1368, Best MSE=813.8476 at index 2
y - Avg MSE=1419.7872, Best MSE=1350.0775 at index 0
w - Avg MSE=5117.6814, Best MSE=4554.2961 at index 0
h - Avg MSE=4838.2068, Best MSE=4295.5821 at index 0
Ended at 1732885904.000462
Training model SVR. Description: krnl-poly--C-0.1
Started at: 1732885904.0005078
x - Avg MSE=846.6235, Best MSE=750.9788 at index 2
y - Avg MSE=1313.2814, Best MSE=1227.4244 at index 0
w - Avg MSE=4494.0145, Best MSE=4090.9379 at index 0 \,
h - Avg MSE=4147.3053, Best MSE=3754.5803 at index 0
Ended at 1732885905.978851
Training model SVR. Description: krnl-poly--C-1
Started at: 1732885905.978983
x - Avg MSE=672.0959, Best MSE=576.5439 at index 2
y - Avg MSE=891.3330, Best MSE=832.1370 at index 0
w - Avg MSE=2574.9339, Best MSE=2275.1830 at index 0
h - Avg MSE=2369.4762, Best MSE=2148.0367 at index 0
Ended at 1732885907.968416
Training model SVR. Description: krnl-poly--C-10
Started at: 1732885907.9684658
x - Avg MSE=382.6956, Best MSE=298.8897 at index 1
y - Avg MSE=452.1923, Best MSE=422.8060 at index 0
w - Avg MSE=1194.5595, Best MSE=1051.9923 at index 1 \,
h - Avg MSE=1095.8407, Best MSE=1004.8301 at index 1
Ended at 1732885910.021605
```

Training model SVR. Description: krnl-poly--C-100

Started at: 1732885910.0217311 x - Avg MSE=224.8615, Best MSE=205.8520 at index 1 y - Avg MSE=302.7942, Best MSE=282.8373 at index 0 w - Avg MSE=679.7936, Best MSE=521.9794 at index 1 h - Avg MSE=725.0279, Best MSE=702.1854 at index 0 Ended at 1732885912.399449

Training model SVR. Description: krnl-rbf--C-0.01 Started at: 1732885912.399582 x - Avg MSE=904.2718, Best MSE=824.0082 at index 2 y - Avg MSE=1433.5681, Best MSE=1361.5384 at index 0 w - Avg MSE=5259.9276, Best MSE=4651.4614 at index 0 h - Avg MSE=4997.3530, Best MSE=4384.2343 at index 0 Ended at 1732885914.990347

Training model SVR. Description: krnl-rbf--C-0.1 Started at: 1732885914.9904761 x - Avg MSE=903.7715, Best MSE=822.1107 at index 2 y - Avg MSE=1432.3463, Best MSE=1363.5609 at index 0 w - Avg MSE=5235.8638, Best MSE=4628.7088 at index 0 h - Avg MSE=4969.8623, Best MSE=4356.8919 at index 0 Ended at 1732885917.60111

Training model SVR. Description: krnl-rbf--C-1 Started at: 1732885917.601156 x - Avg MSE=891.9854, Best MSE=805.4997 at index 2 y - Avg MSE=1404.4577, Best MSE=1333.9578 at index 0 w - Avg MSE=5042.1147, Best MSE=4458.5852 at index 0 h - Avg MSE=4750.1555, Best MSE=4198.7299 at index 0 Ended at 1732885920.218326

Training model SVR. Description: krnl-rbf--C-10 Started at: 1732885920.21841 x - Avg MSE=792.0855, Best MSE=693.4426 at index 2 y - Avg MSE=1227.4440, Best MSE=1144.5136 at index 0 w - Avg MSE=3854.9410, Best MSE=3443.6127 at index 0 h - Avg MSE=3637.1657, Best MSE=3198.5658 at index 0 Ended at 1732885922.891287

Training model SVR. Description: krnl-rbf--C-100 Started at: 1732885922.891335 x - Avg MSE=526.3954, Best MSE=431.8823 at index 1 y - Avg MSE=656.4794, Best MSE=588.7548 at index 1 w - Avg MSE=1733.3432, Best MSE=1566.9456 at index 0 h - Avg MSE=1592.2043, Best MSE=1406.4131 at index 0 Ended at 1732885925.572624

Training model SVR. Description: krnl-sigmoid--C-0.01 Started at: 1732885925.572653 x - Avg MSE=904.2673, Best MSE=824.2169 at index 2 y - Avg MSE=1433.7375, Best MSE=1361.3731 at index 0 w - Avg MSE=5262.0034, Best MSE=4652.4794 at index 0 h - Avg MSE=5000.5466, Best MSE=4387.5661 at index 0 Ended at 1732885927.5948942

Training model SVR. Description: krnl-sigmoid--C-0.1 Started at: 1732885927.595084 x - Avg MSE=904.2505, Best MSE=824.2015 at index 2 y - Avg MSE=1433.7574, Best MSE=1361.4733 at index 0 w - Avg MSE=5262.1368, Best MSE=4652.5994 at index 0 h - Avg MSE=5000.7941, Best MSE=4387.8099 at index 0 Ended at 1732885929.610518

Training model SVR. Description: krnl-sigmoid--C-1 Started at: 1732885929.610676 x - Avg MSE=904.1914, Best MSE=824.0368 at index 2 y - Avg MSE=1433.9540, Best MSE=1362.5043 at index 0 w - Avg MSE=5263.4794, Best MSE=4653.8055 at index 0 h - Avg MSE=5003.2890, Best MSE=4390.2717 at index 0 Ended at 1732885931.623591

Training model SVR. Description: krnl-sigmoid--C-10 Started at: 1732885931.62372 \times - Avg MSE=905.1359, Best MSE=823.0558 at index 2

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y - Avg MSE=1433.9428, Best MSE=1370.1577 at index 0
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        h - Avg MSE=5027.9287, Best MSE=4417.2456 at index 0
        Ended at 1732885933.6401038
        Training model SVR. Description: krnl-sigmoid--C-100
        Started at: 1732885933.640248
        x - Avg MSE=1574.0886, Best MSE=1385.6201 at index 2
        y - Avg MSE=1910.0432, Best MSE=1836.6530 at index 0 \,
        w - Avg MSE=5803.8740, Best MSE=5160.6499 at index 0
        h - Avg MSE=5609.9626, Best MSE=4734.1798 at index 0
        Ended at 1732885935.665422
In [112... with open(os.path.join(model path, "SVR krnl-C 1732885935665518.sav"), "rb") as svr grid2 exp f:
             svr_grid2_exp_loaded = pickle.load(svr_grid2_exp_f)
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             'w': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(5803.873955971059),
              'model': SVR(C=100, kernel='sigmoid')},
             'h': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(5609.962574465761),
              'model': SVR(C=100, kernel='sigmoid')}}}]
In [114... Y_test = get_labels(data_type="Test")
         X test = get images(data type="Test", image names=Y test[:,0])
         svr_grid2_results = test(exp_list=svr_grid2_exp_loaded, Y_test=Y_test, X_test=X_test)
In [115... svr_grid2_results
```

```
Out[115... [{'krnl': 'linear',
               C': 0.01,
             'weighted_avg_mse': np.float64(1581.1840668728994)},
            {'krnl': 'linear',
              'C': 0.1.
              'weighted avg mse': np.float64(1581.1840668728994)},
            {'krnl': 'linear',
              'C': 1,
              'weighted avg mse': np.float64(1581.1840668728994)},
            {'krnl': 'linear',
              'C': 10,
             'weighted_avg_mse': np.float64(1581.1840668728994)},
            {'krnl': 'linear',
              'C': 100,
             'weighted_avg_mse': np.float64(1581.1840668728994)},
            {'krnl': 'poly',
              'C': 0.01.
              'weighted_avg_mse': np.float64(1880.1085308176234)},
            {'krnl': 'poly', 'C': 0.1, 'weighted_avg_mse': np.float64(1614.385705927301)}, {'krnl': 'poly', 'C': 1, 'weighted_avg_mse': np.float64(923.7676284396246)},
            {'krnl': 'poly', 'C': 10, 'weighted_avg_mse': np.float64(892.2569922758053)}, {'krnl': 'poly',
              'C': 100,
             'weighted_avg_mse': np.float64(1227.5168107888653)},
            {'krnl': 'rbf',
              'C': 0.01,
             'weighted avg mse': np.float64(1939.4852304151748)},
            {'krnl': 'rbf', 'C': 0.1, 'weighted_avg_mse': np.float64(1930.8324008354684)},
{'krnl': 'rbf', 'C': 1, 'weighted_avg_mse': np.float64(1845.9187159982262)},
{'krnl': 'rbf', 'C': 10, 'weighted_avg_mse': np.float64(1398.5448203731798)},
            {'krnl': 'rbf', 'C': 100, 'weighted_avg_mse': np.float64(788.4857448259537)},
            {'krnl': 'sigmoid',
              'C': 0.01,
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              'C': 0.1,
              'weighted avg mse': np.float64(1940.3444406818187)},
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              'C': 1.
             'weighted avg_mse': np.float64(1940.4732162311595)},
            {'krnl': 'sigmoid',
              'C': 10,
             'weighted avg mse': np.float64(1942.6019290575855)},
            {'krnl': 'sigmoid',
              C': 100,
              'weighted_avg_mse': np.float64(2446.5445497979276)}]
In [116... svr_grid2_mean = np.mean([res["weighted_avg_mse"] for res in svr_grid2_results])
           svr grid2 best = min(svr grid2 results, key=lambda x: x["weighted avg mse"])
           print(f"Best:{svr grid2 best}\nDiff=:{svr grid2 best["weighted avg mse"]-svr grid2 mean}")
         Best:{'krnl': 'rbf', 'C': 100, 'weighted avg mse': np.float64(788.4857448259537)}
         Diff=:-839.3900155510004
           3.2.2 Grid Search 3: Epsilon and Gamma
                                           hyper params=svr grid3,
                                           hyper_param_names=["epsl", "gamm"],
```

```
In [90]: svr_grid3_exp = grid_search(ModelClass=SVR,
                                      kwarg names=["epsilon", "gamma"],
                                      # Settled Parameters
                                      kernel="rbf",
                                      C=100)
        Training model SVR. Description: epsl-0.01--gamm-scale
        Started at: 1732886577.4301
        x - Avg MSE=526.5641, Best MSE=432.0645 at index 1
        y - Avg MSE=656.2642, Best MSE=588.4727 at index 1
        w - Avg MSE=1733.6229, Best MSE=1567.1903 at index 0 \,
        h - Avg MSE=1592.6447, Best MSE=1406.3219 at index 0 \,
        Ended at 1732886580.112839
        Training model SVR. Description: epsl-0.01--gamm-auto
        Started at: 1732886580.112881
        x - Avg MSE=891.0212, Best MSE=826.4564 at index 1
        y - Avg MSE=1413.6084, Best MSE=1354.1260 at index 0
        w - Avg MSE=5205.9253, Best MSE=4625.3975 at index 0
        h - Avg MSE=4934.5779, Best MSE=4342.2064 at index 0
        Ended at 1732886582.783846
```

Started at: 1732886582.7838762 x - Avg MSE=891.0212, Best MSE=826.4564 at index 1 y - Avg MSE=1413.6084, Best MSE=1354.1260 at index 0 w - Avg MSE=5205.9253, Best MSE=4625.3975 at index 0 h - Avg MSE=4934.5779, Best MSE=4342.2064 at index 0 Ended at 1732886585.437207

Training model SVR. Description: epsl-0.01--gamm-0.1 Started at: 1732886585.437232 x - Avg MSE=891.0212, Best MSE=826.4564 at index 1 y - Avg MSE=1413.6084, Best MSE=1354.1260 at index 0 w - Avg MSE=5205.9253, Best MSE=4625.3975 at index 0 h - Avg MSE=4934.5779, Best MSE=4342.2064 at index 0 Ended at 1732886588.060579

Training model SVR. Description: epsl-0.01--gamm-1 Started at: 1732886588.0607219 x - Avg MSE=891.0212, Best MSE=826.4564 at index 1 y - Avg MSE=1413.6084, Best MSE=1354.1260 at index 0 w - Avg MSE=5205.9253, Best MSE=4625.3975 at index 0 h - Avg MSE=4934.5779, Best MSE=4342.2064 at index 0 Ended at 1732886590.6861901

Training model SVR. Description: epsl-0.05--gamm-scale Started at: 1732886590.686235 x - Avg MSE=526.4832, Best MSE=431.9815 at index 1 y - Avg MSE=656.3718, Best MSE=588.6035 at index 1 w - Avg MSE=1733.4921, Best MSE=1567.1005 at index 0 h - Avg MSE=1592.4511, Best MSE=1406.3534 at index 0 Ended at 1732886593.332267

Training model SVR. Description: epsl-0.05--gamm-auto Started at: 1732886593.332313 x - Avg MSE=891.0221, Best MSE=826.4571 at index 1 y - Avg MSE=1413.6074, Best MSE=1354.1291 at index 0 w - Avg MSE=5205.8999, Best MSE=4625.3850 at index 0 h - Avg MSE=4934.5685, Best MSE=4342.2068 at index 0 Ended at 1732886595.971176

Training model SVR. Description: epsl-0.05--gamm-0.01 Started at: 1732886595.9712949 x - Avg MSE=891.0221, Best MSE=826.4571 at index 1 y - Avg MSE=1413.6074, Best MSE=1354.1291 at index 0 w - Avg MSE=5205.8999, Best MSE=4625.3850 at index 0 h - Avg MSE=4934.5685, Best MSE=4342.2068 at index 0 Ended at 1732886598.590092

Training model SVR. Description: epsl-0.05--gamm-0.1 Started at: 1732886598.590254 x - Avg MSE=891.0221, Best MSE=826.4571 at index 1 y - Avg MSE=1413.6074, Best MSE=1354.1291 at index 0 w - Avg MSE=5205.8999, Best MSE=4625.3850 at index 0 h - Avg MSE=4934.5685, Best MSE=4342.2068 at index 0 Ended at 1732886601.218598

Training model SVR. Description: epsl-0.05--gamm-1 Started at: 1732886601.218716 x - Avg MSE=891.0221, Best MSE=826.4571 at index 1 y - Avg MSE=1413.6074, Best MSE=1354.1291 at index 0 w - Avg MSE=5205.8999, Best MSE=4625.3850 at index 0 h - Avg MSE=4934.5685, Best MSE=4342.2068 at index 0 Ended at 1732886603.845707

Training model SVR. Description: epsl-0.1--gamm-scale Started at: 1732886603.845866 x - Avg MSE=526.3954, Best MSE=431.8823 at index 1 y - Avg MSE=656.4794, Best MSE=588.7548 at index 1 w - Avg MSE=1733.3432, Best MSE=1566.9456 at index 0 h - Avg MSE=1592.2043, Best MSE=1406.4131 at index 0 Ended at 1732886606.502934

Training model SVR. Description: epsl-0.1--gamm-auto Started at: 1732886606.50298 x - Avg MSE=891.0234, Best MSE=826.4580 at index 1

y - Avg MSE=1413.6063, Best MSE=1354.1330 at index 0 w - Avg MSE=5205.8682, Best MSE=4625.3695 at index 0 h - Avg MSE=4934.5569, Best MSE=4342.2073 at index 0 Ended at 1732886609.1737878

Training model SVR. Description: epsl-0.1--gamm-0.01 Started at: 1732886609.173814 x - Avg MSE=891.0234, Best MSE=826.4580 at index 1 y - Avg MSE=1413.6063, Best MSE=1354.1330 at index 0 w - Avg MSE=5205.8682, Best MSE=4625.3695 at index 0 h - Avg MSE=4934.5569, Best MSE=4342.2073 at index 0 Ended at 1732886611.790575

Training model SVR. Description: epsl-0.1--gamm-0.1 Started at: 1732886611.790601 x - Avg MSE=891.0234, Best MSE=826.4580 at index 1 y - Avg MSE=1413.6063, Best MSE=1354.1330 at index 0 w - Avg MSE=5205.8682, Best MSE=4625.3695 at index 0 h - Avg MSE=4934.5569, Best MSE=4342.2073 at index 0 Ended at 1732886614.487093

Training model SVR. Description: epsl-0.1--gamm-1 Started at: 1732886614.487155 x - Avg MSE=891.0234, Best MSE=826.4580 at index 1 y - Avg MSE=1413.6063, Best MSE=1354.1330 at index 0 w - Avg MSE=5205.8682, Best MSE=4625.3695 at index 0 h - Avg MSE=4934.5569, Best MSE=4342.2073 at index 0 Ended at 1732886617.170048

Training model SVR. Description: epsl-0.5--gamm-scale Started at: 1732886617.1701 x - Avg MSE=525.6412, Best MSE=431.2557 at index 1 y - Avg MSE=657.1046, Best MSE=589.2915 at index 1 w - Avg MSE=1732.0910, Best MSE=1565.7336 at index 0 h - Avg MSE=1590.7126, Best MSE=1406.7905 at index 0 Ended at 1732886619.776503

Training model SVR. Description: epsl-0.5--gamm-auto Started at: 1732886619.77667 x - Avg MSE=891.0323, Best MSE=826.4681 at index 1 y - Avg MSE=1413.5966, Best MSE=1354.1625 at index 0 w - Avg MSE=5205.6181, Best MSE=4625.2474 at index 0 h - Avg MSE=4934.4645, Best MSE=4342.2135 at index 0 Ended at 1732886622.397131

Training model SVR. Description: epsl-0.5--gamm-0.01 Started at: 1732886622.397336 x - Avg MSE=891.0323, Best MSE=826.4681 at index 1 y - Avg MSE=1413.5966, Best MSE=1354.1625 at index 0 w - Avg MSE=5205.6181, Best MSE=4625.2474 at index 0 h - Avg MSE=4934.4645, Best MSE=4342.2135 at index 0 Ended at 1732886625.0026062

Training model SVR. Description: epsl-0.5--gamm-0.1 Started at: 1732886625.00277 x - Avg MSE=891.0323, Best MSE=826.4681 at index 1 y - Avg MSE=1413.5966, Best MSE=1354.1625 at index 0 w - Avg MSE=5205.6181, Best MSE=4625.2474 at index 0 h - Avg MSE=4934.4645, Best MSE=4342.2135 at index 0 Ended at 1732886627.716536

Training model SVR. Description: epsl-0.5--gamm-1 Started at: 1732886627.716565 x - Avg MSE=891.0323, Best MSE=826.4681 at index 1 y - Avg MSE=1413.5966, Best MSE=1354.1625 at index 0 w - Avg MSE=5205.6181, Best MSE=4625.2474 at index 0 h - Avg MSE=4934.4645, Best MSE=4342.2135 at index 0 Ended at 1732886630.433105

Training model SVR. Description: epsl-1--gamm-scale Started at: 1732886630.4332879 \times - Avg MSE=524.4596, Best MSE=431.1472 at index 1

y - Avg MSE=657.8476, Best MSE=589.2239 at index 1 w - Avg MSE=1730.8319, Best MSE=1564.6114 at index 0

```
Training model SVR. Description: epsl-1--gamm-auto
        Started at: 1732886633.014391
        x - Avg MSE=891.0554, Best MSE=826.4908 at index 1
        y - Avg MSE=1413.5915, Best MSE=1354.2072 at index 0
        w - Avg MSE=5205.3396, Best MSE=4625.0910 at index 0
        h - Avg MSE=4934.3544, Best MSE=4342.2249 at index 0
        Ended at 1732886635.614023
        Training model SVR. Description: epsl-1--gamm-0.01
        Started at: 1732886635.61407
        x - Avg MSE=891.0554, Best MSE=826.4908 at index 1
        y - Avg MSE=1413.5915, Best MSE=1354.2072 at index 0
        w - Avg MSE=5205.3396, Best MSE=4625.0910 at index 0
        h - Avg MSE=4934.3544, Best MSE=4342.2249 at index 0
        Ended at 1732886638.2309299
        Training model SVR. Description: epsl-1--gamm-0.1
        Started at: 1732886638.230983
        x - Avg MSE=891.0554, Best MSE=826.4908 at index 1
        y - Avg MSE=1413.5915, Best MSE=1354.2072 at index 0 \,
        w - Avg MSE=5205.3396, Best MSE=4625.0910 at index 0
        h - Avg MSE=4934.3544, Best MSE=4342.2249 at index 0
        Ended at 1732886640.824859
        Training model SVR. Description: epsl-1--gamm-1
        Started at: 1732886640.824943
        x - Avg MSE=891.0554, Best MSE=826.4908 at index 1 \,
        y - Avg MSE=1413.5915, Best MSE=1354.2072 at index 0
        w - Avg MSE=5205.3396, Best MSE=4625.0910 at index 0
        h - Avg MSE=4934.3544, Best MSE=4342.2249 at index 0
        Ended at 1732886643.413711
In [10]: with open(os.path.join(model_path, "SVR_epsl-gamm_1732886643413752.sav"), "rb") as svr grid3 exp f:
             svr grid3 exp loaded = pickle.load(svr grid3 exp f)
In [11]: svr grid3 exp loaded
Out[11]: [{'epsl': 0.01,
            'gamm': 'scale',
            'exp': {'x': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(526.5640500306386),
              'model': SVR(C=100, epsilon=0.01)},
             'y': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(656.264165902226),
              'model': SVR(C=100, epsilon=0.01)},
             'w': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(1733.6228936698847),
              'model': SVR(C=100, epsilon=0.01)},
             'h': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(1592.6446730060773),
              'model': SVR(C=100, epsilon=0.01)}}},
           {'epsl': 0.01,
             gamm': 'auto'
            'exp': {'x': {'Best MSE': inf,
              'Best Fold': np.int64(1),
              'Avg MSE': np.float64(891.0211827316698),
              'model': SVR(C=100, epsilon=0.01, gamma='auto')},
             'y': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(1413.6083942731318),
              'model': SVR(C=100, epsilon=0.01, gamma='auto')},
             'w': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(5205.925279647147),
              'model': SVR(C=100, epsilon=0.01, gamma='auto')},
             'h': {'Best MSE': inf,
              'Best Fold': np.int64(0),
              'Avg MSE': np.float64(4934.577867353456),
              'model': SVR(C=100, epsilon=0.01, gamma='auto')}}},
           {'epsl': 0.01,
```

h - Avg MSE=1588.6821, Best MSE=1406.6098 at index 0

Ended at 1732886633.014171

```
'gamm': 0.01,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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  'y': {'Best MSE': inf,
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   'model': SVR(C=100, epsilon=0.01, gamma=0.01)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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   'model': SVR(C=100, epsilon=0.01, gamma=0.01)}}},
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   'model': SVR(C=100, epsilon=0.01, gamma=0.1)},
   y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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   'model': SVR(C=100, epsilon=0.01, gamma=0.1)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.9252796471455),
   'model': SVR(C=100, epsilon=0.01, gamma=0.1)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.577867353457),
   'model': SVR(C=100, epsilon=0.01, gamma=0.1)}}},
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   'model': SVR(C=100, epsilon=0.01, gamma=1)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.6083942731318),
   'model': SVR(C=100, epsilon=0.01, gamma=1)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.9252796471455),
   'model': SVR(C=100, epsilon=0.01, gamma=1)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.577867353457),
   'model': SVR(C=100, epsilon=0.01, gamma=1)}}},
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 'exp': {'x': {'Best MSE': inf,
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   'Avg MSE': np.float64(526.4832308451253),
   'model': SVR(C=100, epsilon=0.05)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(656.3717892054897),
   'model': SVR(C=100, epsilon=0.05)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1733.4921081272987),
   'model': SVR(C=100, epsilon=0.05)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1592.4510628310993),
   'model': SVR(C=100, epsilon=0.05)}}},
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 'gamm': 'auto'
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(891.0221432916697),
   'model': SVR(C=100, epsilon=0.05, gamma='auto')},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.6074419660542),
   'model': SVR(C=100, epsilon=0.05, gamma='auto')},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
```

```
'Avg MSE': np.float64(5205.899881193801),
   'model': SVR(C=100, epsilon=0.05, gamma='auto')},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.568516884226),
   'model': SVR(C=100, epsilon=0.05, gamma='auto')}}},
{'epsl': 0.05,
  gamm': 0.01,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(891.0221432916697),
   'model': SVR(C=100, epsilon=0.05, gamma=0.01)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.6074419660542),
   'model': SVR(C=100, epsilon=0.05, gamma=0.01)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.899881193801),
   'model': SVR(C=100, epsilon=0.05, gamma=0.01)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.568516884226),
   'model': SVR(C=100, epsilon=0.05, gamma=0.01)}}},
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   'Avg MSE': np.float64(891.0221432916697),
   'model': SVR(C=100, epsilon=0.05, gamma=0.1)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.6074419660542),
   'model': SVR(C=100, epsilon=0.05, gamma=0.1)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.899881193801),
   'model': SVR(C=100, epsilon=0.05, gamma=0.1)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.568516884226),
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  gamm': 1,
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(891.0221432916697),
   'model': SVR(C=100, epsilon=0.05, gamma=1)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.6074419660542),
   'model': SVR(C=100, epsilon=0.05, gamma=1)},
  'w': {'Best MSE': inf,
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   'model': SVR(C=100, epsilon=0.05, gamma=1)},
  'h': {'Best MSE': inf,
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   'model': SVR(C=100, epsilon=0.05, gamma=1)}}},
{'epsl': 0.1,
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 'exp': {'x': {'Best MSE': inf,
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   'model': SVR(C=100)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(1),
   'Avg MSE': np.float64(656.4794102639777),
   'model': SVR(C=100)},
  'w': {'Best MSE': inf
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   'model': SVR(C=100)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1592.2043411488794),
   'model': SVR(C=100)}}},
{'epsl': 0.1,
 'gamm': 'auto',
 'exp': {'x': {'Best MSE': inf,
   'Best Fold': np.int64(1),
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```

```
'model': SVR(C=100, gamma='auto')},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.6062858931764),
   'model': SVR(C=100, gamma='auto')},
  'w': {'Best MSE': inf,
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   'model': SVR(C=100, gamma='auto')},
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   'model': SVR(C=100, gamma=0.01)},
  'h': {'Best MSE': inf,
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  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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{'epsl': 0.5,
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  'y': {'Best MSE': inf,
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  'w': {'Best MSE': inf,
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  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
```

```
'Avg MSE': np.float64(1590.7125693548287),
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   'model': SVR(C=100, epsilon=0.5, gamma='auto')},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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  'h': {'Best MSE': inf,
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  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
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  'w': {'Best MSE': inf,
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  'y': {'Best MSE': inf,
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```

```
'model': SVR(C=100, epsilon=1)},
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   'model': SVR(C=100, epsilon=1)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1588.682134827092),
   'model': SVR(C=100, epsilon=1)}}},
{'epsl': 1,
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   'Best Fold': np.int64(1),
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   'model': SVR(C=100, epsilon=1, gamma='auto')},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.5914935629287),
   'model': SVR(C=100, epsilon=1, gamma='auto')},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.339623170628),
   'model': SVR(C=100, epsilon=1, gamma='auto')},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.354446916778),
   'model': SVR(C=100, epsilon=1, gamma='auto')}}},
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 'exp': {'x': {'Best MSE': inf,
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   'model': SVR(C=100, epsilon=1, gamma=0.01)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.5914935629287),
   'model': SVR(C=100, epsilon=1, gamma=0.01)},
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   'Best Fold': np.int64(0),
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   'model': SVR(C=100, epsilon=1, gamma=0.01)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.354446916778),
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   'model': SVR(C=100, epsilon=1, gamma=0.1)},
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   'Best Fold': np.int64(0),
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   'model': SVR(C=100, epsilon=1, gamma=0.1)},
  'w': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.339623170629),
   'model': SVR(C=100, epsilon=1, gamma=0.1)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.354446916778),
   'model': SVR(C=100, epsilon=1, gamma=0.1)}}},
{'epsl': 1,
 'gamm': 1,
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   'model': SVR(C=100, epsilon=1, gamma=1)},
  'y': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(1413.5914935629287),
   'model': SVR(C=100, epsilon=1, gamma=1)},
  'w': {'Best MSE': inf,
  'Best Fold': np.int64(0),
   'Avg MSE': np.float64(5205.339623170629),
   'model': SVR(C=100, epsilon=1, gamma=1)},
  'h': {'Best MSE': inf,
   'Best Fold': np.int64(0),
   'Avg MSE': np.float64(4934.354446916778),
   'model': SVR(C=100, epsilon=1, gamma=1)}}}]
```

```
X test = get images(data type="Test", image names=Y test[:,0])
          svr grid3 results = test(exp list=svr grid3 exp loaded, Y test=Y test, X test=X test)
In [13]: svr grid3 results
Out[13]: [{'epsl': 0.01,
             'gamm': 'scale',
            'weighted_avg_mse': np.float64(788.6830908613668)},
           {'epsl': 0.01.
             gamm': 'auto'
             'weighted_avg_mse': np.float64(1856.6190083696765)},
           {'epsl': 0.01,
             'gamm': 0.01,
             'weighted_avg_mse': np.float64(1856.6190083696767)},
           {'epsl': 0.01,
             'damm': 0.1.
             'weighted avg mse': np.float64(1856.6190083696767)},
            {'epsl': 0.01, 'gamm': 1, 'weighted_avg_mse': np.float64(1856.6190083696767)},
           {'epsl': 0.05,
             'gamm': 'scale',
             'weighted avg mse': np.float64(788.5910605860047)},
           {'epsl': 0.05,
             'gamm': 'auto',
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           {'epsl': 0.05,
             gamm': 0.01,
             'weighted avg mse': np.float64(1856.553132874258)},
           {'epsl': 0.05,
             gamm': 0.1,
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            {'epsl': 0.05, 'gamm': 1, 'weighted avg mse': np.float64(1856.553132874258)},
            {'epsl': 0.1,
             gamm': 'scale',
             'weighted avg mse': np.float64(788.4857448259537)},
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             'gamm': 'auto',
             'weighted avg mse': np.float64(1856.4708598992315)},
           {'epsl': 0.1,
             gamm': 0.01,
             'weighted_avg_mse': np.float64(1856.4708598992315)},
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             'gamm': 0.1.
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           {'epsl': 0.1, 'gamm': 1, 'weighted_avg_mse': np.float64(1856.4708598992315)},
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             'gamm': 'scale',
            'weighted avg mse': np.float64(787.761941729204)},
           {'epsl': 0.5,
             gamm': 'auto',
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           {'epsl': 0.5,
             'gamm': 0.01.
             'weighted_avg_mse': np.float64(1855.847525637413)},
           {'epsl': 0.5, 'gamm': 0.1, 'weighted_avg_mse': np.float64(1855.847525637413)},
{'epsl': 0.5, 'gamm': 1, 'weighted_avg_mse': np.float64(1855.847525637413)},
           {'epsl': 1, 'gamm': 'scale',
             'weighted avg mse': np.float64(786.886030613608)},
           {'epsl': 1,
             'gamm': 'auto'.
             'weighted_avg_mse': np.float64(1855.1163311642163)},
           {'epsl': 1, 'gamm': 0.01, 'weighted_avg_mse': np.float64(1855.1163311642163)},
{'epsl': 1, 'gamm': 0.1, 'weighted_avg_mse': np.float64(1855.1163311642163)},
           {'epsl': 1, 'gamm': 1, 'weighted avg mse': np.float64(1855.1163311642163)}}
          3.2.3 Store Best SVR
In [21]: svr grid3 mean = np.mean([res["weighted avg mse"] for res in svr grid3 results])
          svr_grid3_best = min(svr_grid3_results, key=lambda x: x["weighted_avg_mse"])
          svr grid3 best index = svr grid3 results.index(svr grid3 best)
          print(f"Best:{svr grid3 best}\nDiff=:{svr grid3 best["weighted avg mse"]-svr grid3 mean}\nAt:{svr grid3 best inc
         Best:{'epsl': 1, 'gamm': 'scale', 'weighted_avg_mse': np.float64(786.886030613608)}
         Diff=:-855.627381402205
         At:20
In [115... time str = str(time.time()).replace(".","")
          best model svr exp = svr grid3 exp loaded[svr grid3 best index] # Experiment object where the best model is stolength.
          best model svr = {
               "x": best model svr exp["exp"]["x"]["model"],
              "y": best model svr exp["exp"]["y"]["model"],
```

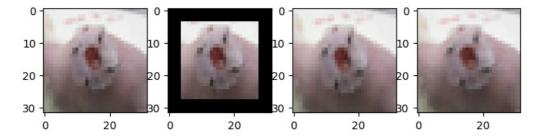
"w": best_model_svr_exp["exp"]["w"]["model"],
"h": best_model_svr_exp["exp"]["h"]["model"],

4. Visualization

4.1 Visualize Image Augmentation

```
In [179... def visualize image augmentation():
                                           # Data Augmentation
                                           # Change some useless information
                                           Y_ori = get_labels(data_type="Training")
                                          X ori = get images(data type="Training", image names=Y ori[:, 0], flatten=False)
                                           # Add black edge
                                          Y_be = get_labels(data_type="Training")
                                          X\_be = \texttt{get\_images}(\texttt{data\_type="Training"}, \texttt{image\_names=Y\_be[:, 0]}, \texttt{augmentation=add\_black\_edge}, \texttt{w=4}, \texttt{flatten=Fallianes})
                                           # Stretch height
                                          Y_sh = get_labels(data_type="Training")
                                           X_{sh} = get_{images}(data_{type="Training"}, image_{names=Y_{sh}[:, 0]}, augmentation=stretch, f=[1.0, 1.05], flatter for the first of the first 
                                           Y_{sh}[:, 4] *= 1.05
                                           # Stretch Width
                                           Y sw = get labels(data type="Training")
                                           X\_sw = \texttt{get\_images}(\texttt{data\_type="Training"}, \texttt{image\_names=Y\_sw}[:, \texttt{0}], \texttt{augmentation=stretch}, \texttt{f=[1.05, 1.0]}, \texttt{flatten})
                                           Y_sw[:, 3] *= 1.05
                                           fig, axs = plt.subplots(1,4, figsize=(8,32))
                                           image\_samples = [X\_ori[0], X\_be[0], X\_sh[0], X\_sw[0]]
                                           for i, ax in enumerate(axs.flatten()):
                                                        ax.imshow(image_samples[i])
                                           plt.show()
```

In [180_ visualize_image_augmentation()



4.2 Visualize Model Inference

```
In [181... def visualize(model dict):
             Visualize the inference result of the model.
             :param model_dict: Dictionary of the four models.
             # Test Data
             Y_inference = get_labels(data_type="Test")
              X\_inference = get\_images(data\_type="Test", image\_names=Y\_test[:, 0], flatten=True, resize=True) 
             X\_inference\_noresize = get\_images(data\_type="Test", image\_names=Y\_test[:, 0], flatten=False, resize=False)
             # Randomly nine pics
             # Use 3x3 image grid to demonstrate
             num images = X inference.shape[0]
             random indices = random.sample(range(num images), 9)
             fig, axs = plt.subplots(3, 3, figsize=(15, 15))
             for i, ax in enumerate(axs.flatten()):
                 random_index = random_indices[i]
                 # Flattened for inference, Original for visualization
                 X_sample = np.array([X_inference[random_index]])
                 X sample noresize = X inference noresize[random index].copy()
                 # Prediction & Ground Truth
                 predictions = inference(model dict=model dict, X=X sample)
                 truths = {
```

```
"x": Y inference[random index, 1],
                      "y": Y_inference[random_index, 2],
                      "w": Y_inference[random_index, 3],
                      "h": Y_inference[random_index, 4],
                 }
                 ellipse_center_prediction = int(predictions["x"]), int(predictions["y"])
                 ellipse axilen prediction = int(predictions["w"]), int(predictions["h"])
                 cv2.ellipse(
                      img=X_sample_noresize,
                      center=list(ellipse center prediction),
                      axes=list(ellipse_axilen_prediction),
                      angle=0.
                      startAngle=0,
                      endAngle=360,
                      color=(255, 0, 0),
                      thickness=5,
                 )
                 ellipse_center_truth = int(truths["x"]), int(truths["y"])
                 ellipse_axilen_truth = int(truths["w"]), int(truths["h"])
                 cv2.ellipse(
                      img=X sample noresize,
                      center=list(ellipse_center_truth),
                      axes=list(ellipse axilen truth),
                      angle=0,
                      startAngle=0,
                      endAngle=360,
                      color=(0, 255, 0),
                      thickness=5,
                 # Plot
                 # Also, show prediction values & legend.
                 description = (
                      f"Image: {random_index + 1}/{num_images}\n"
                      f"Pre: x={predictions["x"]:.1f}, y={predictions["y"]:.1f}, "
                      f"w=\{predictions["w"]:.1f\}, h=\{predictions["h"]:.1f\} \setminus n"
                      f"Tru: x={truths["x"]:.1f}, y={truths["y"]:.1f},
                      f"w={truths["w"]:.1f}, h={truths["h"]:.1f}"
                 ax.set_title(description, fontsize=10, color="black", loc="center")
                 fig.legend (handles=[mlines.Line2D([],\ [],\ color='red',\ linestyle='-',\ linewidth=2,\ label='Prediction'), \\
                                      mlines.Line2D([], [], color='green', linestyle='-', linewidth=2, label='Ground Trutl
                             loc='upper center'
                             ncol=2, fontsize=12, frameon=True)
                 ax.imshow(X sample noresize)
                 # ax.set title(f"Image: {random index + 1}/{num images}")
             plt.tight layout()
             # plt.subplots_adjust(top=0.9)
             plt.show()
In [135... with open(os.path.join(model_path, "best_model_rfr_1733156550837645.sav"), "rb") as best_model_rfr_f:
             best model rfr loaded = pickle.load(best model rfr f)
         with open(os.path.join(model_path, "best_model_svr_1733156169715915.sav"), "rb") as best_model_svr_f:
             best model svr loaded = pickle.load(best model svr f)
In [136... best model rfr loaded
Out[136... {'x': RandomForestRegressor(max_depth=19, min_samples_leaf=6, min_samples_split=8,
                                 n estimators=30),
           'y': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=8,
                                 n_estimators=30),
           'w': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=8,
                                 n_estimators=30),
           'h': RandomForestRegressor(max depth=19, min samples leaf=6, min samples split=8,
                                 n estimators=30)}
In [137... best_model_svr_loaded
Out[137... {'x': SVR(C=100, epsilon=1),
           'y': SVR(C=100, epsilon=1),
           'w': SVR(C=100, epsilon=1),
           'h': SVR(C=100, epsilon=1)}
In [182... visualize(best_model_rfr_loaded)
```

In [183... visualize(best_model_svr_loaded)