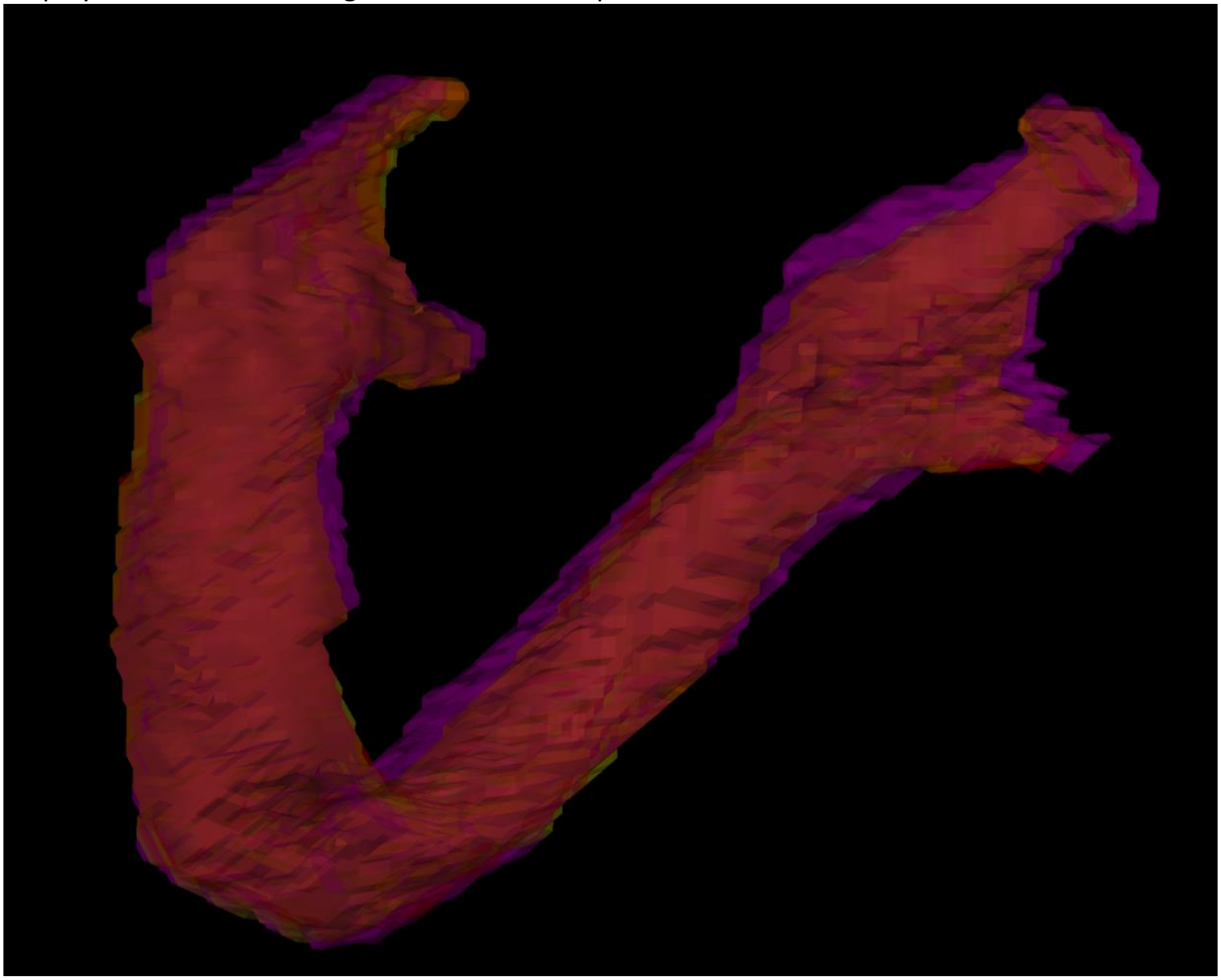
Display of surface renderings of one case from part 1.c



Boxplots of overall results across the 10 cases from 1.d-1.f

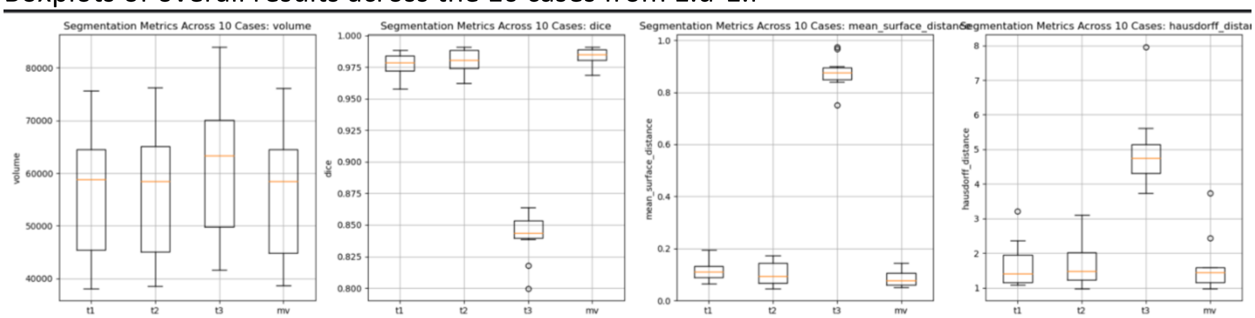


Table of Wilcoxon signed-rank test p-values and significant differences between the different results in 3.c, comparing accuracy among the 3 raters and majority vote

```
Wilcoxon signed-rank test p-values for volume:
    t1  t2  t3  mv
t1  NaN 0.770   0.002   0.695
t2  0.770   NaN 0.002   0.922
t3  0.002   0.002   NaN 0.002
mv  0.695   0.922   0.002   NaN

Significant differences for volume (p < 0.05):
Between t1 and t3: YES (p = 0.002)
Between t2 and t3: YES (p = 0.002)
Between t3 and mv: YES (p = 0.002)
/Users/leonslaptop/anaconda3/envs/python39/lib/py
  warnings.warn("Exact p-value calculation does
/Users/leonslaptop/anaconda3/envs/python39/lib/py
  warnings.warn("Sample size too small for norma
Wilcoxon signed-rank test p-values for dice:
    t1  t2  t3  mv
t1  NaN 0.232   0.002   0.002
t2  0.232   NaN 0.002   0.049
t3  0.002   0.002   NaN 0.002
mv  0.002   0.049   0.002   NaN

Significant differences for dice (p < 0.05):
Between t1 and t3: YES (p = 0.002)
Between t1 and mv: YES (p = 0.002)
Between t2 and t3: YES (p = 0.002)
Between t2 and mv: YES (p = 0.049)
Between t3 and mv: YES (p = 0.002)
```

```
Wilcoxon signed-rank test p-values for mean_surface_distance:
    t1  t2  t3  mv
t1  NaN 0.322   0.002   0.002
t2  0.322   NaN 0.002   0.049
t3  0.002   0.002   NaN 0.002
mv  0.002   0.049   0.002   NaN

Significant differences for mean_surface_distance (p < 0.05):
Between t1 and t3: YES (p = 0.002)
Between t1 and mv: YES (p = 0.002)
Between t2 and t3: YES (p = 0.002)
Between t2 and mv: YES (p = 0.049)
Between t3 and mv: YES (p = 0.002)
Wilcoxon signed-rank test p-values for hausdorff_distance:
    t1  t2  t3  mv
t1  NaN 0.917   0.002   0.735
t2  0.917   NaN 0.002   0.678
t3  0.002   0.002   NaN 0.002
mv  0.735   0.678   0.002   NaN

Significant differences for hausdorff_distance (p < 0.05):
Between t1 and t3: YES (p = 0.002)
Between t2 and t3: YES (p = 0.002)
Between t3 and mv: YES (p = 0.002)
```

Tables of the overall confusion matrices and sensitivity/specificity values from part 2.

```
Confusion matrix for t1:
            Predicted Positive  |   Predicted Negative
--------------------------------------------------------------------
Actual Positive | 165066        | 3817
Actual Negative | 4190      | 359226351

t1: Sensitivity = 0.9774, Specificity = 1.0000
Dice: 0.9763203889524722

Confusion matrix for t2:
            Predicted Positive  |   Predicted Negative
--------------------------------------------------------------------
Actual Positive | 165970        | 2913
Actual Negative | 3654      | 359226887

t2: Sensitivity = 0.9828, Specificity = 1.0000
Dice: 0.980600105758522

Confusion matrix for t3:
            Predicted Positive  |   Predicted Negative
--------------------------------------------------------------------
Actual Positive | 147980        | 20903
Actual Negative | 35285     | 359195256

t3: Sensitivity = 0.8762, Specificity = 0.9999
Dice: 0.8404420868498472
```

Code:

Surface. py

```
def surfDistances(self, mesh2):
  """
  Calculate surface distances from mesh1 to mesh2, integrating tqdm for
progress tracking.
  """

  triangles = np.array(
    [mesh2.verts[face_indices] for face_indices in mesh2.faces])  # Shape (M,
3, 3)

  # Placeholder for the actual vectorized computation
  distances = vectorized_distance_computation(self.verts, triangles)

  # Step 3: Minimization
  min_distances = np.min(distances, axis=1)  # Assuming distances is of shape
(N, M)
  mean_distance = np.mean(min_distances)
  max_distance = np.max(min_distances)

  return mean_distance, max_distance, None, None

def pointsetDistance(self, t1s):
  """
  Calculate point set distances between two sets of points, including Mean
Absolute Point Set Distance (MAPD),
  Hausdorff Point Distance (HPD), and points of interest related to HPD.

  :param gts: Ground Truth Set, with points as an Nx3 numpy array.
  :param t1s: Target Set 1, with points as an Mx3 numpy array.
  :return: MAPD from gts to t1s, HPD from gts to t1s, and points of interest.
  """
  # Build a KD-tree for the vertices of mesh2
  tree = KDTree(t1s.verts)
```

```
  # Query the KD-tree for the closest point in mesh2 for each vertex in mesh1
  distances, _ = tree.query(self.verts)

  # Calculate MASD and HD
  MASDg1 = np.mean(distances)

  HDg1 = np.max(distances)

  return None, MASDg1, HDg1
```

similarityMatrix.py

```
import nrrd

from Project.surface import *
from Project4.confusionMatrix import *
from Project4.metricFunctions import *
from Project4.plotStatistics import *

# Assuming the base directory and a dictionary of patients are defined
bsdir = '/Users/leonslaptop/Desktop/2024 Spring/ECE 3892/data/'

# Lists to store metrics for each rater and the majority vote
metrics = {
  'volume': {'t1': [], 't2': [], 't3': [], 'mv': []},
  'dice': {'t1': [], 't2': [], 't3': [], 'mv': []},
  'mean_surface_distance': {'t1': [], 't2': [], 't3': [], 'mv': []},
  'hausdorff_distance': {'t1': [], 't2': [], 't3': [], 'mv': []}
}

# Initialize dictionaries to hold the cumulative confusion matrices for each
rater
cumulative_matrices = {
  't1': confusionMatrix(np.array([]), np.array([])),
  't2': confusionMatrix(np.array([]), np.array([])),
  't3': confusionMatrix(np.array([]), np.array([]))
}

pts = {0: '0522c0001', 1: '0522c0002', 2: '0522c0003', 3: '0522c0009', 4:
'0522c0013',
       5: '0522c0014', 6: '0522c0017', 7: '0522c0057', 8: '0522c0070', 9:
'0522c0077'}

# Loop through the first 10 cases
for pt_id, pt in pts.items():
  gt_path = f'{bsdir}{pt}/structures/mandible.nrrd'
  gt, hdr = nrrd.read(gt_path)
  voxsz = [hdr['space directions'][0][0], hdr['space directions'][1][1],
           hdr['space directions'][2][2]]

  # Load segmentations
  t1, _ = nrrd.read(f'{bsdir}{pt}/structures/target1.nrrd')
  t2, _ = nrrd.read(f'{bsdir}{pt}/structures/target2.nrrd')
  t3, _ = nrrd.read(f'{bsdir}{pt}/structures/target3.nrrd')

  # Majority vote
  mv = np.sum([t1, t2, t3], axis=0) > 1.5
```

```
  # Create surfaces for each segmentation
  surfaces = {
    'gt': surface(),
    't1': surface(),
    't2': surface(),
    't3': surface(),
    'mv': surface()
  }
  surfaces['gt'].createSurfaceFromVolume(gt, voxsz, 0.5)
  surfaces['t1'].createSurfaceFromVolume(t1, voxsz, 0.5)
  surfaces['t2'].createSurfaceFromVolume(t2, voxsz, 0.5)
  surfaces['t3'].createSurfaceFromVolume(t3, voxsz, 0.5)
  surfaces['mv'].createSurfaceFromVolume(mv.astype(int), voxsz, 0.5)

  # VTK Visualization (Optional: Uncomment to use if myVtkWin is configured
correctly)
  win = myVtkWin()
  win.addSurf(surfaces['t1'].verts, surfaces['t1'].faces, opacity=0.5)
  win.addSurf(surfaces['t2'].verts, surfaces['t2'].faces, color=[1, 1, 0],
opacity=0.5)
  win.addSurf(surfaces['t3'].verts, surfaces['t3'].faces, color=[1, 0, 1],
opacity=0.5)
  # win.start()

  # Calculate metrics for each rater and the majority vote
  segmentations = {'t1': t1, 't2': t2, 't3': t3, 'mv': mv.astype(int)}

  for rater, seg in segmentations.items():
    dice_score = dice_coefficient(gt, seg)
    metrics['dice'][rater].append(dice_score)

    volume = surfaces[rater].volume()
    metrics['volume'][rater].append(volume)

    MASD_gt_rater, HD_gt_rater, _, _ =
surfaces['gt'].surfDistances(surfaces[rater])
    MASD_rater_gt, HD_rater_gt, _, _ =
surfaces[rater].surfDistances(surfaces['gt'])
    mean_surface_distance = (MASD_gt_rater + MASD_rater_gt) / 2
    hausdorff_distance = max(HD_gt_rater, HD_rater_gt)

    metrics['mean_surface_distance'][rater].append(mean_surface_distance)
    metrics['hausdorff_distance'][rater].append(hausdorff_distance)

  print(f"{pt} DONE!")

  # Temporarily create confusion matrices for current patient and rater to
update cumulative matrices
  for rater, segmentation in [('t1', t1), ('t2', t2), ('t3', t3)]:
    current_matrix = confusionMatrix(gt, segmentation)
    cumulative_matrices[rater].TP += current_matrix.TP
    cumulative_matrices[rater].FP += current_matrix.FP
    cumulative_matrices[rater].FN += current_matrix.FN
    cumulative_matrices[rater].TN += current_matrix.TN

# Calculate and print sensitivity and specificity for each rater
```

```
sensitivity_specificity = {}

# After looping through all patients, calculate and print out the overall
metrics for each rater
for rater, matrix in cumulative_matrices.items():
  print(f"Confusion matrix for {rater}:")
  matrix.print()  # This now uses the print method of the confusionMatrix
class

  sensitivity = matrix.sensitivity()
  specificity = matrix.specificity()

  print(f"{rater}: Sensitivity = {sensitivity:.4f}, Specificity =
{specificity:.4f}")
  print(f"Dice: {matrix.dice()}\n")

plot_metrics(metrics, "Segmentation Metrics Across 10 Cases")

# Perform and print Wilcoxon signed-rank test results
perform_wilcoxon_test(metrics, 'volume')
perform_wilcoxon_test(metrics, 'dice')
perform_wilcoxon_test(metrics, 'mean_surface_distance')
perform_wilcoxon_test(metrics, 'hausdorff_distance')

overall_metrics = calculate_overall_metrics(cumulative_matrices)

# Print the overall confusion matrices and sensitivity/specificity values
for rater, metrics in overall_metrics.items():
  print(f"Rater: {rater}")
  print("Confusion Matrix:")
  cumulative_matrices[rater].print()
  print(f"Sensitivity: {metrics['Sensitivity']:.3f}")
  print(f"Specificity: {metrics['Specificity']:.3f}\n")
```

confusionmatrix.py

```
import numpy as np


class confusionMatrix:
  def __init__(self, gt, pred):
    """Initialize confusion matrix with ground truth and prediction."""
    self.TP = np.sum((gt == 1) & (pred == 1))
    self.FP = np.sum((gt == 0) & (pred == 1))
    self.TN = np.sum((gt == 0) & (pred == 0))
    self.FN = np.sum((gt == 1) & (pred == 0))

  def print(self):
    """Print the confusion matrix."""
    print("\t\t\tPredicted Positive\t|\tPredicted Negative")

print("____________________________________________________________________")
    print(f"Actual Positive\t| {self.TP}\t\t| {self.FN}")
    print(f"Actual Negative\t| {self.FP}\t\t| {self.TN}\n")

  def sensitivity(self):
    """Calculate and return sensitivity (recall)."""
```

```
    return self.TP / (self.TP + self.FN) if (self.TP + self.FN) > 0 else 0

  def specificity(self):
    """Calculate and return specificity."""
    return self.TN / (self.TN + self.FP) if (self.TN + self.FP) > 0 else 0

  def dice(self):
    """Calculate and return the Dice coefficient."""
    return (2 * self.TP) / (2 * self.TP + self.FP + self.FN)
```

metricfunction.py

```
import numpy as np
from tqdm import tqdm


def dice_coefficient(gt, pred):
  """
  Calculate the Dice coefficient, a measure of set similarity.

  Parameters:
  - gt: Ground truth binary segmentation mask as a numpy array.
  - pred: Predicted binary segmentation mask as a numpy array.

  Returns:
  - dice: Dice coefficient as a float.
  """
  # Calculate intersection and union
  intersection = np.logical_and(gt, pred).sum()
  gt_sum = gt.sum() + pred.sum()

  # Calculate Dice coefficient. Add a small epsilon to avoid division by
zero.
  dice = (2. * intersection + 1e-6) / (gt_sum + 1e-6)

  return dice


def vectorized_distance_computation(points, triangles):
  """
    Computes the minimum distance from each point to any of the given
triangles, integrating decision making
    for on-surface or off-surface projection.

    Args:
        points (np.array): Array of shape (N, 3) containing N points in 3D
space.
        triangles (np.array): Array of shape (M, 3, 3) representing M
triangles, each defined by 3 vertices.
        norms (np.array): Array of shape (M, 3) containing the normal vectors
for M triangles.

    Returns:
        np.array: Array of shape (N,) containing the minimum distance from
each point to the closest triangle.
    """
  N = len(points)
```

```
  M = len(triangles)

  distances = np.inf * np.ones((N, M))

  # Calculate normals for each triangle
  edge1 = triangles[:, 1, :] - triangles[:, 0, :]
  edge2 = triangles[:, 2, :] - triangles[:, 0, :]
  norms = np.cross(edge1, edge2)
  norms_magnitude = np.linalg.norm(norms, axis=1, keepdims=True)
  norms = norms / norms_magnitude  # Normalize the normals

  # Iterate over each triangle with progress updates
  for j in tqdm(range(M), desc="Computing distances to triangles"):
    triangle = triangles[j]
    norm = norms[j]

    # Compute projected points and check if inside or outside the triangle
    projected_points, is_inside = project_and_check(points, triangle, norm)

    # Initialize an array to store the minimum distances for this triangle
    min_distances_for_triangle = np.zeros(N)

    if np.any(is_inside):
      points_inside = points[is_inside]
      projected_points_inside = projected_points[is_inside]
      distances_to_plane =
calculate_distances_from_projected_points(points_inside,

projected_points_inside)
      min_distances_for_triangle[is_inside] = distances_to_plane

    # Compute distances for points projecting off the surface (edges and
vertices)
    if np.any(~is_inside):
      points_outside = points[~is_inside]
      edge_distances = vectorized_distance_to_edges(points_outside, triangle)
      min_distances_for_triangle[~is_inside] = np.min(edge_distances, axis=1)

    # Update the distances matrix for this triangle
    distances[:, j] = min_distances_for_triangle

  return distances


def calculate_distances_from_projected_points(points, projected_points):
  """
  Computes the distances from points to their projections on the plane.

  Args:
      points (np.array): Array of shape (N, 3) containing N points in 3D
space.
      projected_points (np.array): Array of shape (N, 3) containing the
projections of points onto a plane.

  Returns:
      np.array: Distances from each point to its projection on the plane.
  """
```

```
  # Calculate the vector differences between points and their projections
  vector_differences = points - projected_points

  # Compute the distances as the norm of these vector differences
  distances = np.linalg.norm(vector_differences, axis=1)

  return distances


def project_and_check(points, triangle, norm):
  # Calculate the vector from the triangle's first vertex to the points
  v0 = triangle[0]
  vectors_to_points = points - v0

  # Calculate the distance from the points to the triangle plane
  distance_to_plane = np.dot(vectors_to_points, norm)

  # Project points onto the plane
  projected_points = points - np.outer(distance_to_plane, norm)

  # Check if the projected points are inside the triangle
  is_inside = is_point_inside_triangle(projected_points, triangle)

  return projected_points, is_inside


def is_point_inside_triangle(pts, tri):
  # Barycentric technique to check if point is inside the triangle
  v0, v1, v2 = tri[0], tri[1], tri[2]
  v0v1 = v1 - v0
  v0v2 = v2 - v0

  # Prepare points
  v0p = pts - v0[np.newaxis, :]  # Vector from v0 to each point

  # Compute dot products
  dot00 = np.dot(v0v2, v0v2)
  dot01 = np.dot(v0v1, v0v2)
  dot11 = np.dot(v0v1, v0v1)
  dot02 = np.einsum('ij,j->i', v0p, v0v2)  # Dot product of v0p vectors with
v0v2
  dot12 = np.einsum('ij,j->i', v0p, v0v1)  # Dot product of v0p vectors with
v0v1

  # Compute barycentric coordinates
  invDenom = 1.0 / (dot00 * dot11 - dot01 * dot01)
  u = (dot11 * dot02 - dot01 * dot12) * invDenom
  v = (dot00 * dot12 - dot01 * dot02) * invDenom

  # Check if point is in triangle
  inside = (u >= 0) & (v >= 0) & (u + v <= 1)

  return inside


def vectorized_distance_to_edges(points, triangle):
  """
```

```
    Computes the vectorized distance from points to the edges of a triangle.

    Args:
        points (np.array): Array of shape (N, 3) containing N points.
        triangle (np.array): Array of shape (3, 3) representing a triangle's
vertices.

    Returns:
        np.array: Array of shape (N, 3) containing distances from each point to
each of the triangle's edges.
    """
    # Calculate edge vectors
    edges = np.array(
      [triangle[1] - triangle[0], triangle[2] - triangle[1], triangle[0] -
triangle[2]])

    # Vector from each vertex to points
    p_to_vertices = np.array([points - triangle[0], points - triangle[1],
points - triangle[2]])

    # Calculate projection coefficients for all edges
    coefficients = np.einsum('ijk,ik->ij', p_to_vertices, edges) / (
        np.linalg.norm(edges, axis=1)[:, np.newaxis] ** 2)

    # Clip coefficients to [0, 1] range
    coefficients_clipped = np.clip(coefficients, 0, 1)

    # Ensure coefficients are correctly broadcastable to (3, 8671, 3) for
multiplication with edges
    coefficients_reshaped = coefficients_clipped[:, :, np.newaxis]

    # Broadcast triangle for addition: reshape triangle for compatibility
    triangle_broadcast = triangle[:, np.newaxis, :]  # Reshape to (3, 1, 3) for
broadcasting

    # Now apply the reshaped coefficients to edges and add the broadcasted
triangle vertices
    projections = triangle_broadcast + coefficients_reshaped * edges[:,
np.newaxis, :]

    # Calculate distances from points to projected points
    distances = np.sqrt(np.sum((points[np.newaxis, :, :] - projections) ** 2,
axis=2))

    # Stack distances into a single array
    distances = distances.T

    return distances
```

plotstatistics.py

```
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import wilcoxon


# Assuming dice_scores_all is a dictionary with rater keys ('t1', 't2', 't3',
```

```
'mv') and lists of Dice scores as values
# Example:
# dice_scores_all = {
#     't1': [0.9, 0.92, 0.93, ...],  # Dice scores for rater 1 across all
cases
#     't2': [0.91, 0.9, 0.92, ...],  # Dice scores for rater 2 across all
cases
#     't3': [0.88, 0.89, 0.9, ...],  # Dice scores for rater 3 across all
cases
#     'mv': [0.94, 0.95, 0.96, ...],  # Dice scores for majority vote across
all cases
# }

# Visualization with boxplots for each metric
def plot_metrics(metric_data, title):
  fig, axs = plt.subplots(1, len(metric_data), figsize=(20, 5))
  for ax, (metric_name, values) in zip(axs, metric_data.items()):
    ax.boxplot(values.values(), labels=values.keys())
    ax.set_title(f'{title}: {metric_name}')
    ax.set_ylabel(metric_name)
    ax.grid(True)
  plt.tight_layout()
  plt.show()


# Function to compare metrics using Wilcoxon signed-rank test
def compare_metrics(metric_data):
  raters = list(metric_data.keys())
  p_values_table = np.zeros((len(raters), len(raters)), dtype=float)

  # Fill the table with p-values
  for i, rater1 in enumerate(raters):
    for j, rater2 in enumerate(raters):
      if i < j:  # Avoid redundant comparisons
        stat, p_value = wilcoxon(metric_data[rater1], metric_data[rater2])
        p_values_table[i, j] = p_value
        p_values_table[j, i] = p_value  # Symmetric matrix
      elif i == j:
        p_values_table[i, j] = np.nan  # NaN for comparisons with themselves

  return p_values_table, raters


# Function to perform Wilcoxon signed-rank test and print results
def perform_wilcoxon_test(metrics, metric_name):
  raters = list(metrics[metric_name].keys())
  num_raters = len(raters)
  p_values_table = np.empty((num_raters, num_raters))
  p_values_table[:] = np.NaN  # Initialize with NaN

  # Perform Wilcoxon signed-rank test between pairs of raters for the
specified metric
  for i in range(num_raters):
    for j in range(i + 1, num_raters):
      scores_i = metrics[metric_name][raters[i]]
      scores_j = metrics[metric_name][raters[j]]
      stat, p_value = wilcoxon(scores_i, scores_j)
```

```
      p_values_table[i, j] = p_value
      p_values_table[j, i] = p_value  # Symmetric matrix

  # Print the table of p-values
  print(f"Wilcoxon signed-rank test p-values for {metric_name}:")
  print("\t" + "\t".join(raters))
  for i, rater in enumerate(raters):
    print(f"{rater}\t" + "\t".join(
      ["{:.3f}".format(p) if not np.isnan(p) else "NaN" for p in
p_values_table[i]]))

  # Identify significant differences
  alpha = 0.05
  print(f"\nSignificant differences for {metric_name} (p < {alpha}):")
  for i in range(num_raters):
    for j in range(i + 1, num_raters):
      if p_values_table[i, j] < alpha:
        print(f"Between {raters[i]} and {raters[j]}: YES (p =
{p_values_table[i, j]:.3f})")
      # else:
        # print(f"Between {raters[i]} and {raters[j]}: NO (p =
{p_values_table[i, j]:.3f})")


# Assuming cumulative_matrices is filled as before, calculate sensitivity and
specificity for each rater
def calculate_overall_metrics(cumulative_matrices):
  results = {}
  for rater, cm in cumulative_matrices.items():
    sensitivity = cm.sensitivity()
    specificity = cm.specificity()
    results[rater] = {'Sensitivity': sensitivity, 'Specificity': specificity}
  return results
```