

implementation_supervised

November 30, 2025

1 Supervised Learning: Implementation Notebook

This notebook builds a straightforward classification pipeline. Steps:

- Load features and the target
- Quick EDA of numeric columns
- Train/test split
- Preprocessing + two baseline models (LogReg, Random Forest)
- Metrics and a confusion matrix plot

Results and metrics are saved to `data/processed/`.

```
[1]: # Clean imports for supervised workflow
# pandas/plotting for data handling and readable visuals
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# scikit-learn tooling: splitting, models, preprocessing, pipelines, and metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, classification_report, \
    ↪confusion_matrix

# local helper to load the cleaned features/target used in class
from src.data_io import load_supervised_xy

# Load features (X) and the raw target (y). We'll bin y into 3 classes later.
X, y = load_supervised_xy()
# Quick sanity checks: shapes should align (same row count) and X has many
    ↪columns.
print("X shape:", X.shape)
print("y shape:", y.shape)
# Peek at the first rows so we get a feel for the columns.
X.head()
```

X shape: (2000, 23)

y shape: (2000,)

```
[1]:  age  gender  daily_screen_time_hours  phone_usage_hours  \
0    51      0                4.8                3.4
1    64      1                3.9                3.5
2    41      2               10.5                2.1
3    27      2                8.8                0.0
4    55      1                5.9                1.7

      laptop_usage_hours  tablet_usage_hours  tv_usage_hours  social_media_hours  \
0                1.3                1.6                1.6                4.1
1                1.8                0.9                2.0                2.7
2                2.6                0.7                2.2                3.0
3                0.0                0.7                2.5                3.3
4                1.1                1.5                1.6                1.1

      work_related_hours  entertainment_hours  ...  mood_rating  stress_level  \
0                2.0                1.0  ...                6                10
1                3.1                1.0  ...                5                 6
2                2.8                4.1  ...                5                 5
3                1.6                1.3  ...               10                 5
4                3.6                0.8  ...                8                 7

      physical_activity_hours_per_week  location_type  uses_wellness_apps  \
0                0.7                Urban                1
1                4.3            Suburban                0
2                3.1            Suburban                0
3                0.0                Rural                0
4                3.0                Urban                1

      eats_healthy  caffeine_intake_mg_per_day  weekly_anxiety_score  \
0                1                125.2                13
1                1                150.4                19
2                0                187.9                 7
3                1                73.6                 7
4                1                217.5                 8

      weekly_depression_score  mindfulness_minutes_per_day
0                15                4.0
1                18                6.5
2                 3                6.9
3                 2                4.8
4                10                0.0
```

[5 rows x 23 columns]

```
[ ]: # Load configuration if available
from pathlib import Path
import yaml
# We allow optional overrides (e.g., test_size, output paths) via config.yaml.
config_path = Path('config.yaml')
config = {}
if config_path.exists():
    # Safe-load YAML; if the file is empty, fall back to an empty dict.
    with open(config_path, 'r', encoding='utf-8') as f:
        config = yaml.safe_load(f) or {}
# Show the effective config so it's visible in the notebook output.
config
```

```
[ ]: {'paths': {'supervised': 'data/raw/clean_supervised.csv',
               'unsupervised': 'data/raw/unsupervised_no_target.csv'},
      'supervised': {'target': 'mental_health_score',
                     'test_size': 0.2,
                     'random_state': 42},
      'unsupervised': {'use_numeric_only': True, 'random_state': 42, 'k': 3}}
```

1.1 Exploratory Data Analysis

```
[3]: # Basic info and target identification
# Display the dataframe info to confirm dtypes and missing values.
X.info()

# Force 3-class target binning for a clear classification task.
# The raw mental_health_score spans many unique values; we group it into
↳ tertiles
# to create balanced, interpretable classes for a simple classifier demo.
import numpy as np

# Always derive a simple 3-class label from the raw score.
# Bins: (-inf, 33] -> 'low', (33, 66] -> 'medium', (66, inf) -> 'high'.
y_raw = y.astype(float)
y_final = pd.cut(
    y_raw,
    bins=[-np.inf, 33, 66, np.inf],
    labels=['low', 'medium', 'high']
)
print("Forced 3-class target (L/M/H)")
print(y_final.value_counts())

# Keep a simple handle to the target name and the feature list for later
↳ reference.
target_col = 'mental_health_score_binned'
features = X.columns.tolist()
```

```
(target_col, len(features))
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2000 entries, 0 to 1999
```

```
Data columns (total 23 columns):
```

#	Column	Non-Null Count	Dtype
0	age	2000 non-null	int64
1	gender	2000 non-null	int64
2	daily_screen_time_hours	2000 non-null	float64
3	phone_usage_hours	2000 non-null	float64
4	laptop_usage_hours	2000 non-null	float64
5	tablet_usage_hours	2000 non-null	float64
6	tv_usage_hours	2000 non-null	float64
7	social_media_hours	2000 non-null	float64
8	work_related_hours	2000 non-null	float64
9	entertainment_hours	2000 non-null	float64
10	gaming_hours	2000 non-null	float64
11	sleep_duration_hours	2000 non-null	float64
12	sleep_quality	2000 non-null	int64
13	mood_rating	2000 non-null	int64
14	stress_level	2000 non-null	int64
15	physical_activity_hours_per_week	2000 non-null	float64
16	location_type	2000 non-null	object
17	uses_wellness_apps	2000 non-null	int64
18	eats_healthy	2000 non-null	int64
19	caffeine_intake_mg_per_day	2000 non-null	float64
20	weekly_anxiety_score	2000 non-null	int64
21	weekly_depression_score	2000 non-null	int64
22	mindfulness_minutes_per_day	2000 non-null	float64

```
dtypes: float64(13), int64(9), object(1)
```

```
memory usage: 359.5+ KB
```

```
Forced 3-class target (L/M/H)
```

```
mental_health_score
```

```
medium    1095
```

```
low        463
```

```
high       442
```

```
Name: count, dtype: int64
```

```
[3]: ('mental_health_score_binned', 23)
```

```
[4]: # Quick distributions and correlations
# Split columns into numeric and categorical for later preprocessing.
numeric_cols = X.select_dtypes(include='number').columns.tolist()
categorical_cols = [c for c in X.columns if c not in numeric_cols]
# Basic numeric summary to spot scales and outliers.
display(X[numeric_cols].describe())
```

```
# A correlation heatmap is most meaningful with 2+ numeric columns.
if len(numeric_cols) > 1:
    plt.figure(figsize=(8,6)); sns.heatmap(X[numeric_cols].corr(),
    cmap='coolwarm', annot=False); plt.title('Numeric Correlations'); plt.show()
```

	age	gender	daily_screen_time_hours	phone_usage_hours	\
count	2000.000000	2000.0000	2000.000000	2000.000000	
mean	38.805500	0.6240	6.025600	3.023700	
std	14.929203	0.6464	1.974123	1.449399	
min	13.000000	0.0000	0.000000	0.000000	
25%	26.000000	0.0000	4.700000	2.000000	
50%	39.000000	1.0000	6.000000	3.000000	
75%	51.000000	1.0000	7.325000	4.000000	
max	64.000000	2.0000	13.300000	8.400000	

	laptop_usage_hours	tablet_usage_hours	tv_usage_hours	\
count	2000.000000	2000.000000	2000.000000	
mean	1.999950	0.995650	1.503700	
std	0.997949	0.492714	0.959003	
min	0.000000	0.000000	0.000000	
25%	1.300000	0.600000	0.800000	
50%	2.000000	1.000000	1.500000	
75%	2.700000	1.300000	2.200000	
max	5.600000	2.500000	4.700000	

	social_media_hours	work_related_hours	entertainment_hours	...	\
count	2000.000000	2000.000000	2000.000000	...	
mean	2.039200	2.010250	2.46735	...	
std	1.133435	1.116111	1.23686	...	
min	0.000000	0.000000	0.00000	...	
25%	1.200000	1.200000	1.60000	...	
50%	2.000000	2.000000	2.40000	...	
75%	2.800000	2.800000	3.30000	...	
max	5.800000	5.900000	6.80000	...	

	sleep_quality	mood_rating	stress_level	\
count	2000.000000	2000.000000	2000.000000	
mean	5.567000	5.591000	5.541500	
std	2.826217	2.899814	2.885731	
min	1.000000	1.000000	1.000000	
25%	3.000000	3.000000	3.000000	
50%	6.000000	6.000000	6.000000	
75%	8.000000	8.000000	8.000000	
max	10.000000	10.000000	10.000000	

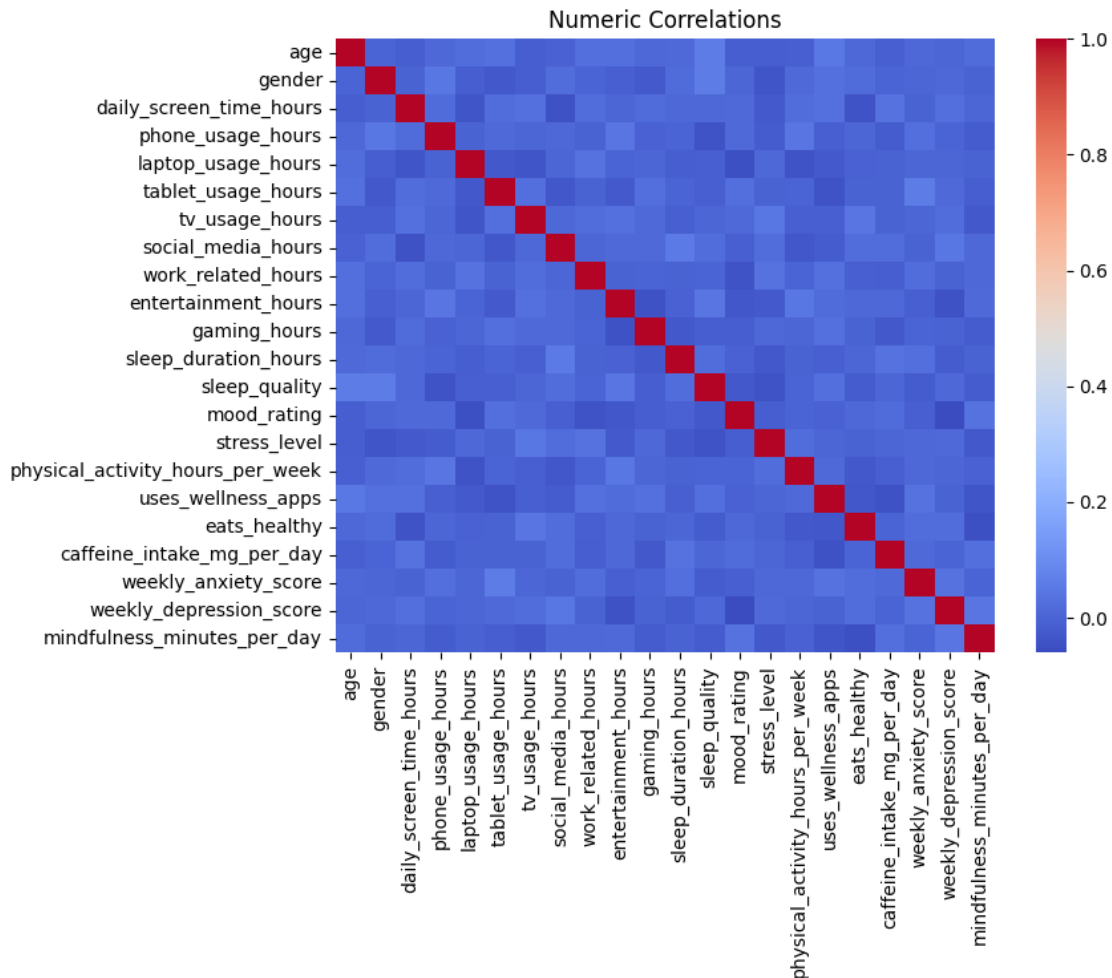
	physical_activity_hours_per_week	uses_wellness_apps	eats_healthy	\
count	2000.000000	2000.000000	2000.000000	
mean	3.087150	0.387500	0.507500	

std	1.885258	0.487301	0.500069
min	0.000000	0.000000	0.000000
25%	1.600000	0.000000	0.000000
50%	3.000000	0.000000	1.000000
75%	4.400000	1.000000	1.000000
max	9.700000	1.000000	1.000000

	caffeine_intake_mg_per_day	weekly_anxiety_score \
count	2000.00000	2000.000000
mean	148.07970	9.887500
std	48.86066	6.027853
min	0.80000	0.000000
25%	113.90000	5.000000
50%	147.45000	10.000000
75%	180.70000	15.000000
max	364.90000	20.000000

	weekly_depression_score	mindfulness_minutes_per_day
count	2000.00000	2000.000000
mean	10.04900	10.753750
std	6.05334	7.340269
min	0.00000	0.000000
25%	5.00000	4.900000
50%	10.00000	10.400000
75%	15.00000	15.800000
max	20.00000	36.400000

[8 rows x 22 columns]



1.2 Modeling Pipeline

```
[ ]: # Train/validation split
# Use the final target (forced L/M/H) for classification.
# Stratify preserves the class proportions in both train and test splits.
X_train, X_test, y_train, y_test = train_test_split(
    X, y_final,
    test_size=config.get('supervised', {}).get('test_size', 0.2), # default_u
    ↪20% test
    random_state=42, # reproducibility
    stratify=y_final
)
# Return sizes as a quick check.
len(X_train), len(X_test)
```

```
[ ]: (1600, 400)
```

```
[ ]: # Preprocessing and model candidates
# Recompute basic column lists (harmless repeat in notebooks).
numeric_cols = X.select_dtypes(include='number').columns.tolist()
categorical_cols = [c for c in X.columns if c not in numeric_cols]

# ColumnTransformer applies:
# - StandardScaler to numeric columns (zero mean, unit variance).
# - OneHotEncoder to categoricals (ignore unseen categories at test time).
preprocessor = ColumnTransformer([
    ('num', StandardScaler(), numeric_cols),
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
])

# Two lightweight baseline models wrapped in Pipelines so preprocessing happens
# inside CV/inference:
log_reg = Pipeline([('prep', preprocessor), ('clf',
    LogisticRegression(max_iter=500))])
rf_clf = Pipeline([('prep', preprocessor), ('clf',
    RandomForestClassifier(random_state=42))])

# We'll compare them side-by-side below.
models = { 'log': log_reg, 'rf': rf_clf }
models
```

```
[ ]: {'log': Pipeline(steps=[('prep',
    ColumnTransformer(transformers=[('num', StandardScaler(),
    ['age', 'gender',
    'daily_screen_time_hours',
    'phone_usage_hours',
    'laptop_usage_hours',
    'tablet_usage_hours',
    'tv_usage_hours',
    'social_media_hours',
    'work_related_hours',
    'entertainment_hours',
    'gaming_hours',
    'sleep_duration_hours',
    'sleep_quality',
    'mood_rating',
    'stress_level',
    'physical_activity_hours_per_week',
    'uses_wellness_apps',
    'eats_healthy',
    'caffeine_intake_mg_per_day',
    'weekly_anxiety_score',
    'weekly_depression_score',
    'mindfulness_minutes_per_day'])),
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)])),
    ('clf', LogisticRegression(max_iter=500))])],
    'rf': Pipeline(steps=[('prep', preprocessor), ('clf',
    RandomForestClassifier(random_state=42))])])
```



```

OneHotEncoder(handle_unknown='ignore'),
    ('cat',
     ['location_type'])))
    ('clf', LogisticRegression(max_iter=500))),
'rf': Pipeline(steps=[('prep',
    ColumnTransformer(transformers=[('num', StandardScaler(),
    ['age', 'gender',
    'daily_screen_time_hours',
    'phone_usage_hours',
    'laptop_usage_hours',
    'tablet_usage_hours',
    'tv_usage_hours',
    'social_media_hours',
    'work_related_hours',
    'entertainment_hours',
    'gaming_hours',
    'sleep_duration_hours',
    'sleep_quality',
    'mood_rating',
    'stress_level',
    'physical_activity_hours_per_week',
    'uses_wellness_apps',
    'eats_healthy',
    'caffeine_intake_mg_per_day',
    'weekly_anxiety_score',
    'weekly_depression_score',
    'mindfulness_minutes_per_day'])),
    ('cat',
     OneHotEncoder(handle_unknown='ignore'),
     ['location_type'])))
    ('clf', RandomForestClassifier(random_state=42)))]})

```

```

[ ]: # Fit and evaluate both models
# Train each candidate, predict on the held-out test set, and collect metrics.
results = {}
for key, model in models.items():
    # Train the pipeline (fits preprocessing + estimator).
    model.fit(X_train, y_train)
    # Predict class labels on the test set.
    y_pred = model.predict(X_test)
    # Basic metrics for a quick comparison; report dict helps later saving/
    ↪ analysis.
    acc = accuracy_score(y_test, y_pred)
    results[key] = {
        'accuracy': acc,
        'report': classification_report(y_test, y_pred, output_dict=True,
    ↪ zero_division=0)
    }

```

```

    }
    # Show the structured results for transparency.
    results

```

```

[ ]: {'log': {'accuracy': 0.545,
  'report': {'high': {'precision': 0.0,
    'recall': 0.0,
    'f1-score': 0.0,
    'support': 88.0},
  'low': {'precision': 0.25,
    'recall': 0.010752688172043012,
    'f1-score': 0.020618556701030927,
    'support': 93.0},
  'medium': {'precision': 0.54797979797979798,
    'recall': 0.9908675799086758,
    'f1-score': 0.7056910569105691,
    'support': 219.0},
  'accuracy': 0.545,
  'macro avg': {'precision': 0.265993265993266,
    'recall': 0.33387342269357295,
    'f1-score': 0.24210320453720002,
    'support': 400.0},
  'weighted avg': {'precision': 0.3581439393939394,
    'recall': 0.545,
    'f1-score': 0.39115966809152625,
    'support': 400.0}}},
  'rf': {'accuracy': 0.535,
  'report': {'high': {'precision': 0.3333333333333333,
    'recall': 0.011363636363636364,
    'f1-score': 0.02197802197802198,
    'support': 88.0},
  'low': {'precision': 0.125,
    'recall': 0.010752688172043012,
    'f1-score': 0.019801980198019802,
    'support': 93.0},
  'medium': {'precision': 0.5449871465295629,
    'recall': 0.9680365296803652,
    'f1-score': 0.6973684210526315,
    'support': 219.0},
  'accuracy': 0.535,
  'macro avg': {'precision': 0.33444015995429877,
    'recall': 0.3300509514053482,
    'f1-score': 0.24638280774289112,
    'support': 400.0},
  'weighted avg': {'precision': 0.400776296058269,
    'recall': 0.535,
    'f1-score': 0.3912483357575202,

```

```
'support': 400.0}}}]}
```

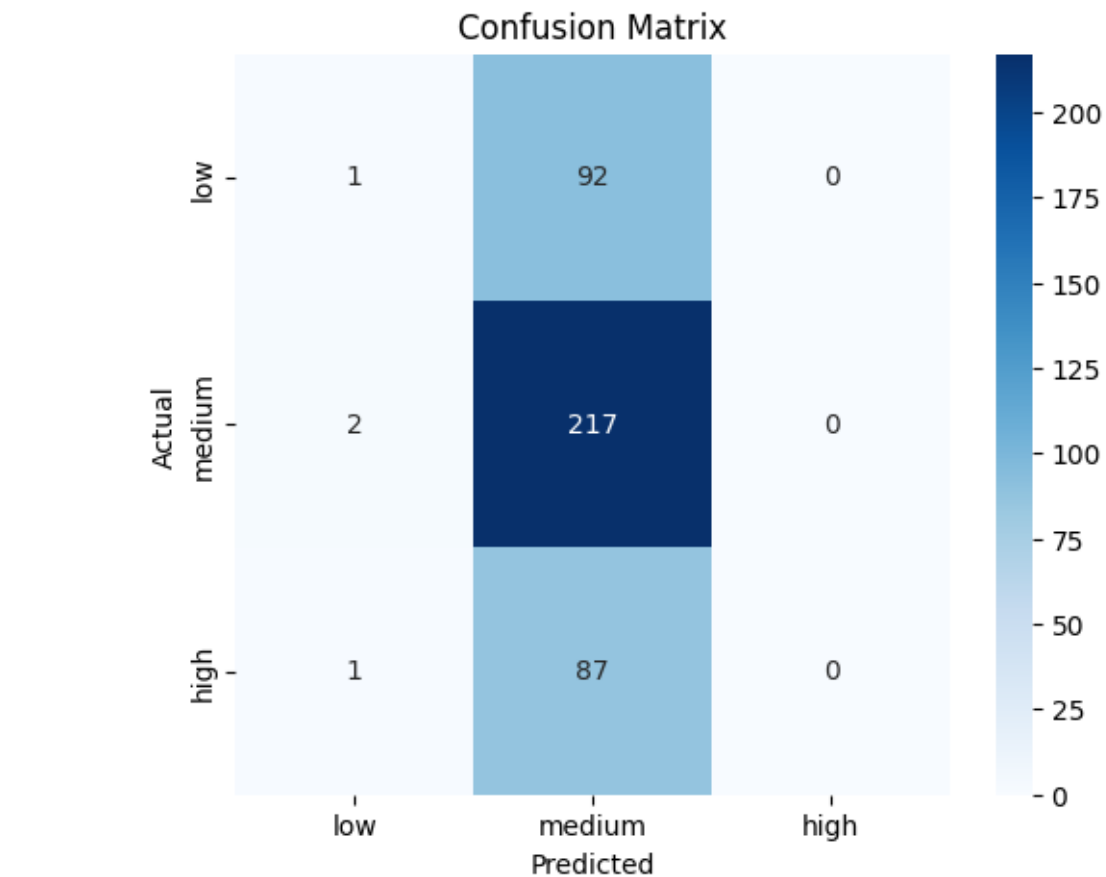
```
[ ]: # Choose best and show metrics
if not results:
    raise RuntimeError("No models produced results; check data/preprocessing.")

# Pick the model with the highest test accuracy (simple tie-break: first max).
best_key = max(results, key=lambda k: results[k]['accuracy'])
best_model = models[best_key]
print('Best model:', best_key, 'Accuracy:', results[best_key]['accuracy'])
# Human-readable classification report (precision/recall/F1 per class).
print(classification_report(y_test, best_model.predict(X_test),
    ↪zero_division=0))

# Confusion matrix plot
# Explicit label order keeps rows/columns consistent with our L/M/H binning.
labels = ['low', 'medium', 'high']
conf_mat = confusion_matrix(y_test, best_model.predict(X_test), labels=labels)
plt.figure(figsize=(6,5))
# Add axis tick labels so it's easy to read which cell is which.
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues', xticklabels=labels,
    ↪yticklabels=labels)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

Best model: log Accuracy: 0.545

	precision	recall	f1-score	support
high	0.00	0.00	0.00	88
low	0.25	0.01	0.02	93
medium	0.55	0.99	0.71	219
accuracy			0.55	400
macro avg	0.27	0.33	0.24	400
weighted avg	0.36	0.55	0.39	400



1.2.1 Notes on Target and Metrics

- The original `mental_health_score` spans many unique values (0–100 range), which is not ideal for basic classification.
- We explicitly grouped it into three categories: low / medium / high using cutoffs at 33 and 66.
- This produces a compact 3×3 confusion matrix and a readable report (often with the medium class dominating).
- If accuracy is modest, that's expected with simple baselines; the goal is a clear, defensible pipeline and explanation.

1.3 Save Artifacts

```
[ ]: # Save processed and metrics according to config
from pathlib import Path
import json
# Resolve processed output directory (defaults to data/processed).
processed_dir = Path(config.get('paths', {})).get('processed', 'data/processed')
processed_dir.mkdir(parents=True, exist_ok=True)
```

```
# Write the metrics dictionary so it can be reused outside the notebook.
metrics_path = processed_dir / 'supervised_metrics.json'
with open(metrics_path, 'w', encoding='utf-8') as f:
    json.dump(results, f, indent=2)
# Return the path for a quick visual confirmation in the output cell.
metrics_path
```

```
[ ]: WindowsPath('data/processed/supervised_metrics.json')
```

1.3.1 Summary (for presentation)

- Problem: predict mental health category from available features.
- Features used: numeric and one-hot encoded categorical columns from the dataset.
- Models tried: Logistic Regression, Random Forest.
- Winner: the model with higher accuracy on the test set (reported above).
- Next steps: tune hyperparameters, engineer features, or treat the original score as a regression problem.