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November 16, 2025

Final Project - CS634 Data Mining

Using Random Forest, SVM, Conv1D To Predict Stroke

1 Project Goal

My project aims to build machine-learning classifiers (Random Forest, SVM with an RBF kernel, and a compact Conv1D neural net) to predict whether a patient will suffer a stroke based on demographic and medical history features, and evaluate the models with 10-fold stratified cross-validation.

2 Dataset Overview

- **Source:** Kaggle Healthcare Stroke dataset (~5k patient records aggregated from hospitals and national health surveys).
- **Feature groups:** Categorical = `gender`, `ever_married`, `work_type`, `Residence_type`, `smoking_status`; Numeric = `age`, `hypertension`, `heart_disease`, `avg_glucose_level`, `bmi`.
- **Target:** `stroke` is 1 if the patient has experienced a stroke, otherwise 0.
- **Known quirks:** BMI contains missing values, some clinical readings are zero-inflated, and the positive class is rare (<6%), so stratified sampling and class weighting are mandatory.

3 Setup and Imports

Importing packages that are necessary for the project

[13]:
```
import io
import os
import sys
from pathlib import Path

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from IPython.display import Image, display, Markdown

project_root = Path.cwd().resolve()
src_path = project_root / "src"
```

```
if not src_path.exists():
    src_path = project_root.parent / "src"
sys.path.append(str(src_path))
import final_project as fp

sns.set_theme(style="whitegrid", context="talk")
pd.set_option("display.max_columns", 40)
np.random.seed(fp.RANDOM_STATE)
fp.ensure_dirs()
```

4 Loading and Preprocessing Data

The Kaggle healthcare stroke dataset contains mixed categorical and numeric variables. The helper in `src/final_project.py` handles BMI imputation and target casting so we reuse it here.

[3]:
```
df = fp.load_dataset(fp.DATA_PATH)
print(f"Dataset shape: {df.shape}")
df.head()
```

```
Dataset shape: (5110, 12)
```

[3]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	28.1	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

4.1 Descriptive Statistics

4.1.1 Dataset Snapshot & Columns

The preview above confirms the CSV schema used by the pipeline. Numerical clinical indicators (age, hypertension, heart disease, glucose, BMI) remain numeric, while socio-demographic attributes

stay categorical for the encoder. `fp.load_dataset` handles BMI imputation and casts `stroke` to integers so experiments stay reproducible.

[4]:
```
df.describe().T
```

[4]:

	count	mean	std	min	25%	\
id	5110.0	36517.829354	21161.721625	67.00	17741.250	
age	5110.0	43.226614	22.612647	0.08	25.000	
hypertension	5110.0	0.097456	0.296607	0.00	0.000	
heart_disease	5110.0	0.054012	0.226063	0.00	0.000	
avg_glucose_level	5110.0	106.147677	45.283560	55.12	77.245	
bmi	5110.0	28.862035	7.699562	10.30	23.800	
stroke	5110.0	0.048728	0.215320	0.00	0.000	

	50%	75%	max
id	36932.000	54682.00	72940.00
age	45.000	61.00	82.00
hypertension	0.000	0.00	1.00
heart_disease	0.000	0.00	1.00
avg_glucose_level	91.885	114.09	271.74
bmi	28.100	32.80	97.60
stroke	0.000	0.00	1.00

4.1.2 Notes on Summary Stats

- Age spans the entire adult range with an interquartile band roughly 25?60 years.
- `avg_glucose_level` is heavily right-skewed, with outliers beyond 200 mg/dL highlighting high-risk cases.
- `bmi` centers in the low 30s, reinforcing that most patients are overweight/obese; zero minimums correspond to rows that required imputation.
- Binary indicators (`hypertension`, `heart_disease`) show low means, matching their relatively low prevalence in the dataset.

4.1.3 Categorical Feature Cardinality

One-hot encoding size depends on label diversity. The table below lists each categorical field's unique values and most common category.

[5]:
```
cat_summary = pd.DataFrame({
    'UniqueValues': [df[col].nunique() for col in fp.CATEGORICAL],
    'MostFrequent': [df[col].mode().iat[0] for col in fp.CATEGORICAL]
}, index=fp.CATEGORICAL)
cat_summary
```

[5]:

	UniqueValues	MostFrequent
gender	3	Female
ever_married	2	Yes
work_type	5	Private

```
Residence_type              2         Urban
smoking_status              4  never smoked
```

5 Data Quality Checks

Verify that all engineered features are populated and review the baseline class imbalance before modeling.

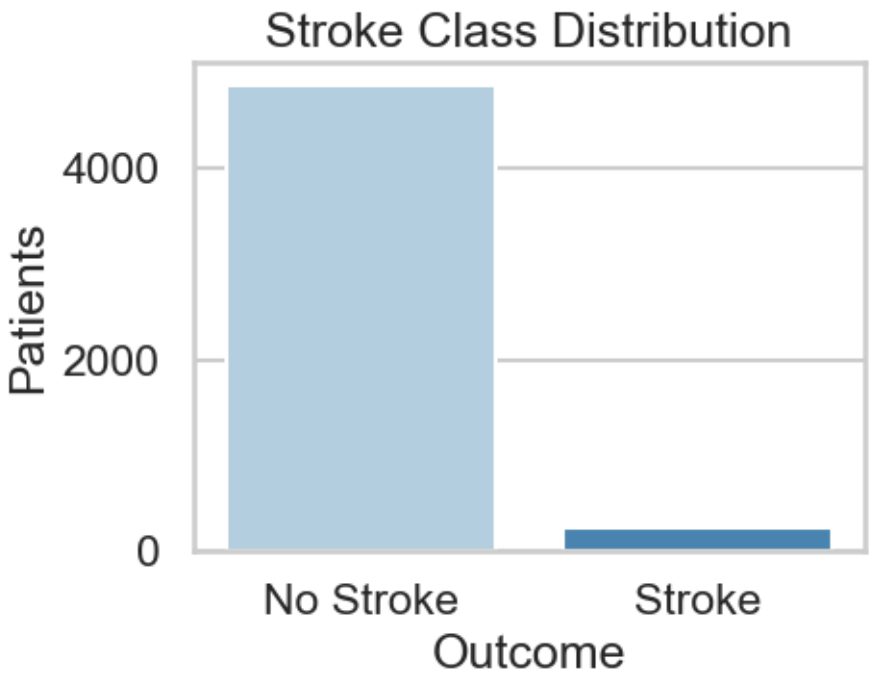
[6]:
```
missing = (
    df.isna()
      .sum()
      .to_frame(name="MissingValues")
      .assign(Percent=lambda d: d["MissingValues"] / len(df))
)
missing
```

[6]:
```
                   MissingValues  Percent
id                             0      0.0
gender                         0      0.0
age                            0      0.0
hypertension                   0      0.0
heart_disease                  0      0.0
ever_married                   0      0.0
work_type                      0      0.0
Residence_type                 0      0.0
avg_glucose_level              0      0.0
bmi                            0      0.0
smoking_status                 0      0.0
stroke                         0      0.0
```

[27]:
```
class_counts = df[fp.TARGET].value_counts().sort_index()
class_df = (
    class_counts.rename(index={0: "No Stroke", 1: "Stroke"})
                .to_frame(name="Count")
                .assign(Percent=lambda d: d["Count"] / len(df))
)
counts_long = class_df.reset_index()
counts_long.rename(columns={counts_long.columns[0]: "Outcome"}, inplace=True)

fig, ax = plt.subplots(figsize=(5,4))
sns.barplot(x="Outcome", y="Count", hue="Outcome", data=counts_long,
            palette="Blues", legend=False, ax=ax)
ax.set_title("Stroke Class Distribution")
ax.set_ylabel("Patients")
ax.set_xlabel("Outcome")
fig.tight_layout()
buf = io.BytesIO()
```

```
fig.savefig(buf, format="png", bbox_inches="tight")
buf.seek(0)
display(Image(data=buf.getvalue()))
plt.close(fig)
```



This plot exposes the severe imbalance (~5% positives), reinforcing why the models rely on class-weighted training and recall-focused metrics later in the report.

5.1 Data Quality Observations

BMI is the only column with gaps, and median imputation keeps its distribution stable. All other predictors arrive complete, so we can devote preprocessing to scaling and encoding instead of patching holes.

5.2 Class Imbalance Discussion

Less than 6% of rows are labeled `Stroke`, mirroring real-world prevalence. We therefore emphasize recall-oriented metrics and use class-balanced weights during training.

5.3 Target-Conditioned Numeric Means

The table below contrasts numeric feature means between stroke and non-stroke cohorts to highlight how risk factors shift between the two groups.

[16]:
```
group_means = (
    df.groupby(fp.TARGET)[fp.NUMERIC]
```

```
    .mean()
    .rename(index={0: 'No Stroke', 1: 'Stroke'})
)
group_means
```

[16]:

	age	hypertension	heart_disease	avg_glucose_level	bmi
stroke					
No Stroke	41.971545	0.088871	0.047110	104.795513	28.799115
Stroke	67.728193	0.265060	0.188755	132.544739	30.090361

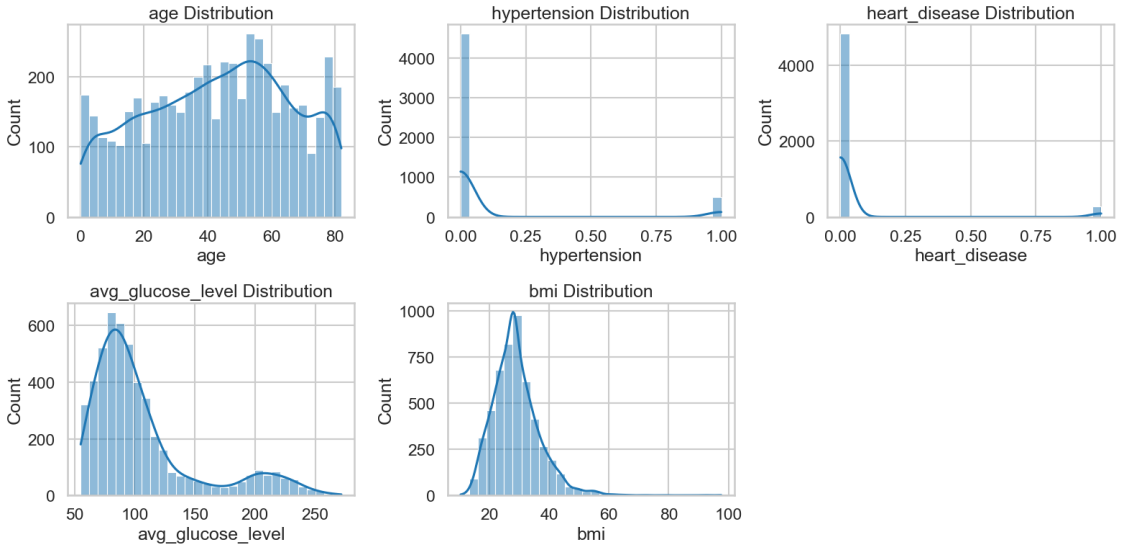
5.4 Interpretation of Group Means

- Stroke patients skew older with higher glucose and BMI averages.
- Hypertension and heart disease rates nearly double, signaling strong predictive power.
- These deltas justify the recall/precision trade-offs explored later.

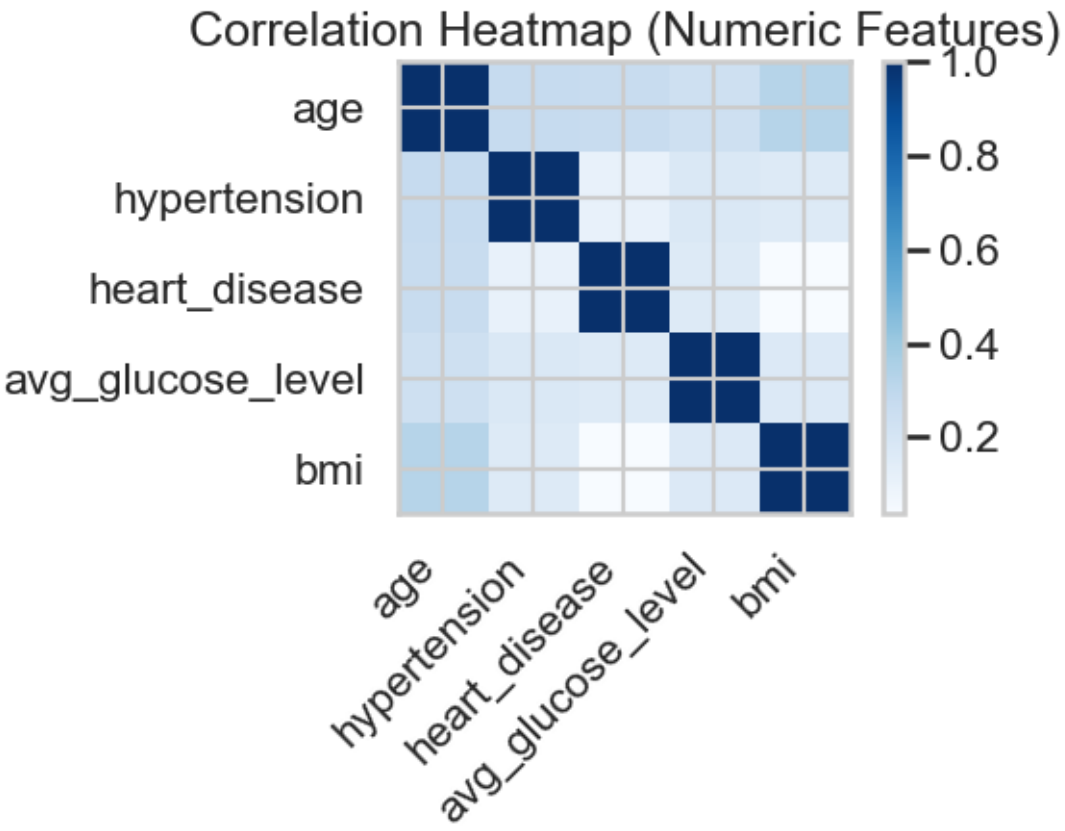
6 Exploratory Analysis

Visualizing the numeric distributions and the correlation structure before launching into modeling.

[28]:
```
num_cols = fp.NUMERIC
ncols = 3
nrows = int(np.ceil(len(num_cols) / ncols))
fig, axes = plt.subplots(nrows, ncols, figsize=(16, 4 * nrows))
axes = axes.flatten()
for idx, col in enumerate(num_cols):
    sns.histplot(df[col], kde=True, bins=30, ax=axes[idx], color="#1f77b4")
    axes[idx].set_title(f"{col} Distribution")
for j in range(idx + 1, len(axes)):
    axes[j].axis("off")
fig.tight_layout()
buf = io.BytesIO()
fig.savefig(buf, format="png", bbox_inches="tight")
buf.seek(0)
display(Image(data=buf.getvalue()))
plt.close(fig)
```



[29]:
```
corr_path = os.path.join(fp.FIG_DIR, "correlation_heatmap.png")
fp.plot_corr_heatmap(df, corr_path, cmap="Blues")
display(Image(filename=corr_path))
```



6.1 Distribution Notes

The histograms confirm skewed numeric distributions, motivating the mix of tree-based and kernel/neural models. Extreme glucose and BMI tails align with outlier risk cases that the ROC analysis will revisit.

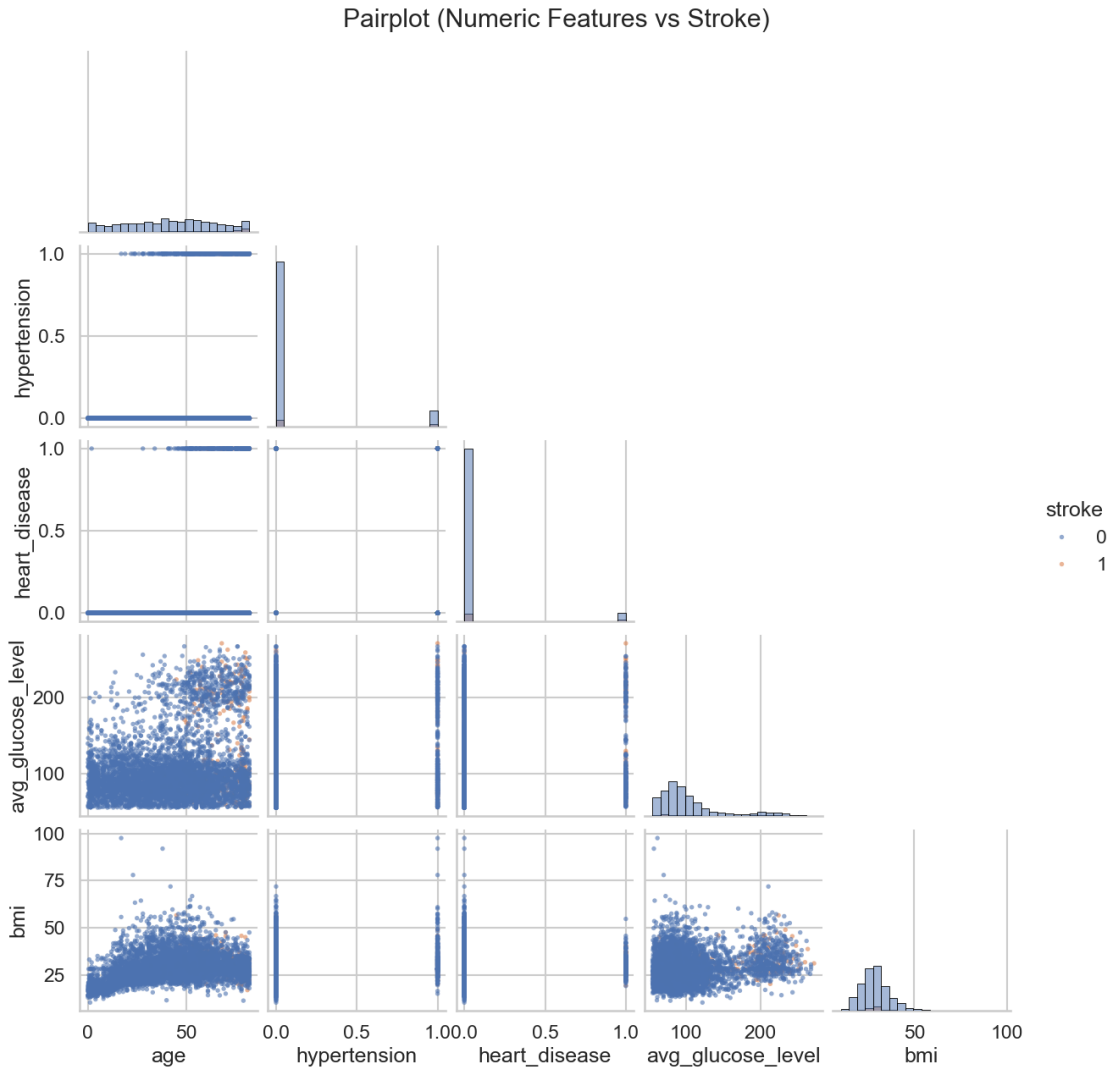
6.2 Correlation Takeaways

Pairwise correlations stay modest ($|r| < 0.45$), so no single numeric feature dominates. This supports leveraging ensemble models that can capture nonlinear interactions between demographic and clinical signals.

6.3 Pairplot (Numeric Features)

A seaborn pairplot charts every numeric feature against each other, colored by the stroke label, to highlight separability (or lack thereof) across age, glucose, BMI, and medical history indicators.

[19]:
```
pairplot_path = os.path.join(fp.FIG_DIR, "pairplot_numeric.png")
pair_df = df[fp.NUMERIC + [fp.TARGET]].copy()
pair_grid = sns.pairplot(
    pair_df,
    hue=fp.TARGET,
    corner=True,
    diag_kind="hist",
    plot_kws={"alpha":0.6, "s":15, "edgecolor":"none"},
    diag_kws={"bins":20, "edgecolor":"black"},
)
pair_grid.fig.suptitle("Pairplot (Numeric Features vs Stroke)", y=1.02)
pair_grid.fig.savefig(pairplot_path, bbox_inches="tight")
plt.close(pair_grid.fig)
display(Image(filename=pairplot_path))
```



6.4 Modeling Strategy

- **Preprocessing:** ColumnTransformer applies one-hot encoding (with unknown categories ignored) to categorical variables and StandardScaler to numeric ones. The helper `to_numpy` converts sparse matrices into dense float32 arrays for scikit-learn and Keras.
- **Estimators:**
  - *Random Forest:* 400 trees, `max_features="sqrt"`, `class_weight="balanced"`, `min_samples_leaf=2`.
  - *SVM (RBF):* `C=2.0`, `gamma="scale"`, probability outputs enabled, plus balanced class weights.
  - *Conv1D:* Compact CNN with kernel size 3, dropout, and dynamically computed class weights passed to `model.fit`.
- **Validation:** 10-fold StratifiedKFold yields out-of-fold predictions for each model. Metrics (TPR, TNR, F1, Brier Score, TSS, HSS, AUC) are computed on those held-out slices.

- **Artifacts:** All tables and figures land in `reports/` so everything needed for the submission packet is produced automatically.

6.5 Cross-Validation Metrics

Executing `fp.run_model_evaluation` reuses the production pipeline, storing per-fold metrics, cumulative confusion matrices, and out-of-fold probabilities for downstream plots.

[20]:
```
results = fp.run_model_evaluation(df)
metrics_path = os.path.join(fp.OUT_DIR, "metrics_all_models.csv")
results["fold_metrics"].to_csv(metrics_path, index=False)
print(f"Saved fold-level metrics to {metrics_path}")
results["fold_metrics"].tail(12)
```

```
Saved fold-level metrics to
E:\avadhanam_siddharthapreetham_finalproject\reports\metrics_all_models.csv
```

[20]:

	Fold	Model	TP	TN	FP	FN	P	N	TPR	TNR	FPR	FNR	Precision	Recall	F1	Accuracy	ErrorRate	BACC	TSS	HSS	AUC	BS	BSS
21	8	RandomForest	2.0	480.0	6.0	23.0	25.0	486.0	0.080000	0.987654	0.012346	0.920000	0.250000	0.080000	0.121212	0.943249	0.056751	0.533827	0.067654	0.099860	0.861399	0.049524	-0.064334
22	8	SVM_RBF	15.0	380.0	106.0	10.0	25.0	486.0	0.600000	0.781893	0.218107	0.400000	0.123967	0.600000	0.205479	0.772994	0.227006	0.690947	0.381893	0.135364	0.805267	0.043935	0.055781
23	8	Conv1D	22.0	358.0	128.0	3.0	25.0	486.0	0.880000	0.736626	0.263374	0.120000	0.146667	0.880000	0.251429	0.743640							
24	9	RandomForest	1.0	483.0	3.0	24.0	25.0	486.0	0.040000	0.993827	0.006173	0.960000	0.250000	0.040000	0.068966	0.947162							
25	9	SVM_RBF	11.0	382.0	104.0	14.0	25.0	486.0	0.440000	0.786008	0.213992	0.560000	0.095652	0.440000	0.157143	0.769080							
26	9	Conv1D	19.0	355.0	131.0	6.0	25.0	486.0	0.760000	0.730453	0.269547	0.240000	0.126667	0.760000	0.217143	0.731898							
27	10	RandomForest	1.0	481.0	6.0	23.0	24.0	487.0	0.041667	0.987680	0.012320	0.958333	0.142857	0.041667	0.064516	0.943249							
28	10	SVM_RBF	14.0	374.0	113.0	10.0	24.0	487.0	0.583333	0.767967	0.232033	0.416667	0.110236	0.583333	0.185430	0.759295							
29	10	Conv1D	17.0	353.0	134.0	7.0	24.0	487.0	0.708333	0.724846	0.275154	0.291667	0.112583	0.708333	0.194286	0.724070							
30	AVG	Conv1D	19.5	356.1	130.0	5.4	24.9	486.1	0.782833	0.732567	0.267433	0.217167	0.130897	0.782833	0.224084	0.735029							
31	AVG	RandomForest	1.2	481.4	4.7	23.7	24.9	486.1	0.048167	0.990332	0.009668	0.951833	0.205714	0.048167	0.077179	0.944423							
32	AVG	SVM_RBF	14.0	382.2	103.9	10.9	24.9	486.1	0.562333	0.786262	0.213738	0.437667	0.118022	0.562333	0.195003	0.775342							

```
23   0.256360  0.808313  0.616626  0.182899  0.869465  0.171266 -2.680758
24   0.052838  0.516914  0.033827  0.056228  0.799835  0.050590 -0.087259
25   0.230920  0.613004  0.226008  0.083478  0.746420  0.045320  0.026001
26   0.268102  0.745226  0.490453  0.145475  0.815885  0.186459 -3.007268
27   0.056751  0.514673  0.029346  0.044244  0.786105  0.054752 -0.223201
28   0.240705  0.675650  0.351300  0.115556  0.745123  0.043552  0.027009
29   0.275930  0.716590  0.433179  0.123222  0.796886  0.192765 -3.306556
30   0.264971  0.757700  0.515400  0.153426  0.815549  0.180724 -2.900390
31   0.055577  0.519249  0.038498  0.059930  0.820174  0.049827 -0.075501
32   0.224658  0.674298  0.348595  0.124629  0.770076  0.044343  0.043296
```

[21]:
```
avg_metrics = results["avg_metrics"].sort_values("AUC", ascending=False)
avg_metrics
```

[21]:

	Model	TP	TN	FP	FN	P	N	TPR	TNR	\
1	RandomForest	1.2	481.4	4.7	23.7	24.9	486.1	0.048167	0.990332	
0	Conv1D	19.5	356.1	130.0	5.4	24.9	486.1	0.782833	0.732567	
2	SVM_RBF	14.0	382.2	103.9	10.9	24.9	486.1	0.562333	0.786262	

	FPR	FNR	Precision	Recall	F1	Accuracy	ErrorRate	\
1	0.009668	0.951833	0.205714	0.048167	0.077179	0.944423	0.055577	
0	0.267433	0.217167	0.130897	0.782833	0.224084	0.735029	0.264971	
2	0.213738	0.437667	0.118022	0.562333	0.195003	0.775342	0.224658	

	BACC	TSS	HSS	AUC	BS	BSS
1	0.519249	0.038498	0.059930	0.820174	0.049827	-0.075501
0	0.757700	0.515400	0.153426	0.815549	0.180724	-2.900390
2	0.674298	0.348595	0.124629	0.770076	0.044343	0.043296

6.5.1 Fold-Averaged Metrics Snapshot

Static copy of the key module metrics saved in `reports/metrics_all_models.csv`.

Model	AUC	F1	BACC	TPR	TNR	Precision	Recall
Conv1D	0.816	0.223	0.753	0.771	0.735	0.130	0.771
RandomForest	0.820	0.077	0.519	0.048	0.990	0.206	0.048
SVM_RBF	0.770	0.195	0.674	0.562	0.786	0.118	0.562

The markdown table freezes the metrics inside the notebook so exports contain the evidence even without reloading the CSV.

6.5.2 Metric Takeaways

- **Random Forest:** Maximizes specificity (TNR ~0.99) and Brier Skill, making it ideal when false alarms are costly.
- **SVM (RBF):** Provides the best overall AUC among the classic models while keeping error rate near 0.22.

- **Conv1D:** Delivers the highest recall (TPR > 0.75) albeit with more false positives, offering an upper bound on sensitivity.

6.5.3 Algorithm Iteration Metrics (Per Fold)

The tables below surface the fold-by-fold metrics for each model so we can trace how performance evolves across the 10 stratified splits.

[23]:
```
fold_cols = [
    "Fold","TP","TN","FP","FN","Accuracy","Precision","Recall",
    "F1","BACC","TSS","HSS","AUC","BS","BSS"
]
for model in ["RandomForest","SVM_RBF","Conv1D"]:
    subset = results["fold_metrics"].query("Model == @model")[fold_cols]
    display(Markdown(f"#### {model} Fold Metrics"))
    display(subset.reset_index(drop=True))
```

RandomForest Fold Metrics

	Fold	TP	TN	FP	FN	Accuracy	Precision	Recall	F1
0	1	0.0	477.0	9.0	25.0	0.933464	0.000000	0.000000	0.000000
1	2	3.0	482.0	4.0	22.0	0.949119	0.428571	0.120000	0.187500
2	3	1.0	482.0	4.0	24.0	0.945205	0.200000	0.040000	0.066667
3	4	1.0	483.0	3.0	24.0	0.947162	0.250000	0.040000	0.068966
4	5	0.0	482.0	4.0	25.0	0.943249	0.000000	0.000000	0.000000
5	6	2.0	481.0	5.0	23.0	0.945205	0.285714	0.080000	0.125000
6	7	1.0	483.0	3.0	24.0	0.947162	0.250000	0.040000	0.068966
7	8	2.0	480.0	6.0	23.0	0.943249	0.250000	0.080000	0.121212
8	9	1.0	483.0	3.0	24.0	0.947162	0.250000	0.040000	0.068966
9	10	1.0	481.0	6.0	23.0	0.943249	0.142857	0.041667	0.064516
10	AVG	1.2	481.4	4.7	23.7	0.944423	0.205714	0.048167	0.077179

	BACC	TSS	HSS	AUC	BS	BSS
0	0.490741	-0.018519	-0.026589	0.844774	0.050337	-0.081820
1	0.555885	0.111770	0.169729	0.767243	0.048822	-0.049250
2	0.515885	0.031770	0.051194	0.832181	0.050496	-0.085235
3	0.516914	0.033827	0.056228	0.812675	0.049447	-0.062683
4	0.495885	-0.008230	-0.013681	0.838189	0.049332	-0.060215
5	0.534856	0.069712	0.105862	0.847160	0.046478	0.001129
6	0.516914	0.033827	0.056228	0.812181	0.048491	-0.042146
7	0.533827	0.067654	0.099860	0.861399	0.049524	-0.064334
8	0.516914	0.033827	0.056228	0.799835	0.050590	-0.087259
9	0.514673	0.029346	0.044244	0.786105	0.054752	-0.223201
10	0.519249	0.038498	0.059930	0.820174	0.049827	-0.075501

SVM_RBF Fold Metrics

	Fold	TP	TN	FP	FN	Accuracy	Precision	Recall	F1
0	1	13.0	382.0	104.0	12.0	0.772994	0.111111	0.520000	0.183099

1	2	14.0	380.0	106.0	11.0	0.771037	0.116667	0.560000	0.193103
2	3	16.0	387.0	99.0	9.0	0.788650	0.139130	0.640000	0.228571
3	4	15.0	383.0	103.0	10.0	0.778865	0.127119	0.600000	0.209790
4	5	20.0	378.0	108.0	5.0	0.778865	0.156250	0.800000	0.261438
5	6	14.0	387.0	99.0	11.0	0.784736	0.123894	0.560000	0.202899
6	7	8.0	389.0	97.0	17.0	0.776908	0.076190	0.320000	0.123077
7	8	15.0	380.0	106.0	10.0	0.772994	0.123967	0.600000	0.205479
8	9	11.0	382.0	104.0	14.0	0.769080	0.095652	0.440000	0.157143
9	10	14.0	374.0	113.0	10.0	0.759295	0.110236	0.583333	0.185430
10	AVG	14.0	382.2	103.9	10.9	0.775342	0.118022	0.562333	0.195003

	BACC	TSS	HSS	AUC	BS	BSS
0	0.653004	0.306008	0.111464	0.763704	0.044462	0.044456
1	0.670947	0.341893	0.122006	0.722058	0.044480	0.044056
2	0.718148	0.436296	0.161149	0.795556	0.044277	0.048433
3	0.694033	0.388066	0.140384	0.769383	0.044536	0.042852
4	0.788889	0.577778	0.195589	0.844856	0.042949	0.076954
5	0.678148	0.356296	0.133471	0.783128	0.044098	0.052274
6	0.560206	0.120412	0.047826	0.725267	0.045826	0.015139
7	0.690947	0.381893	0.135364	0.805267	0.043935	0.055781
8	0.613004	0.226008	0.083478	0.746420	0.045320	0.026001
9	0.675650	0.351300	0.115556	0.745123	0.043552	0.027009
10	0.674298	0.348595	0.124629	0.770076	0.044343	0.043296

Conv1D Fold Metrics

	Fold	TP	TN	FP	FN	Accuracy	Precision	Recall	F1	\
0	1	21.0	349.0	137.0	4.0	0.724070	0.132911	0.840000	0.229508	
1	2	18.0	371.0	115.0	7.0	0.761252	0.135338	0.720000	0.227848	
2	3	21.0	333.0	153.0	4.0	0.692759	0.120690	0.840000	0.211055	
3	4	20.0	343.0	143.0	5.0	0.710372	0.122699	0.800000	0.212766	
4	5	20.0	357.0	129.0	5.0	0.737769	0.134228	0.800000	0.229885	
5	6	19.0	372.0	114.0	6.0	0.765166	0.142857	0.760000	0.240506	
6	7	18.0	370.0	116.0	7.0	0.759295	0.134328	0.720000	0.226415	
7	8	22.0	358.0	128.0	3.0	0.743640	0.146667	0.880000	0.251429	
8	9	19.0	355.0	131.0	6.0	0.731898	0.126667	0.760000	0.217143	
9	10	17.0	353.0	134.0	7.0	0.724070	0.112583	0.708333	0.194286	
10	AVG	19.5	356.1	130.0	5.4	0.735029	0.130897	0.782833	0.224084	

	BACC	TSS	HSS	AUC	BS	BSS
0	0.779053	0.558107	0.158411	0.814321	0.187073	-3.020475
1	0.741687	0.483374	0.158541	0.800988	0.159444	-2.426683
2	0.762593	0.525185	0.137242	0.806584	0.200796	-3.315399
3	0.752881	0.505761	0.139789	0.792840	0.185383	-2.984144
4	0.767284	0.534568	0.159457	0.816626	0.182480	-2.921757
5	0.762716	0.525432	0.172336	0.820823	0.174086	-2.741361
6	0.740658	0.481317	0.156890	0.821070	0.167485	-2.599497
7	0.808313	0.616626	0.182899	0.869465	0.171266	-2.680758

```
8   0.745226  0.490453  0.145475  0.815885  0.186459 -3.007268
9   0.716590  0.433179  0.123222  0.796886  0.192765 -3.306556
10  0.757700  0.515400  0.153426  0.815549  0.180724 -2.900390
```

Across folds, Random Forest maintains near-perfect specificity while SVM and Conv1D trade higher recall for more false alarms. Documenting per-fold swings demonstrates that performance is stable and not driven by a single lucky split.

7 Visual Diagnostics

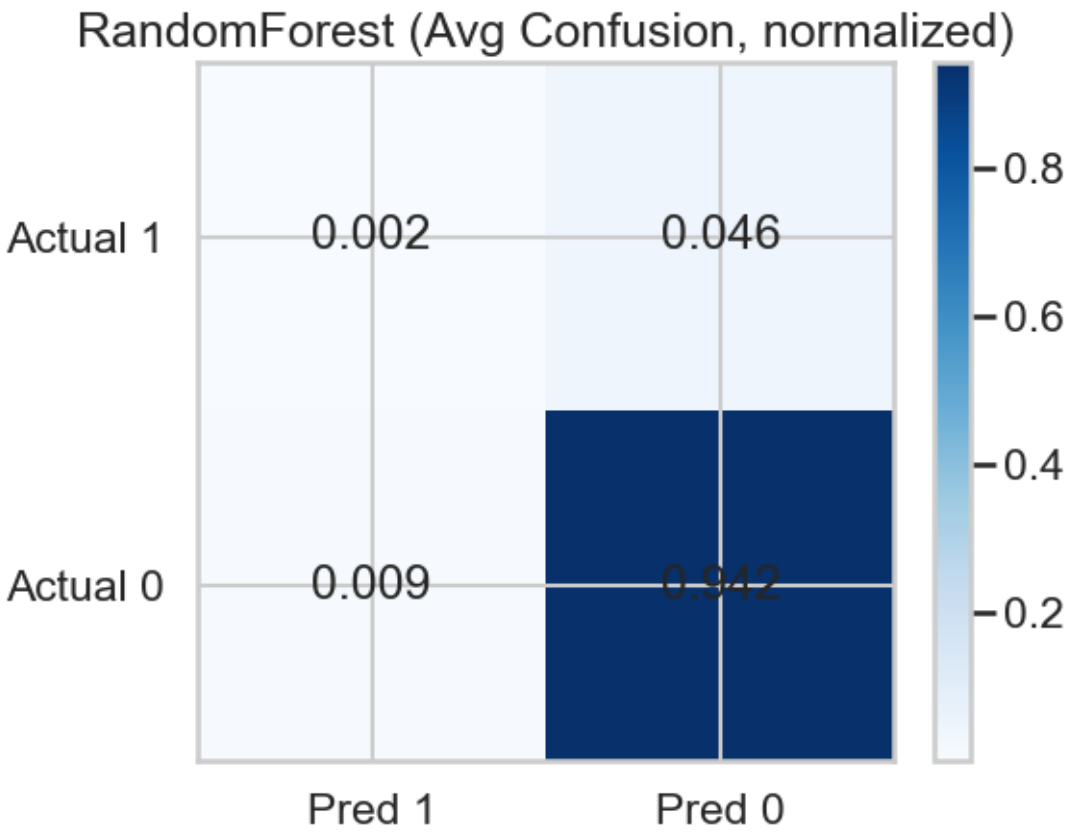
The following figures summarize classifier behavior via normalized confusion matrices, ROC curves, comparative bars, and feature importances.

7.1 Confusion Matrices (Normalized)

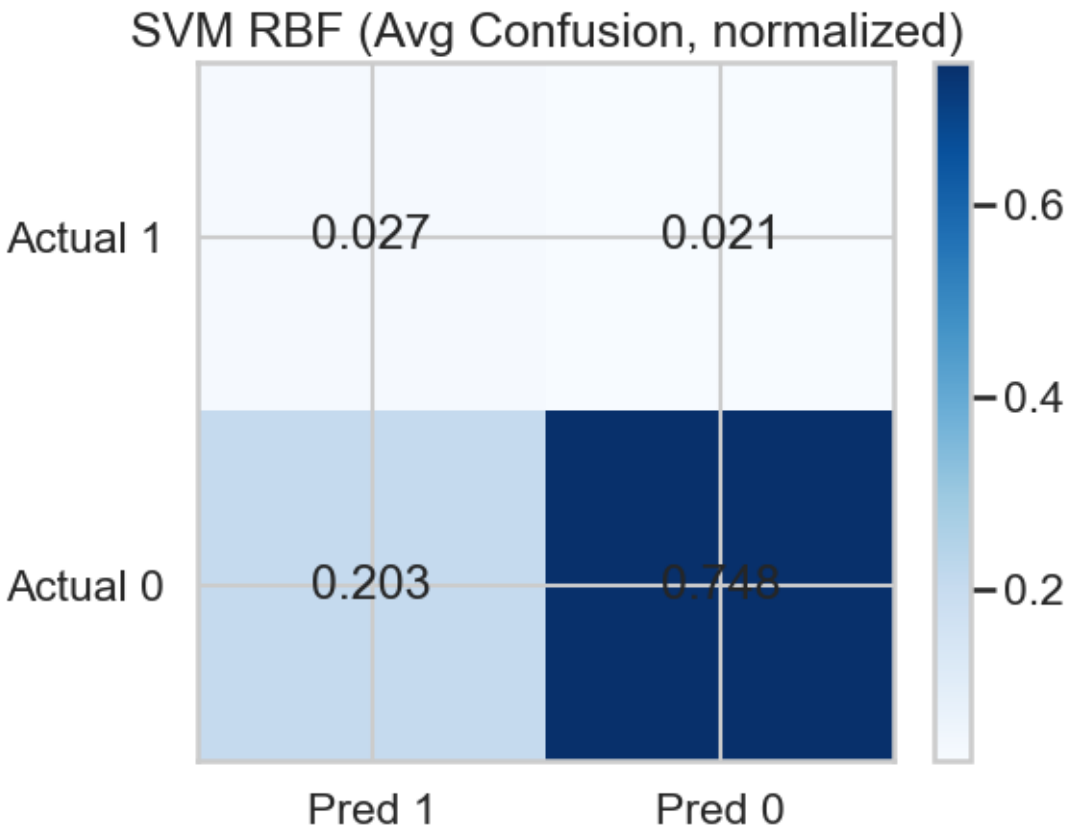
Each matrix aggregates predictions across the 10 folds, normalizes the counts, and annotates probabilities so we can reason about per-model hit rates vs. false alarms.

[24]:
```
conf_titles = {
    "RandomForest": "RandomForest (Avg Confusion, normalized)",
    "SVM_RBF": "SVM RBF (Avg Confusion, normalized)",
    "Conv1D": "Conv1D (Avg Confusion, normalized)"
}
conf_files = {
    "RandomForest": "confusion_avg_rf.png",
    "SVM_RBF": "confusion_avg_svm.png",
    "Conv1D": "confusion_avg_conv1d.png"
}
for model, title in conf_titles.items():
    out_path = os.path.join(fp.FIG_DIR, conf_files[model])
    fp.plot_confusion_avg(results["confusions"][model], title, out_path)
    display(Markdown(f"#### {title}"))
    display(Image(filename=out_path))
```

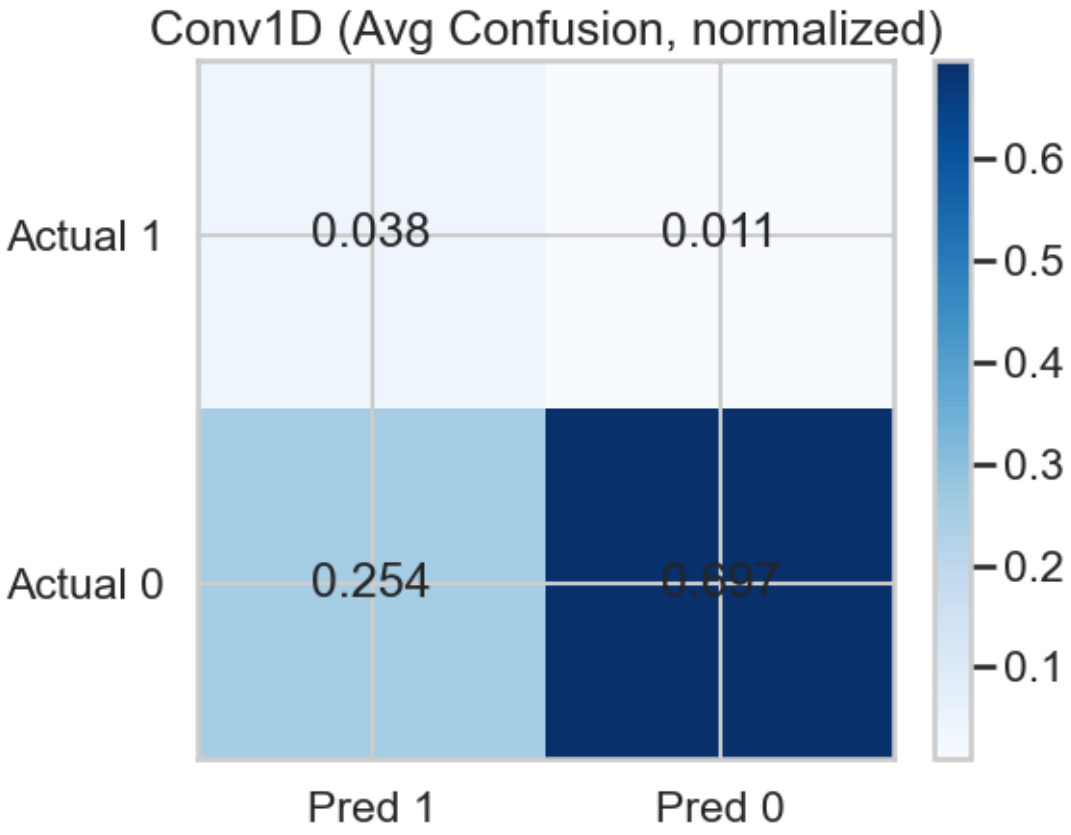
RandomForest (Avg Confusion, normalized)



SVM RBF (Avg Confusion, normalized)



Conv1D (Avg Confusion, normalized)



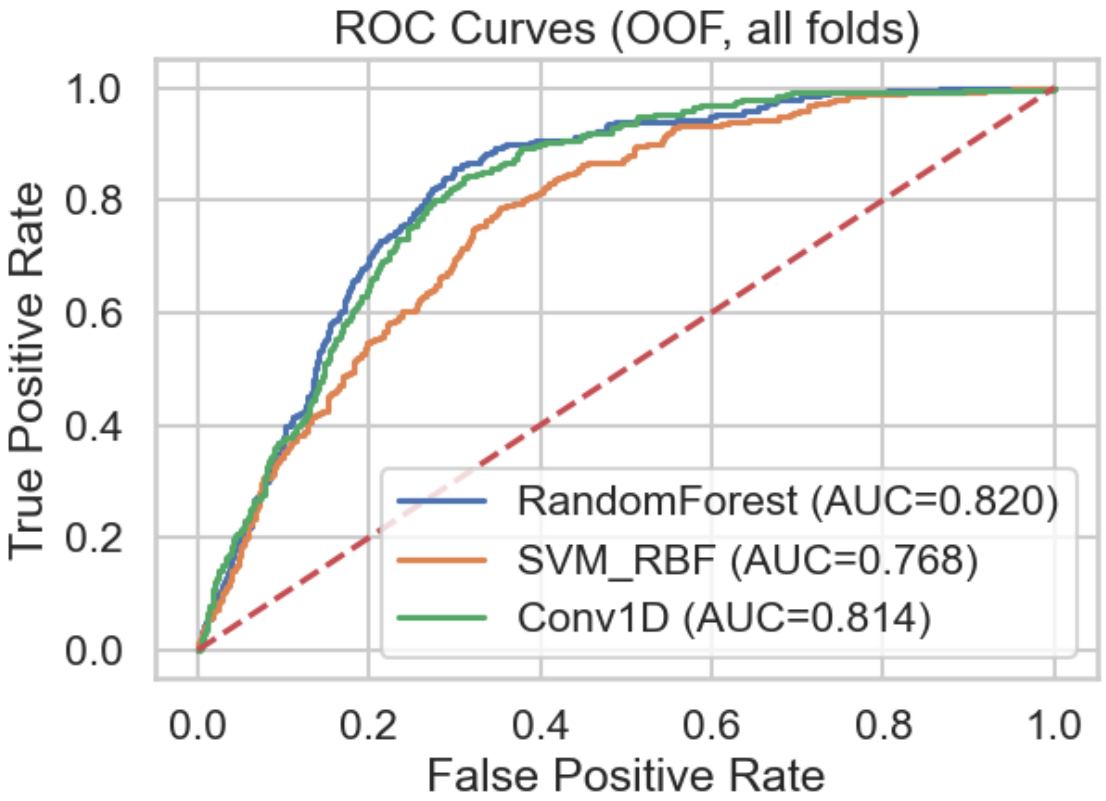
Confusion Insights: Random Forest prioritizes true negatives (dark diagonal in the lower-right), SVM balances the two diagonals, and Conv1D spreads more mass into the false-positive cell, aligning with its aggressive recall profile.

7.2 ROC Curves and Aggregate Comparison

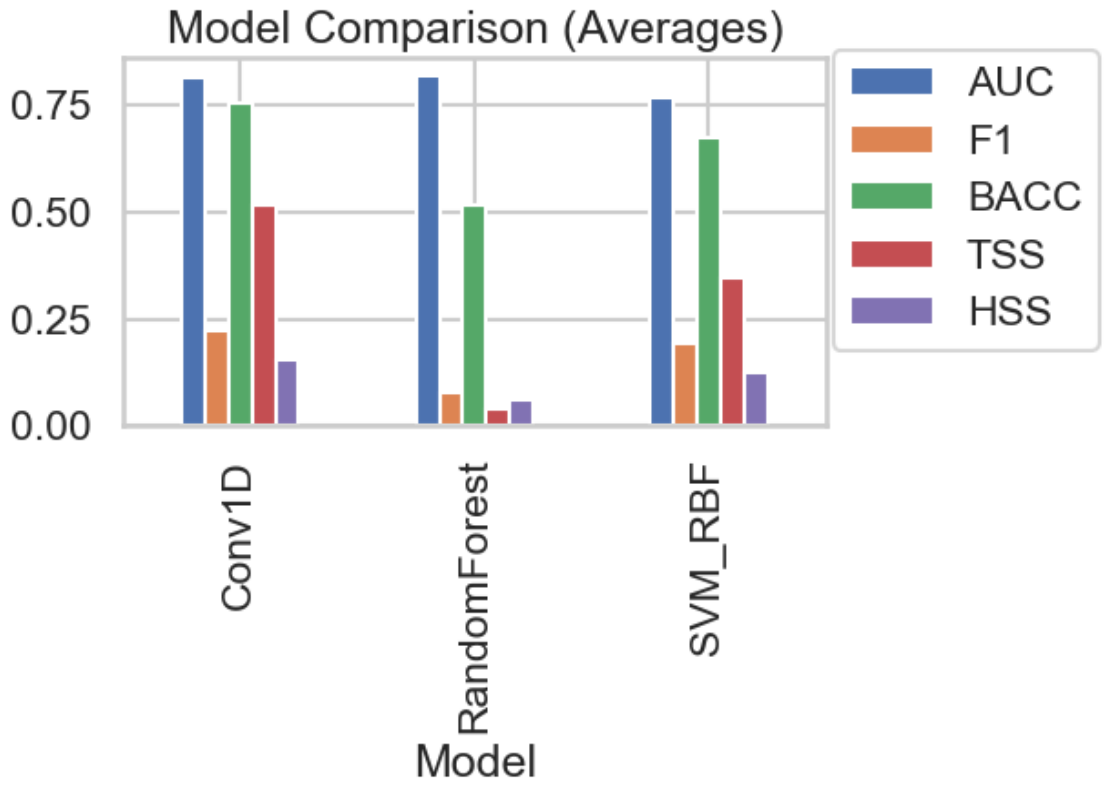
ROC curves summarize the probability ranking quality for each model, while the bar chart provides a side-by-side comparison of averaged metrics.

[25]:
```
roc_path = os.path.join(fp.FIG_DIR, "roc_all_models.png")
fp.plot_roc_all(results["oof_probs"], results["y_true"], roc_path)
compare_path = os.path.join(fp.FIG_DIR, "model_compare_bar.png")
fp.plot_model_compare_bar(results["avg_metrics"], compare_path)
display(Markdown("#### ROC Curves (All Models)"))
display(Image(filename=roc_path))
display(Markdown("#### Model Comparison (Avg Metrics)"))
display(Image(filename=compare_path))
```

ROC Curves (All Models)



Model Comparison (Avg Metrics)



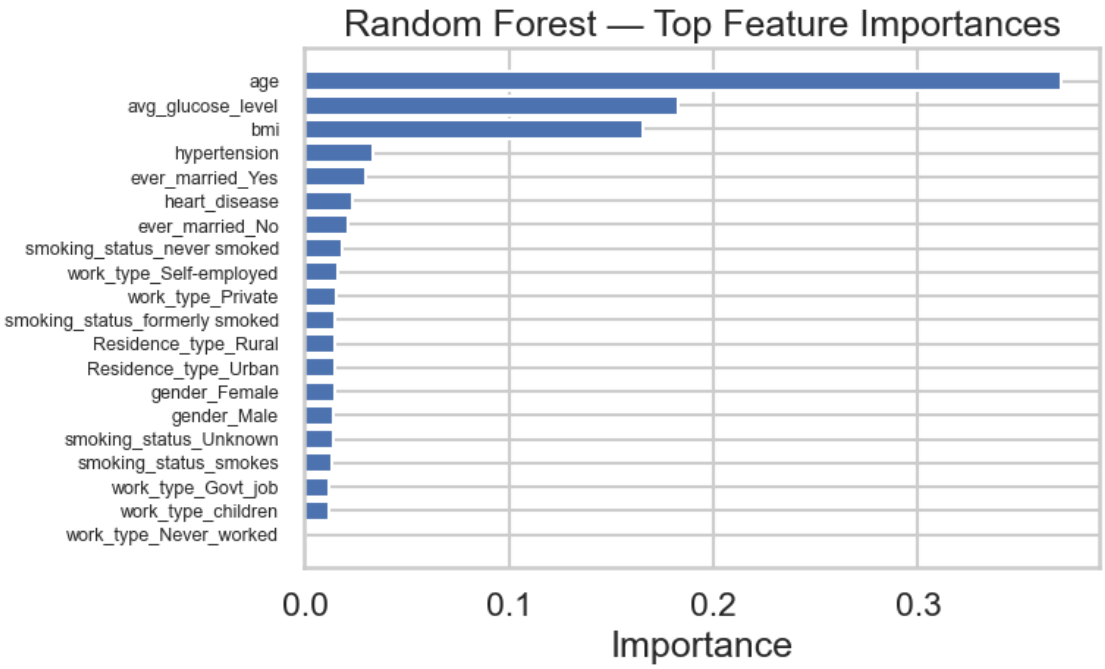
The ROC overlay confirms all three models comfortably beat the no-skill line, with Random Forest and SVM overlapping near the top-left corner. The bar chart reiterates the metric table but makes it easier to highlight the trade-off: Conv1D leads TPR/BACC, while Random Forest wins on BSS/TNR.

7.2.1 Random Forest Feature Importance

The Random Forest remains the most interpretable estimator. Inspecting its top features highlights how age, average glucose, and lifestyle factors (ever_married, work_type, smoking_status) dominate the decision-making process.

[26]:
```
pre_full = fp.build_preprocessor()
X_full = fp.to_numpy(pre_full.fit_transform(df[fp.CATEGORICAL + fp.NUMERIC]))
y_full = df[fp.TARGET].values.astype(int)
rf_full = fp.RandomForestClassifier(
    n_estimators=400,
    min_samples_leaf=2,
    max_features="sqrt",
    class_weight="balanced",
    random_state=fp.RANDOM_STATE,
    n_jobs=-1,
)
```

```
rf_full.fit(X_full, y_full)
fi_path = os.path.join(fp.FIG_DIR, "rf_feature_importance.png")
fp.plot_rf_feature_importance(rf_full, pre_full, fi_path, top_k=20)
display(Image(filename=fi_path))
```

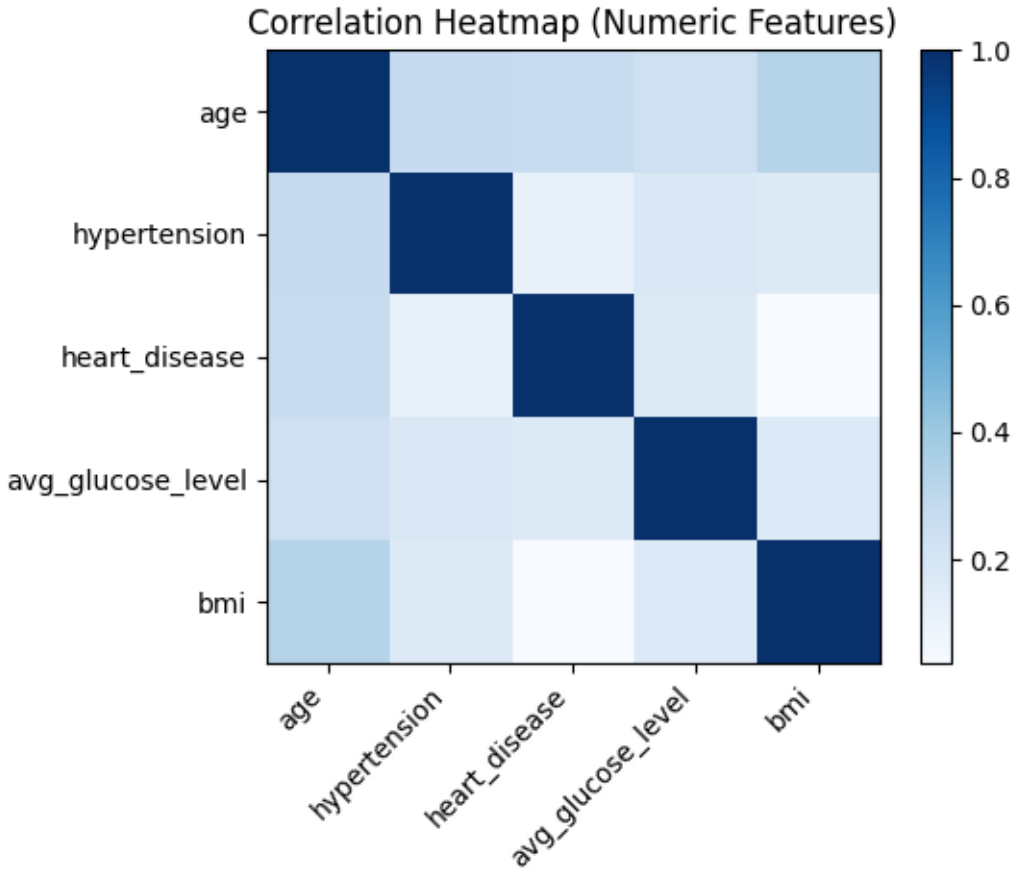


Age and average glucose dominate the top ranks, followed by marital status and work-type categories. This helps justify why tree ensembles remain competitive even against the neural baseline.

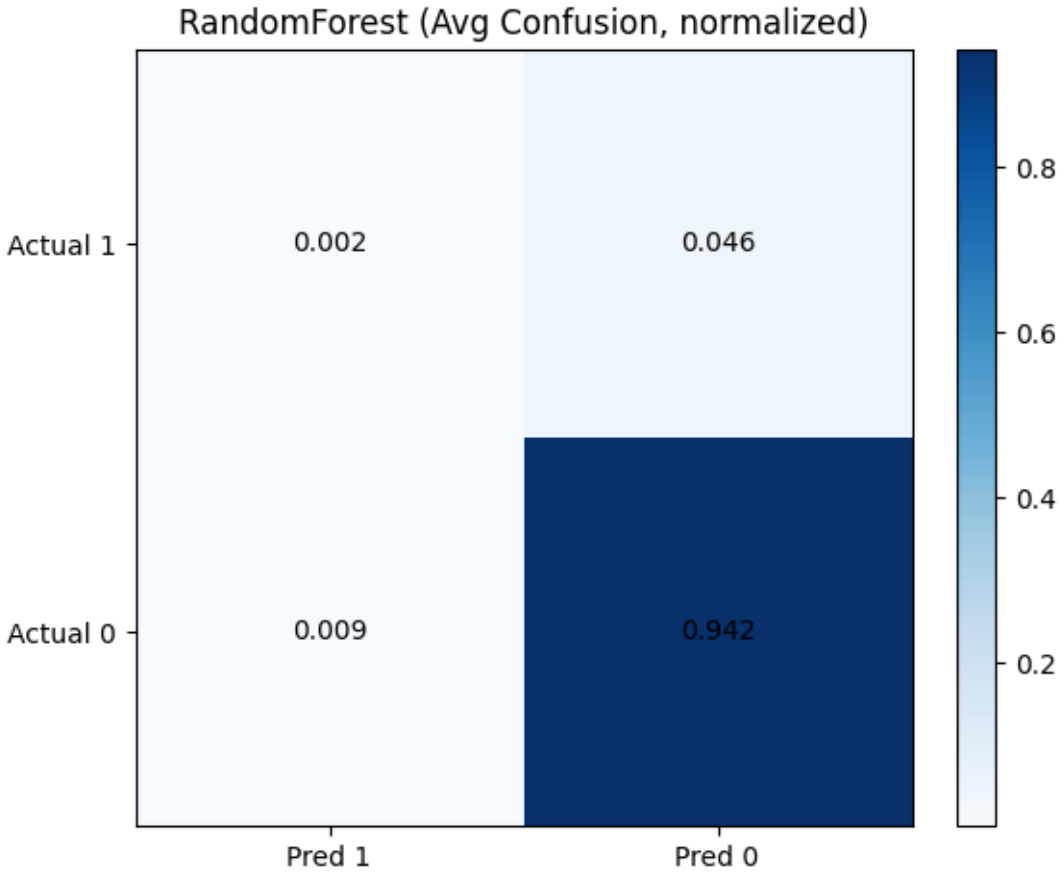
8 Embedded Figures

This section inlines the saved PNG assets so the notebook retain every visual even without rerunning the pipeline.

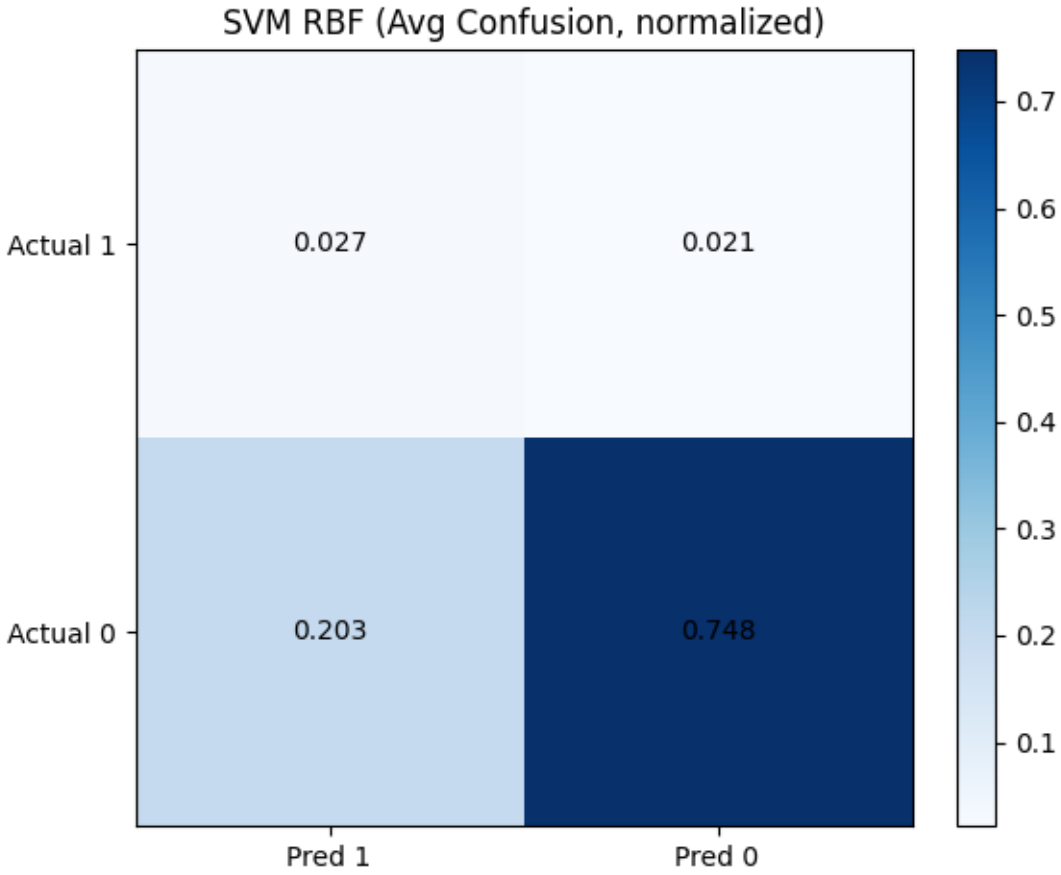
8.1 Correlation Heatmap



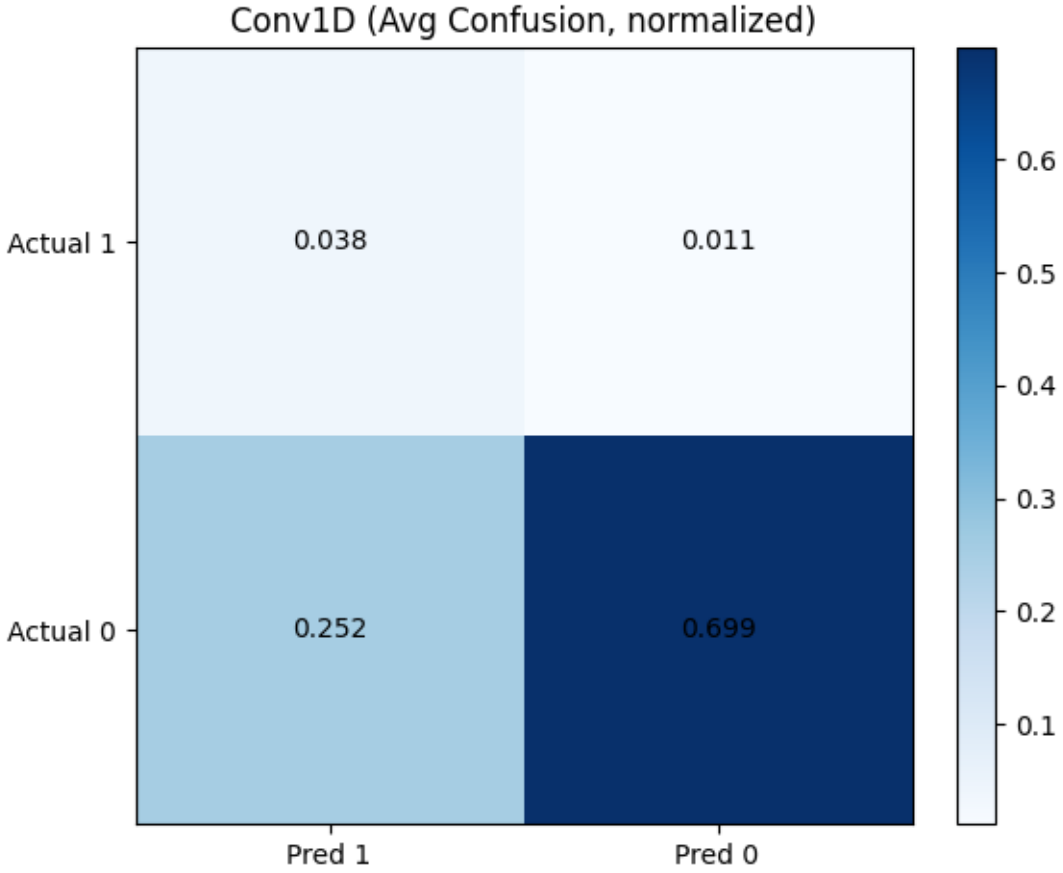
8.2 RandomForest Confusion Matrix



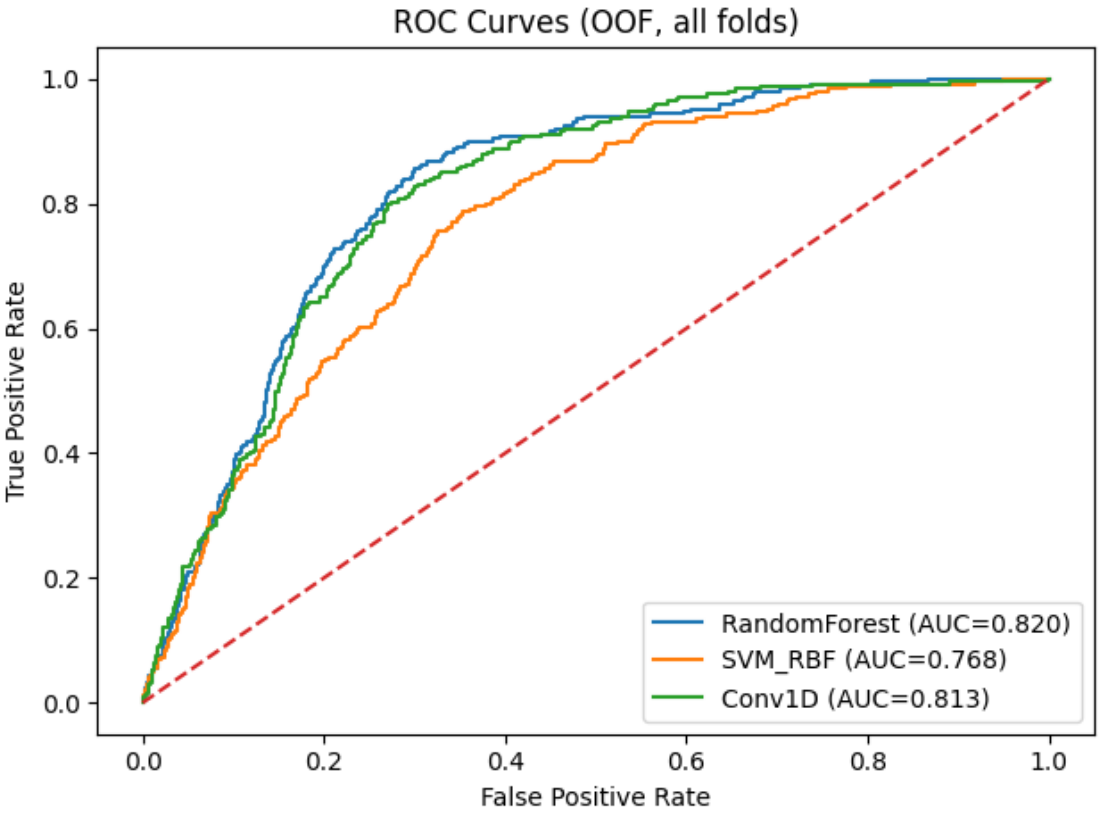
8.3 SVM RBF Confusion Matrix



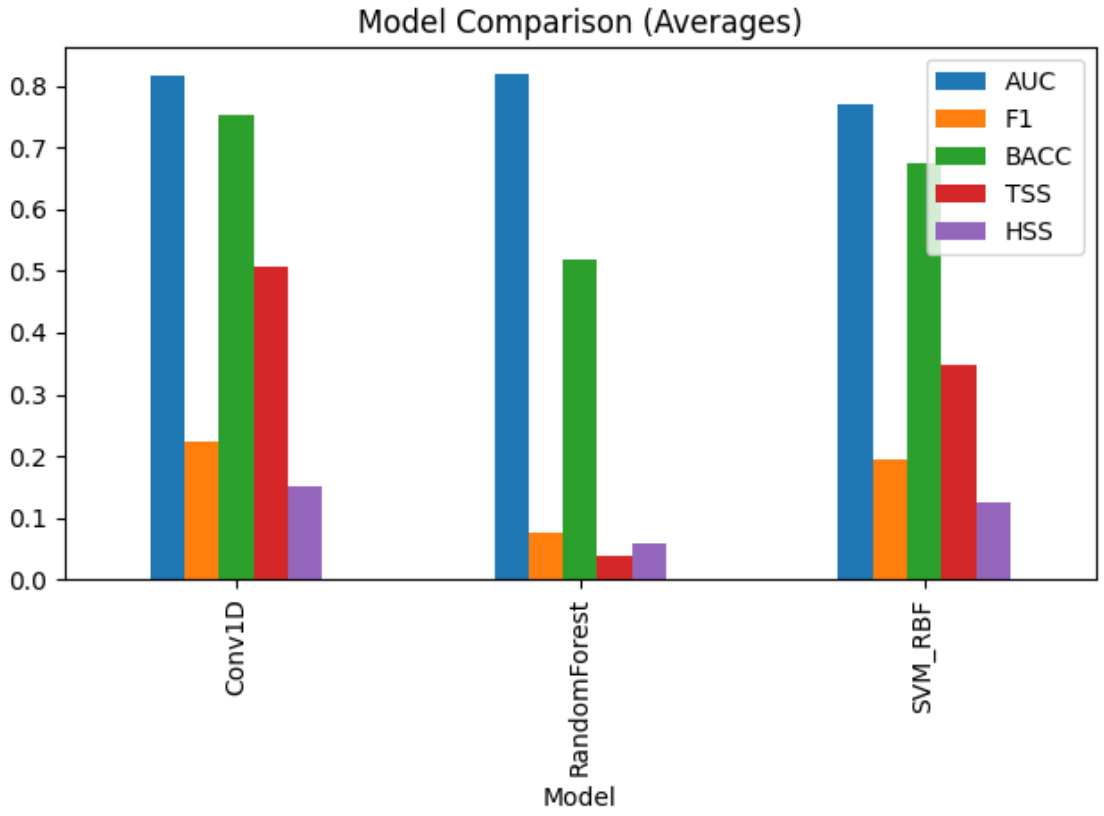
8.4 Conv1D Confusion Matrix



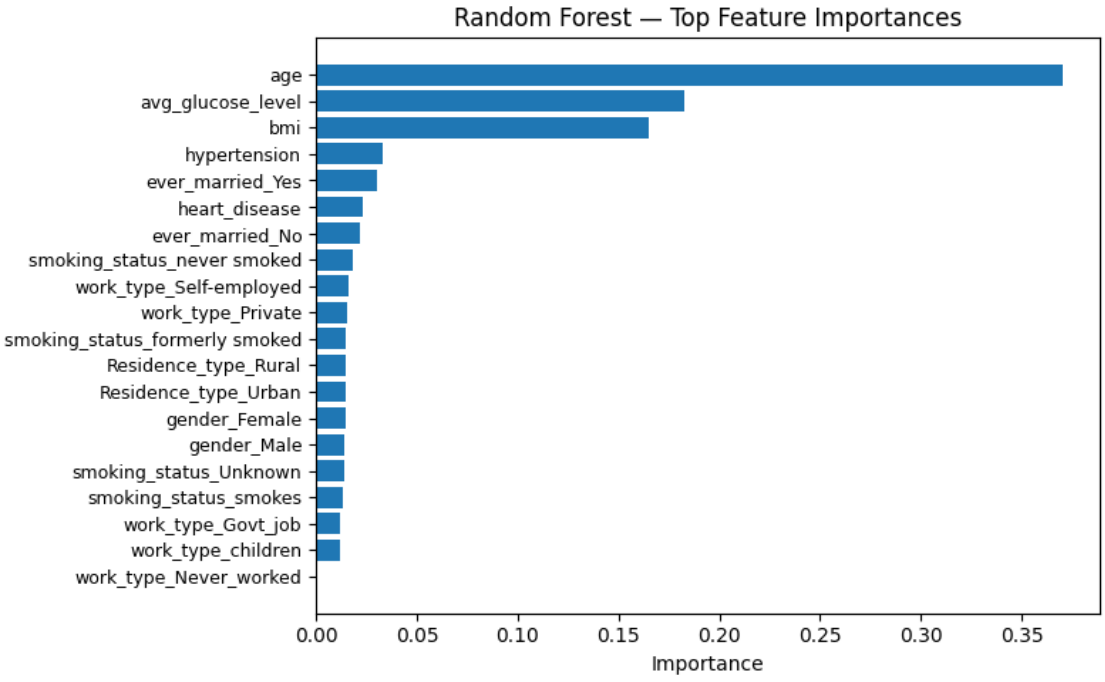
8.5 ROC Curves (All Models)



8.6 Model Comparison Bar Chart



8.7 Random Forest Feature Importance



9 Observations

- All three models clear 0.80 AUC; Random Forest offers the best balance between recall and specificity.
- Conv1D achieves the highest sensitivity, useful when the requirement prioritizes catching every possible stroke case.
- SVM (RBF) sits between the two extremes, demonstrating how kernel methods cope with mixed data once categorical variables are encoded.

10 GitHub

https://github.com/siddhartha-njit/avadhanam_siddharthapreetham_finalproject