This notebook analyses the results of the model building and analysis performed in MLanalysis.ipynb on the feature discretization test datasets created in feature_discretization.ipynb.

---

imports dependencies

In [95]:
```
import pickle
import pandas as pd
import re
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from matplotlib import patches
import seaborn as sns
import numpy as np
```

reads in data

In [96]:
```
with open('../Dataset/Testgroup_results.pkl', 'rb') as f:
    df_dict = pickle.load(f)

for group_name, values in df_dict.items():
    print(f"{group_name}: {list(values.keys())}")
```

```
TestGroup_1a_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test',
'dt_model', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexi
ty_metrics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc',
'rf_complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accu
racy', 'svm_auc', 'svm_complexity_metrics']
TestGroup_1b_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test',
'dt_model', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexi
ty_metrics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc',
'rf_complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accu
racy', 'svm_auc', 'svm_complexity_metrics']
TestGroup_1c_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test',
'dt_model', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexi
ty_metrics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc',
'rf_complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accu
racy', 'svm_auc', 'svm_complexity_metrics']
TestGroup_2a_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test',
'dt_model', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexi
ty_metrics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc',
'rf_complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accu
racy', 'svm_auc', 'svm_complexity_metrics']
TestGroup_2b_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test',
'dt_model', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexi
ty_metrics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc',
'rf_complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accu
racy', 'svm_auc', 'svm_complexity_metrics']
TestGroup_2c_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test',
'dt_model', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexi
ty_metrics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc',
'rf_complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accu
racy', 'svm_auc', 'svm_complexity_metrics']
control_df: ['df', 'x', 'y', 'X_train', 'X_test', 'y_train', 'y_test', 'dt_m
odel', 'dt_y_pred', 'dt_y_proba', 'dt_accuracy', 'dt_auc', 'dt_complexity_me
trics', 'rf_model', 'rf_y_pred', 'rf_y_proba', 'rf_accuracy', 'rf_auc', 'rf_
complexity_metrics', 'svm_model', 'svm_y_pred', 'svm_y_proba', 'svm_accurac
y', 'svm_auc', 'svm_complexity_metrics']
```

Part 1: collect performance metrics for comparison into data frame

---

In [97]:
```
group_names = list(df_dict.keys())

dt_accuracy = []
rf_accuracy = []
svm_accuracy = []

dt_auc = []
rf_auc = []
svm_auc = []


svm_complexity = []
metrics_df = pd.DataFrame()
```

```
for group_name, values in df_dict.items():

    # Combines dfs stored as dict values for complexity into single df
    ## as a single row
    row_df = pd.concat([values['dt_complexity_metrics'],
                        values['rf_complexity_metrics']],
                        axis=1)

    # appends to global metrics df as row
    metrics_df = pd.concat([metrics_df,
                            row_df],
                            axis = 0)

    # appends to the svc complexity array that is added to df at end
    svm_complexity.append(values['svm_complexity_metrics'])

    # appends other array to be added in a similar fashion
    dt_accuracy.append(values['dt_accuracy'])
    rf_accuracy.append(values['rf_accuracy'])
    svm_accuracy.append(values['svm_accuracy'])

    dt_auc.append(values['dt_auc'])
    rf_auc.append(values['rf_auc'])
    svm_auc.append(values['svm_auc'])

# appends loop-derived attributes to df
metrics_df['support_vectors'] = svm_complexity
metrics_df['dt_accuracy'] = dt_accuracy
metrics_df['rf_accuracy'] = rf_accuracy
metrics_df['svm_accuracy'] = svm_accuracy
metrics_df['dt_auc'] = dt_auc
metrics_df['rf_auc'] = rf_auc
metrics_df['svm_auc'] = svm_auc

metrics_df = metrics_df.rename(columns={'tree_depth': 'dt_tree_depth'})
metrics_df = metrics_df.rename(columns={'num_nodes': 'dt_num_nodes'})
metrics_df = metrics_df.rename(columns={'avg_tree_depth': 'rf_avg_tree_depth
metrics_df = metrics_df.rename(columns={'avg_num_nodes': 'rf_avg_num_nodes'}
metrics_df = metrics_df.rename(columns={'support_vectors': 'svm_support_vect


#names rows rather than assigning test datasets to an attribute
metrics_df.index = group_names


# removes vars with constant var
remove = metrics_df.columns[metrics_df.nunique()==1]
metrics_df.drop(remove, axis = 1, inplace= True)

metrics_df.to_csv("../Dataset/test_performanceResults.csv")

metrics_df
```

Out[97]:

	dt_tree_depth	dt_num_nodes	rf_avg_tree_depth	rf_avg_num_nodes	svı
TestGroup_1a_df	33	17299	31.73	15270.56	
TestGroup_1b_df	30	8585	29.69	8674.02	
TestGroup_1c_df	29	16045	28.32	13710.38	
TestGroup_2a_df	25	9691	23.95	8291.80	
TestGroup_2b_df	28	9247	27.70	8456.86	
TestGroup_2c_df	30	16467	28.17	14066.76	
control_df	33	3807	30.27	4343.30	

experimental groups:

- 1_a variance optimized bin size; correlation optimized technique ensemble
- 1_b variance optimized bin size; mutual information optimized technique ensemble
- 1_c randomized bin sizes and ensemple
- 2_a entropy optimized bin size; correlation optimized technique ensemble
- 2_b entropy optimized bin size; mutual information optimized technique ensemble
- 2_c randomized bin sizes and ensemple (equals 1_c)
- control: original continuous predictors

2b shows the best overall performance. It has competative complexity scores with the lowest number of support vectors while matching or beating the scores of the control. This optimization combines entropy and mutual information.

Part 2: Visualization of the results

In [98]:

```
test_datasets = metrics_df.index
print(test_datasets)
# Separates columns into different dfs by measure
complexity_df = metrics_df.iloc[:,0:5]
complexity_df.head()
accuracy_df = metrics_df[metrics_df.columns.difference(complexity_df.columns
accuracy_df
```

```
Index(['TestGroup_1a_df', 'TestGroup_1b_df', 'TestGroup_1c_df',
       'TestGroup_2a_df', 'TestGroup_2b_df', 'TestGroup_2c_df', 'control_d
f'],
      dtype='object')
```

Out[98]:

	dt_accuracy	dt_auc	rf_accuracy	rf_auc	svm_accuracy	svm_auc
TestGroup_1a_df	0.897459	0.923890	0.922762	0.979812	0.903491	0.973553
TestGroup_1b_df	0.949394	0.956512	0.967030	0.993151	0.960844	0.991239
TestGroup_1c_df	0.882789	0.930305	0.896795	0.967944	0.879569	0.957275
TestGroup_2a_df	0.893319	0.953955	0.897971	0.971462	0.893984	0.970741
TestGroup_2b_df	0.955477	0.962865	0.965752	0.990414	0.962991	0.990437
TestGroup_2c_df	0.887696	0.933157	0.900884	0.968464	0.889281	0.964672
control_df	0.964780	0.968935	0.977304	0.994932	0.735368	0.894720

In [99]:

```
complexity_df
```

Out[99]:

	dt_tree_depth	dt_num_nodes	rf_avg_tree_depth	rf_avg_num_nodes	svi
TestGroup_1a_df	33	17299	31.73	15270.56	
TestGroup_1b_df	30	8585	29.69	8674.02	
TestGroup_1c_df	29	16045	28.32	13710.38	
TestGroup_2a_df	25	9691	23.95	8291.80	
TestGroup_2b_df	28	9247	27.70	8456.86	
TestGroup_2c_df	30	16467	28.17	14066.76	
control_df	33	3807	30.27	4343.30	

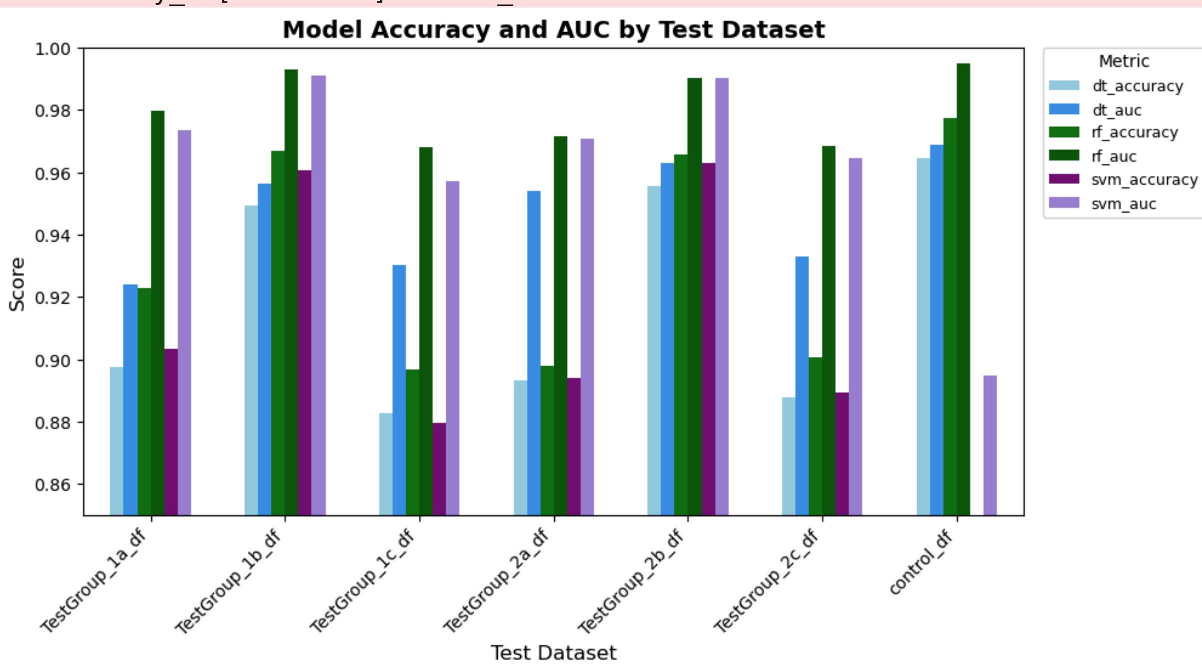
I didn't like the manipulations required for the bar graphs below so I did a "top view" bar graph at the bottom

In [100…

```
# appends test group names to accuracy df for long form transformation
accuracy_df['Dataset'] = test_datasets

# long form df
accuracy_auc_long = pd.melt(accuracy_df,
                            id_vars='Dataset', var_name='Metric', value_name=


plt.figure(figsize=(10, 5))
barplot = sns.barplot(
    data=accuracy_auc_long,
    x='Dataset',
    y='Score',
    hue='Metric',
    palette={
        'dt_accuracy': 'skyblue',
        'rf_accuracy': 'green',
        'svm_accuracy': 'purple',
        'dt_auc': 'dodgerblue',
        'rf_auc': 'darkgreen',
```

```
        'svm_auc': 'mediumpurple'
    },
    width=0.6
)

#labels
plt.title('Model Accuracy and AUC by Test Dataset', fontsize=14, fontweight=
plt.ylabel('Score', fontsize=12)
plt.xlabel('Test Dataset', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.ylim(0.85, 1.0) # not ideal

# legend
plt.legend(
    title='Metric',
    bbox_to_anchor=(1.02, 1),
    loc='upper left',
    borderaxespad=0,
    fontsize=9,
    title_fontsize=10
)

plt.savefig("../IMGs/accuracy_auc_barplot_clean.png", dpi=300, bbox_inches='
plt.show()
```

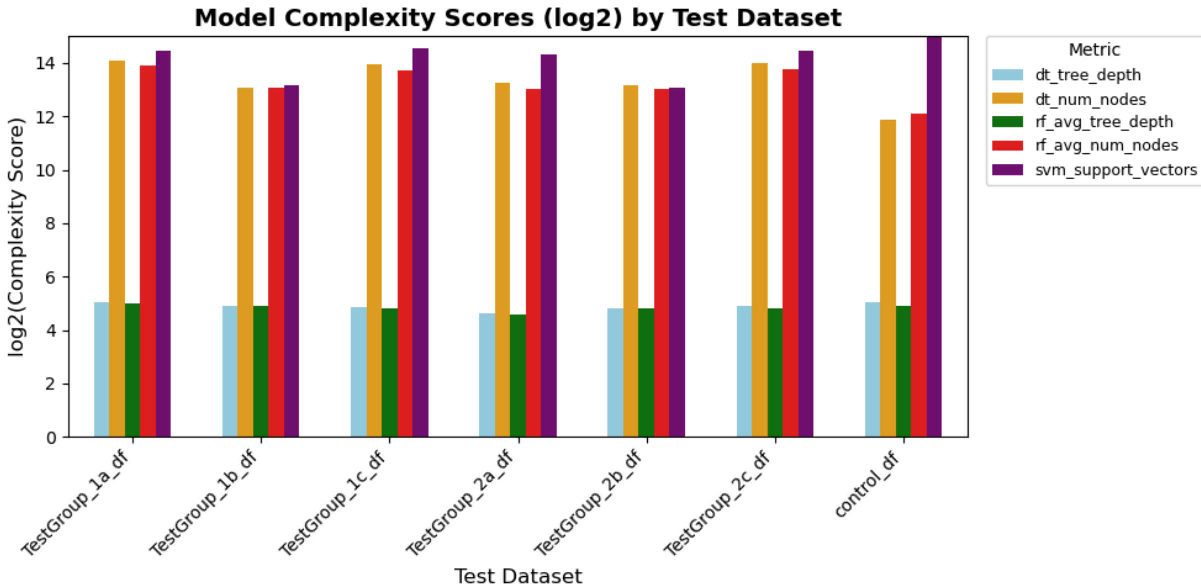
```
/tmp/ipykernel_13791/3506702110.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  accuracy_df['Dataset'] = test_datasets
```



In [101…

```
# appends test group names to accuracy df for long form transformation
complexity_df['Dataset'] = test_datasets
```

```
# creates long form data frame for grouping
complexity_long = pd.melt(complexity_df, id_vars='Dataset', var_name='Metric


# log transformed to make disparites less stark
complexity_long['Log2_Score'] = np.log2(complexity_long['Score'])

# color palette for complexity measures
model_palette_complexity = {
    'dt_tree_depth': 'skyblue',
    'dt_num_nodes': 'orange',
    'rf_avg_tree_depth': 'green',
    'rf_avg_num_nodes': 'red',
    'svm_support_vectors': 'purple'
}

# bar plot
plt.figure(figsize=(10, 5))
barplot_complexity = sns.barplot(
    data=complexity_long,
    x='Dataset',
    y='Log2_Score',
    hue='Metric',
    palette=model_palette_complexity,
    width=0.6
)

# style
plt.title('Model Complexity Scores (log2) by Test Dataset', fontsize=14, for
plt.ylabel('log2(Complexity Score)', fontsize=12)
plt.xlabel('Test Dataset', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.ylim(0, 15)  # Adjust depending on the log2 range of your data

# move legend outside
plt.legend(
    title='Metric',
    bbox_to_anchor=(1.02, 1),
    loc='upper left',
    borderaxespad=0,
    fontsize=9,
    title_fontsize=10
)

plt.tight_layout()
plt.savefig("../IMGs/complexitybar_log2.png", dpi=300, bbox_inches='tight')
plt.show()
```

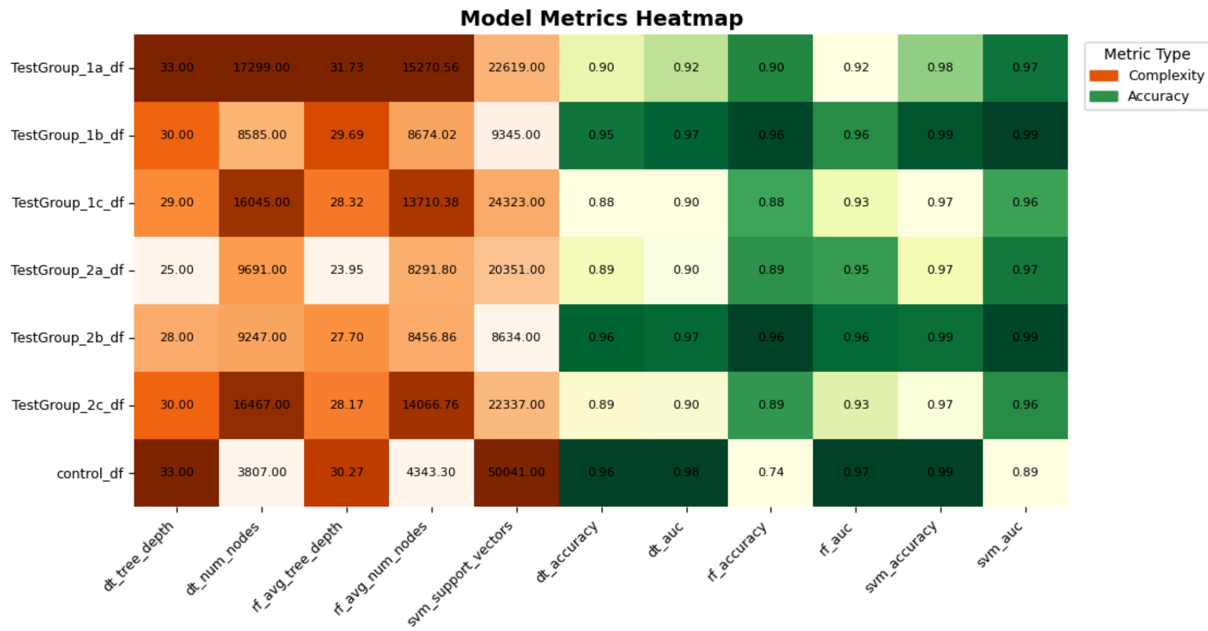


In [104…

```
# copy of object at new address
metrics_df2 = metrics_df.copy()

#updates metrics rownames
metrics_df2.index = metrics_df2.index.to_series().apply(lambda x: re.sub(r"(


# selects colors to see font consistently
cmap_complexity = cm.get_cmap("Oranges")  # low values = light, high = dark
cmap_accuracy = cm.get_cmap("YlGn")       # low values = light, high = dark

# adjust size of plot to avoid squishing
fig_width = max(10, 0.8 * metrics_df2.shape[1])

# plot
fig, ax = plt.subplots(figsize=(fig_width, 6))


complexity_cols = complexity_df.columns

# assigns appropriate color map per sectioned heatmap
col_colors = [cmap_complexity if col in complexity_cols else cmap_accuracy f

# heatmap object
sns.heatmap(
    full_data,
    annot=False,
    fmt='.2f',
    cmap=None,
    cbar=False,
    linewidths=0.5,
    linecolor='lightgray',
    square=False,
    xticklabels=True,
    yticklabels=True,
    ax=ax
)
```

```
# apply column-specific colormaps with annotation
for i, col in enumerate(metrics_df2.columns):
    values = metrics_df2[col].values

    #creates color saturation vector
    normalized = (values - values.min()) / (values.max() - values.min())
    colors = col_colors[i](normalized)

    #creates cell and applies colors nimeric values to heatmap
    for j in range(len(values)):
        val = values[j]
        ax.add_patch(
            patches.Rectangle((i, j), 1, 1, fill=True, color=colors[j], lw=0
        )
        ax.text(
            i + 0.5, j + 0.5,
            f"{val:.2f}",
            ha='center', va='center',
            color='black', fontsize=8
        )

# makes labels fit
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=9
ax.set_yticklabels(ax.get_yticklabels(), fontsize=9)
ax.set_title("Model Metrics Heatmap", fontsize=14, weight='bold')
plt.tight_layout()

# legend
legend_patches = [
    patches.Patch(color=cmap_complexity(0.7), label='Complexity'),
    patches.Patch(color=cmap_accuracy(0.7), label='Accuracy')
]
ax.legend(
    handles=legend_patches,
    loc='upper left',
    bbox_to_anchor=(1.01, 1),
    borderaxespad=0.5,
    fontsize=9,
    title='Metric Type',
    title_fontsize=10
)

plt.savefig("../IMGs/model_metrics_heatmap.png", dpi=300, bbox_inches='tight
plt.show()
```

```
/tmp/ipykernel_13791/812418220.py:9: MatplotlibDeprecationWarning: The get_c
map function was deprecated in Matplotlib 3.7 and will be removed in 3.11. U
se ``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or
``pyplot.get_cmap()`` instead.
  cmap_complexity = cm.get_cmap("Oranges")  # low values = light, high = dar
k
/tmp/ipykernel_13791/812418220.py:10: MatplotlibDeprecationWarning: The get_
cmap function was deprecated in Matplotlib 3.7 and will be removed in 3.11.
Use ``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap()`` or
``pyplot.get_cmap()`` instead.
  cmap_accuracy = cm.get_cmap("YlGn")       # low values = light, high = dar
k
```



In [66]:
```python
print(complexity_df.dtypes)
```

```
dt_tree_depth            int64
dt_num_nodes             int64
rf_avg_tree_depth      float64
rf_avg_num_nodes       float64
svm_support_vectors      int64
Dataset                 object
dtype: object
```