```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
```

```
df = pd.read_csv('/content/T_ML_Dataset151025.csv')
```

```
/tmp/ipython-input-4092072916.py:1: DtypeWarning: Columns (15) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('/content/T_ML_Dataset151025.csv')
```

```
# Show size and columns
print(df.shape)
df.head()
```

```
(594687, 28)
```

| | device_id | ts | power_w | voltage_v | current_a | relay_on | energy_wh_acc | firmware | location | illuminance_lux | ... | outlet_id | is_110v | is_220v | Bracker_amp | max_watts | hour | weekday | Month | is_weekend | is_anomaly |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 2024-10-07 23:50:00 | 732.770186 | 118.880771 | 6.163908 | 1 | 6660455 | 1.12.3 | 77327 | 0.0 | ... | 1 | 1 | 0 | 30 | 3800 | 23 | 0 | 10 | 0 | 1 |
| **1** | 1 | 2024-10-07 23:50:00 | 768.632021 | 120.267027 | 6.391045 | 1 | 6658628 | 1.12.3 | 77327 | 0.0 | ... | 1 | 1 | 0 | 30 | 3800 | 23 | 0 | 10 | 0 | 1 |
| **2** | 1 | 2024-10-08 00:00:00 | 835.137039 | 119.387939 | 6.995154 | 1 | 139 | 1.12.3 | 77327 | 0.0 | ... | 1 | 1 | 0 | 30 | 3800 | 0 | 1 | 10 | 0 | 1 |
| **3** | 1 | 2024-10-08 00:10:00 | 619.227933 | 119.496472 | 5.181977 | 0 | 242 | 1.12.3 | 77327 | 0.0 | ... | 1 | 1 | 0 | 30 | 3800 | 0 | 1 | 10 | 0 | 0 |
| **4** | 1 | 2024-10-08 00:20:00 | 524.165806 | 118.527716 | 4.422306 | 1 | 330 | 1.12.3 | 77327 | 0.0 | ... | 1 | 1 | 0 | 30 | 3800 | 0 | 1 | 10 | 0 | 1 |

5 rows × 28 columns

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 594687 entries, 0 to 594686
Data columns (total 28 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   device_id            594687 non-null  int64  
 1   ts                   594687 non-null  object 
 2   power_w              594687 non-null  float64
 3   voltage_v            594687 non-null  float64
 4   current_a            594687 non-null  float64
 5   relay_on             594687 non-null  int64  
 6   energy_wh_acc        594687 non-null  int64  
 7   firmware             594687 non-null  object 
 8   location             594687 non-null  int64  
 9   illuminance_lux      594687 non-null  float64
 10  presence             594687 non-null  int64  
 11  presence_confidence  594687 non-null  float64
 12  temp_c_avg           594687 non-null  float64
 13  Hostname             594687 non-null  object 
 14  vendor               594687 non-null  object 
 15  model                594687 non-null  object 
 16  device_type          594687 non-null  int64  
 17  area                 594687 non-null  int64  
 18  outlet_id            594687 non-null  int64  
 19  is_110v              594687 non-null  int64  
 20  is_220v              594687 non-null  int64  
 21  Bracker_amp          594687 non-null  int64  
 22  max_watts            594687 non-null  int64  
 23  hour                 594687 non-null  int64  
 24  weekday              594687 non-null  int64  
 25  Month                594687 non-null  int64  
 26  is_weekend           594687 non-null  int64  
 27  is_anomaly           594687 non-null  int64  
dtypes: float64(6), int64(17), object(5)
memory usage: 127.0+ MB
```

| | device_id | power_w | voltage_v | current_a | relay_on | energy_wh_acc | location | illuminance_lux | presence | presence_confidence | ... | outlet_id | is_110v | is_220v | Bracker_amp | max_watts | hour | weekday | Month |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 | 5.946870e+05 | 594687.0 | 594687.000000 | 594687.000000 | 594687.000000 | ... | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 | 594687.000000 |
| **mean** | 2.772495 | 755.884727 | 119.998537 | 6.300036 | 0.849776 | 3.246057e+06 | 77327.0 | 177.830669 | 0.226075 | 0.435731 | ... | 4.544991 | 0.291002 | 0.708998 | 37.089982 | 7344.990894 | 11.497964 | 2.996775 | 6.626491 |
| **std** | 1.475042 | 154.625994 | 1.443347 | 1.291154 | 0.357291 | 1.946336e+06 | 0.0 | 257.105611 | 0.418289 | 0.247317 | ... | 2.347872 | 0.454225 | 0.454225 | 9.567233 | 2930.795056 | 6.922330 | 2.001259 | 3.465153 |
| **min** | 1.000000 | 488.753063 | 117.500005 | 3.991846 | 0.000000 | 8.200000e+01 | 77327.0 | 0.000000 | 0.000000 | 0.200000 | ... | 1.000000 | 0.000000 | 0.000000 | 30.000000 | 3800.000000 | 0.000000 | 0.000000 | 1.000000 |
| **25%** | 1.000000 | 638.631636 | 118.748183 | 5.319629 | 1.000000 | 1.529204e+06 | 77327.0 | 0.000000 | 0.000000 | 0.258118 | ... | 1.000000 | 0.000000 | 0.000000 | 30.000000 | 3800.000000 | 5.000000 | 1.000000 | 4.000000 |
| **50%** | 3.000000 | 745.410975 | 119.997166 | 6.212132 | 1.000000 | 3.232541e+06 | 77327.0 | 0.000000 | 0.000000 | 0.329961 | ... | 6.000000 | 0.000000 | 1.000000 | 30.000000 | 6600.000000 | 11.000000 | 3.000000 | 7.000000 |
| **75%** | 4.000000 | 850.103272 | 121.249308 | 7.084141 | 1.000000 | 4.935722e+06 | 77327.0 | 387.113497 | 0.000000 | 0.439590 | ... | 6.000000 | 1.000000 | 1.000000 | 50.000000 | 11000.000000 | 17.000000 | 5.000000 | 10.000000 |
| **max** | 5.000000 | 1178.743914 | 122.499999 | 10.023153 | 1.000000 | 6.667095e+06 | 77327.0 | 719.948380 | 1.000000 | 0.999999 | ... | 7.000000 | 1.000000 | 1.000000 | 50.000000 | 11000.000000 | 23.000000 | 6.000000 | 12.000000 |

8 rows × 23 columns

```
# Number of Nulls
df.isnull().sum()
```

| | 0 |
|---|---|
| device_id | 0 |
| ts | 0 |
| power_w | 0 |
| voltage_v | 0 |
| current_a | 0 |
| relay_on | 0 |
| energy_wh_acc | 0 |
| firmware | 0 |
| location | 0 |
| illuminance_lux | 0 |
| presence | 0 |
| presence_confidence | 0 |
| temp_c_avg | 0 |
| Hostname | 0 |
| vendor | 0 |
| model | 0 |
| device_type | 0 |
| area | 0 |
| outlet_id | 0 |
| is_110v | 0 |
| is_220v | 0 |
| Bracker_amp | 0 |
| max_watts | 0 |
| hour | 0 |
| weekday | 0 |
| Month | 0 |
| is_weekend | 0 |
| is_anomaly | 0 |

**dtype:** int64

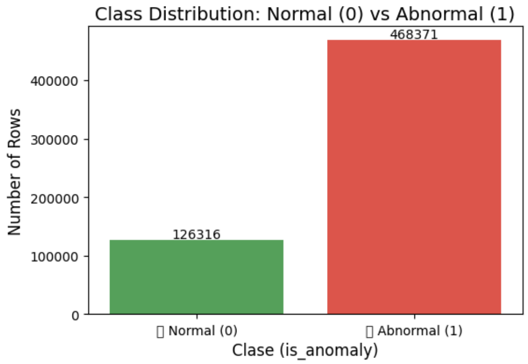
```
df.dropna(inplace=True)
print("✅ Filas con valores nulos eliminadas.")
```

✅ Filas con valores nulos eliminadas.

```
# ============================================================
# 1️⃣ Análisis de balance de clases
# ============================================================
import matplotlib.pyplot as plt
import seaborn as sns

# Contar los valores
conteo = df['is_anomaly'].value_counts().sort_index()

# Mostrar resultados numéricos
print("📊 Class distribution (is_anomaly):")
for etiqueta, cantidad in conteo.items():
    print(f"  Class {etiqueta}: {cantidad} rows ({cantidad/len(df)*100:.2f}%)")

# ============================================================
# 2️⃣ Visualización con gráfico de barras
# ============================================================
plt.figure(figsize=(6,4))
sns.barplot(x=conteo.index, y=conteo.values, palette=['#4CAF50','#F44336'])
plt.title('Class Distribution: Normal (0) vs Abnormal (1)', fontsize=14)
plt.xlabel('Clase (is_anomaly)', fontsize=12)
plt.ylabel('Number of Rows', fontsize=12)
plt.xticks([0,1], ['🟢 Normal (0)', '🔴 Abnormal (1)'])
for i, v in enumerate(conteo.values):
    plt.text(i, v + len(df)*0.005, str(v), ha='center', fontsize=10)
plt.show()

# ============================================================
# 3️⃣ Evaluación de balance
# ============================================================
minor = conteo.min()
major = conteo.max()
ratio = minor / major
```

```
if ratio < 0.5:
    print(f"⚠️ Unbalanced dataset: minor class = {minor}, Senior class = {major} (ratio = {ratio:.2f})")
    print("👉 Sugerencia: usar SMOTE, RandomUnderSampler o class_weight='balanced' Model.")
else:
    print(f"✅ Dataset balanceado (ratio = {ratio:.2f})")
```

```
📊 Class distribution (is_anomaly):
  Class 0: 126316 rows (21.24%)
  Class 1: 468371 rows (78.76%)
/tmp/ipython-input-1737811432.py:19: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=conteo.index, y=conteo.values, palette=['#4CAF50','#F44336'])
/usr/local/lib/python3.12/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128994 (\N{LARGE GREEN CIRCLE}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
/usr/local/lib/python3.12/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128308 (\N{LARGE RED CIRCLE}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```




```
⚠️ Unbalanced dataset: minor class = 126316, Senior class = 468371 (ratio = 0.27)
👉 Sugerencia: usar SMOTE, RandomUnderSampler o class_weight='balanced' Model.
```

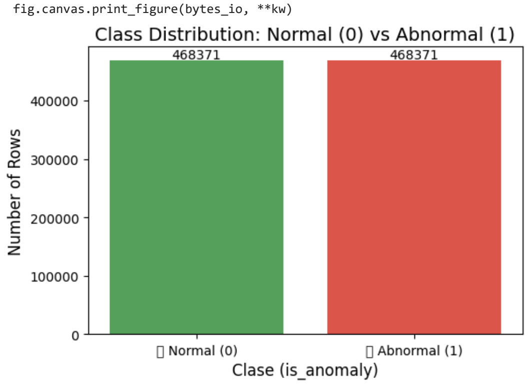
```
# ============================================================
# 1️⃣ Instalar e importar SMOTE
# ============================================================
!pip install imbalanced-learn --quiet
from imblearn.over_sampling import SMOTE
import pandas as pd

# ============================================================
# 2️⃣ Aplicar balanceo con SMOTE
# ============================================================
smote = SMOTE(random_state=42)
X_bal, y_bal = smote.fit_resample(X, y)

# ============================================================
# 3️⃣ Reconstruir el DataFrame balanceado
# ============================================================
# X_bal es un numpy array, y_bal es un vector → hay que unirlos
df_bal = pd.DataFrame(X_bal, columns=X.columns)
df_bal['is_anomaly'] = y_bal

# ============================================================
# 4️⃣ Verificar el nuevo balance
# ============================================================
conteo = df_bal['is_anomaly'].value_counts()
print("📊 Nueva distribución tras SMOTE:")
for k, v in conteo.items():
    print(f"  Clase {k}: {v} registros ({v/len(df_bal)*100:.2f}%)")

# ============================================================
# 5️⃣ Dividir dataset balanceado
# ============================================================
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    df_bal.drop('is_anomaly', axis=1),
    df_bal['is_anomaly'],
    test_size=0.2,
    random_state=42,
    stratify=df_bal['is_anomaly']
)

print(f"\n✅ Dataset listo. Tamaño final:")
print(f"  Train: {len(X_train)} | Test: {len(X_test)}")
```

```
📊 Nueva distribución tras SMOTE:
  Clase 1: 468371 registros (50.00%)
  Clase 0: 468371 registros (50.00%)
```

```
✅ Dataset listo. Tamaño final:
  Train: 749393 | Test: 187349
```

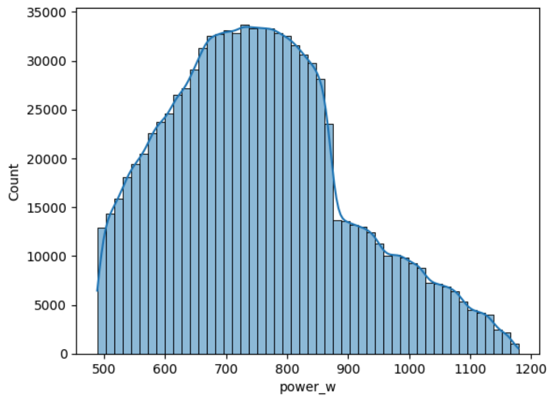
```python
# ============================================================
# 1️⃣ Análisis de balance de clases
# ============================================================
import matplotlib.pyplot as plt
import seaborn as sns

# Contar los valores
conteo =  df_bal['is_anomaly'].value_counts().sort_index()

# Mostrar resultados numéricos
print("📊 Class distribution (is_anomaly):")
for etiqueta, cantidad in conteo.items():
    print(f"  Class {etiqueta}: {cantidad} rows ({cantidad/len(df_bal)*100:.2f}%)")

# ============================================================
# 2️⃣ Visualización con gráfico de barras
# ============================================================
plt.figure(figsize=(6,4))
sns.barplot(x=conteo.index, y=conteo.values, palette=['#4CAF50','#F44336'])
plt.title('Class Distribution: Normal (0) vs Abnormal (1)', fontsize=14)
plt.xlabel('Clase (is_anomaly)', fontsize=12)
plt.ylabel('Number of Rows', fontsize=12)
plt.xticks([0,1], ['🟢 Normal (0)', '🔴 Abnormal (1)'])
for i, v in enumerate(conteo.values):
    plt.text(i, v + len(df)*0.005, str(v), ha='center', fontsize=10)
plt.show()

# ============================================================
# 3️⃣ Evaluación de balance
# ============================================================
minor = conteo.min()
major = conteo.max()
ratio = minor / major

if ratio < 0.5:
    print(f"⚠️ Unbalanced dataset: minor class = {minor}, Senior class = {major} (ratio = {ratio:.2f})")
    print("👉 Sugerencia: usar SMOTE, RandomUnderSampler o class_weight='balanced' Model.")
else:
    print(f"✅ Dataset balanceado (ratio = {ratio:.2f})")
```

```
📊 Class distribution (is_anomaly):
  Class 0: 468371 rows (50.00%)
  Class 1: 468371 rows (50.00%)
/tmp/ipython-input-2088039122.py:19: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=conteo.index, y=conteo.values, palette=['#4CAF50','#F44336'])
/usr/local/lib/python3.12/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128994 (\N{LARGE GREEN CIRCLE}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
/usr/local/lib/python3.12/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 128308 (\N{LARGE RED CIRCLE}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```

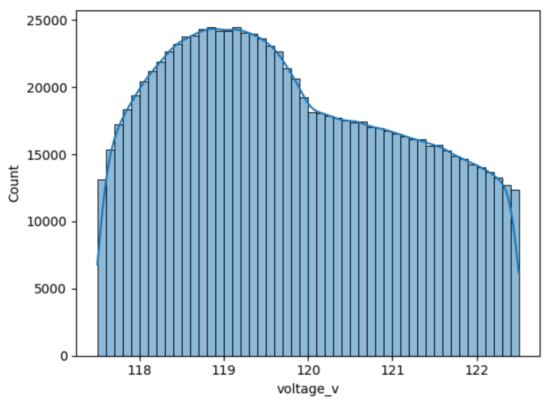



```
✅ Dataset balanceado (ratio = 1.00)
```

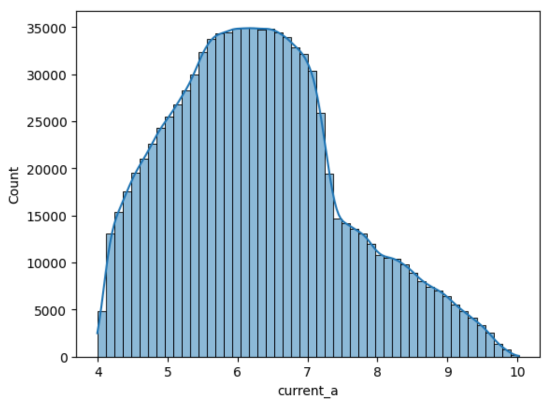
```python
sns.histplot(df_bal['power_w'], bins=50, kde=True)
plt.show()
```



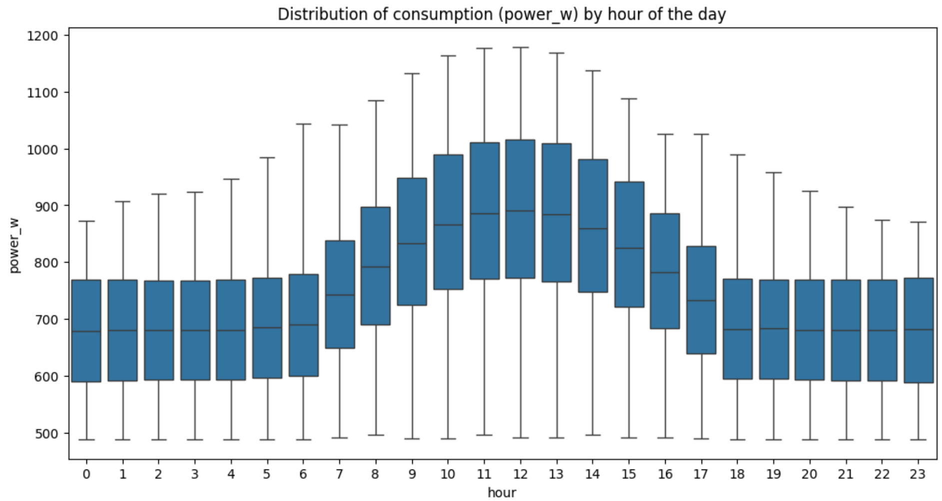

```
sns.histplot(df_bal['voltage_v'], bins=50, kde=True)
plt.show()
```




```
sns.histplot(df_bal['current_a'], bins=50, kde=True)
plt.show()
```

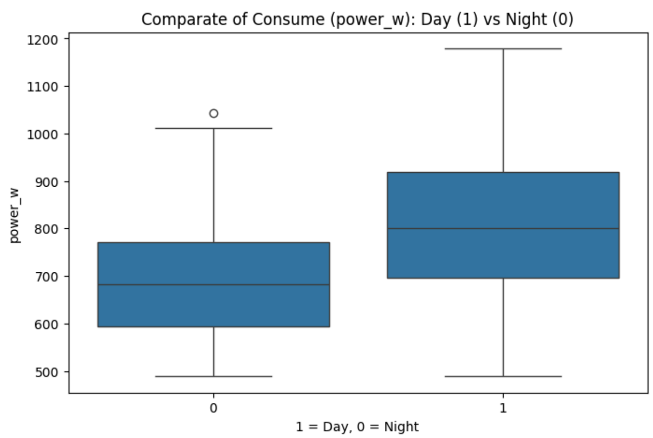



```
# df_bal['ts'] = pd.to_datetime(df_bal['ts']) # This line is removed
# df_bal['hour'] = df_bal['ts'].df_bal.hour # This line is removed


plt.figure(figsize=(12,6))
sns.boxplot(x='hour', y='power_w', data=df_bal)
plt.title('Distribution of consumption (power_w) by hour of the day')
plt.show()
```

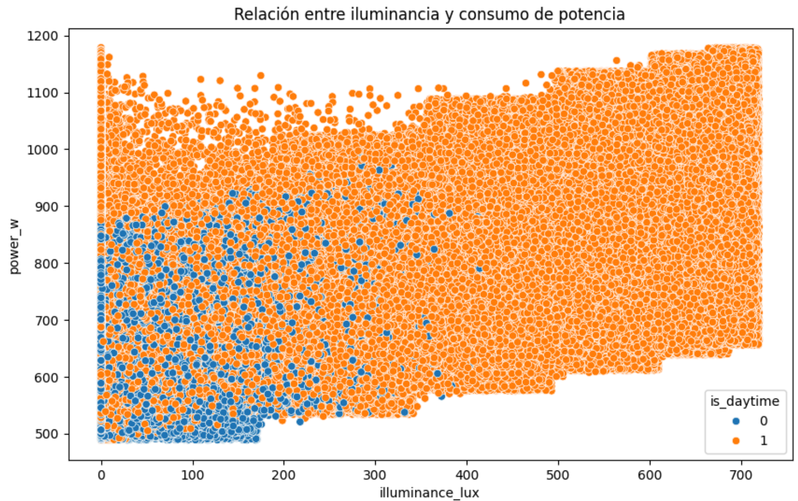



```
df_bal['is_daytime'] = ((df_bal['hour'] >= 7) & (df_bal['hour'] <= 19)).astype(int)
```

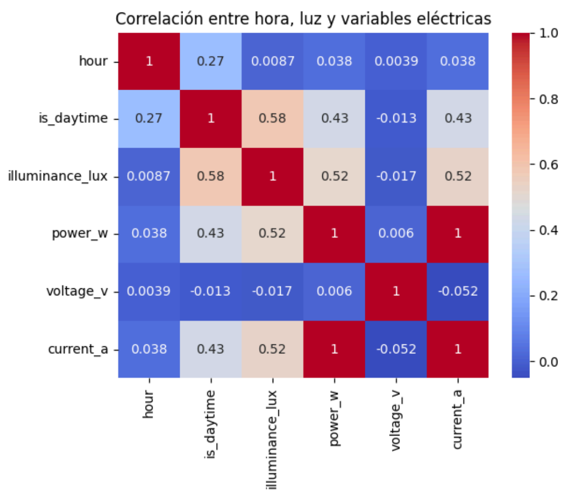
```
plt.figure(figsize=(8,5))
sns.boxplot(x='is_daytime', y='power_w', data=df_bal)
plt.title('Comparate of Consume (power_w): Day (1) vs Night (0)')
plt.xlabel('1 = Day, 0 = Night')
plt.show()
```




```
plt.figure(figsize=(10,6))
sns.scatterplot(x='illuminance_lux', y='power_w', hue='is_daytime', data=df_bal)
plt.title('Relación entre iluminancia y consumo de potencia')
plt.show()
```




```python
context_vars = ['hour', 'is_daytime', 'illuminance_lux', 'power_w', 'voltage_v', 'current_a']
sns.heatmap(df_bal[context_vars].corr(), annot=True, cmap='coolwarm')
plt.title('Correlación entre hora, luz y variables eléctricas')
plt.show()
```




```python
# Clean Data
```

```python
# Revisar columnas actuales
print("Columnas originales:", df_bal.columns.tolist())

# Eliminar columnas irrelevantes
columns_to_drop = ['firmware', 'vendor', 'Hostname', 'location']

# Eliminar una de is_110v o is_220v (mantener solo una)
# Ejemplo: creamos una columna combinada y borramos ambas
df_bal['voltage_type'] = df['is_220v'].apply(lambda x: '220V' if x == 1 else '110V')

# Luego eliminamos las originales
columns_to_drop.extend(['is_110v', 'is_220v'])

# Aplicar eliminación
df_bal.drop(columns=columns_to_drop, inplace=True, errors='ignore')

print("Columnas después de limpieza:", df_bal.columns.tolist())
```

```
Columnas originales: ['power_w', 'voltage_v', 'current_a', 'relay_on', 'energy_wh_acc', 'illuminance_lux', 'presence', 'presence_confidence', 'temp_c_avg', 'device_type', 'area', 'outlet_id', 'is_110v', 'is_220v', 'Bracker_amp', 'max_watts', 'hour', 'weekday', 'Month', 'is_week
Columnas después de limpieza: ['power_w', 'voltage_v', 'current_a', 'relay_on', 'energy_wh_acc', 'illuminance_lux', 'presence', 'presence_confidence', 'temp_c_avg', 'device_type', 'area', 'outlet_id', 'Bracker_amp', 'max_watts', 'hour', 'weekday', 'Month', 'is_weekend', 'is_anc
```

```
# Featuring Engeniering
```

```
# Aplicar One-Hot Encoding a 'device_type' y 'area'
df_encoded = pd.get_dummies(df_bal, columns=['device_type', 'area'], prefix=['dev', 'area'])

# Verificar las nuevas columnas
print("Nuevas columnas:", [col for col in df_encoded.columns if 'dev_' in col or 'area_' in col])
```

```
Nuevas columnas: ['dev_1', 'dev_3', 'dev_4', 'dev_5', 'dev_6', 'dev_7', 'dev_8', 'area_1', 'area_2', 'area_3', 'area_4']
```

```
print(df_encoded.head())
```

```
      power_w   voltage_v  current_a  relay_on  energy_wh_acc  \
0  732.770186  118.880771   6.163908         1        6660455
1  768.632021  120.267027   6.391045         1        6658628
2  835.137039  119.387939   6.995154         1            139
3  619.227933  119.496472   5.181977         0            242
4  524.165806  118.527716   4.422306         1            330

   illuminance_lux  presence  presence_confidence  temp_c_avg  outlet_id  ...  \
0              0.0         0             0.276138   16.479134          1  ...
1              0.0         0             0.375432   16.308392          1  ...
2              0.0         0             0.379196   14.872813          1  ...
3              0.0         0             0.225525   14.872813          1  ...
4              0.0         0             0.304784   14.872813          1  ...

   dev_3  dev_4  dev_5  dev_6  dev_7  dev_8  area_1  area_2 area_3  area_4
0  False  False  False  False  False  False    True   False  False   False
1  False  False  False  False  False  False    True   False  False   False
2  False  False  False  False  False  False    True   False  False   False
3  False  False  False  False  False  False    True   False  False   False
4  False  False  False  False  False  False    True   False  False   False

[5 rows x 30 columns]
```

```
print(f"Dataset cargado: {df_bal.shape[0]} registros, {df_bal.shape[1]} columnas")

# 2️⃣ Seleccionar features y variable objetivo
# --------------------------------------------------------------
# Usamos variables eléctricas y contextuales como features,
# y 'is_anomaly' como etiqueta (target)
target = 'is_anomaly'

# Excluir columnas no predictivas o de identificación
excluded_cols = ['device_id', 'ts']
X = df.drop(columns=excluded_cols + [target], errors='ignore')
y = df[target]

print(f"Variables predictoras: {X.shape[1]} | Target: '{target}'")
```

```
Dataset cargado: 936742 registros, 21 columnas
Variables predictoras: 25 | Target: 'is_anomaly'
```

```
if 'voltage_type' in X.columns:
    X['voltage_type'] = X['voltage_type'].replace({'110V': 0, '220V': 1})
```

```
# Detectar columnas no numéricas
non_numeric_cols = X.select_dtypes(exclude=[np.number]).columns.tolist()
print("Columnas no numéricas eliminadas:", non_numeric_cols)

# Eliminar columnas de texto
X = X.drop(columns=non_numeric_cols, errors='ignore')
```

```
Columnas no numéricas eliminadas: ['firmware', 'Hostname', 'vendor', 'model']
```

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
from sklearn.model_selection import train_test_split

# División del dataset: 80% entrenamiento, 20% prueba
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled,
    y,
    test_size=0.2,      # 20% de los datos para prueba
    random_state=42,    # reproducibilidad
    stratify=y          # mantiene la proporción de anomalías
)

print(f"Entrenamiento: {X_train.shape[0]} muestras | Prueba: {X_test.shape[0]} muestras")
```

```
Entrenamiento: 475749 muestras | Prueba: 118938 muestras
```

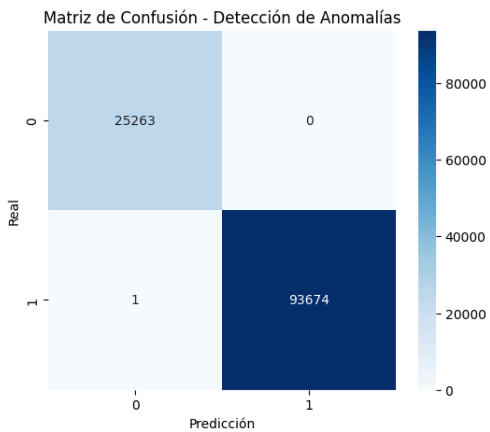
```
from sklearn.ensemble import RandomForestClassifier
```

```python
model = RandomForestClassifier(
    n_estimators=200,
    random_state=42,
    class_weight='balanced'
)

model.fit(X_train, y_train)
print("✅ Modelo entrenado correctamente.")
```

```
✅ Modelo entrenado correctamente.
```

```python
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt

y_pred = model.predict(X_test)

# Métricas principales
print(f"🎯 Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print("\n📊 Classification Report:")
print(classification_report(y_test, y_pred))

# Matriz de confusión
plt.figure(figsize=(6,5))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues')
plt.title('Matriz de Confusión - Detección de Anomalías')
plt.xlabel('Predicción')
plt.ylabel('Real')
plt.show()
```

```
🎯 Accuracy: 1.0000

📊 Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     25263
           1       1.00      1.00      1.00     93675

    accuracy                           1.00    118938
   macro avg       1.00      1.00      1.00    118938
weighted avg       1.00      1.00      1.00    118938
```




Start coding or generate with AI.

```python
# Ejemplo: registro de HVAC
nuevo_registro = {
    'power_w': 0,
    'voltage_v': 0,
    'current_a': 0,
    'relay_on': 1,
    'energy_wh_acc': 128200,
    'presence': 1,
    'presence_confidence': 0.9,
    'temp_c_avg': 23.5,
    'Bracker_amp': 30,
    'max_watts': 6000,
    'power_rate': 0 / 6000,   # 0.8
    'hour': 14,
    'is_daytime': 1,
    'weekday': 2,
    'area_1': 0, 'area_2': 1, 'area_3': 0,  # depende del encoding
    'device_type_1': 0, 'device_type_2': 1, 'device_type_3': 0,
```

```
    'device_type_4': 0, 'device_type_5': 0, 'device_type_6': 0,
    'device_type_7': 0, 'device_type_8': 0,
    'voltage_type': 1   # 220V
}
```

```
# Nuevo registro (dentro de rango normal)
nuevo_registro = {
    'power_w': 4200,            # normal
    'voltage_v': 230,           # normal (200–240 V)
    'current_a': 18.3,          # normal (15–30 A)
    'relay_on': 1,
    'energy_wh_acc': 550000,
    'presence': 1,
    'presence_confidence': 0.95,
    'temp_c_avg': 45.2,
    'Bracker_amp': 30,
    'max_watts': 5500,
    'power_rate': 4200 / 5500,  # ≈0.76
    'hour': 10,
    'is_daytime': 1,
    'weekday': 2,
    'voltage_type': 1,  # 220 V
    # 🔶 Encoding de ejemplo
    'area_1': 1, 'area_2': 0, 'area_3': 0,
    'device_type_1': 1, 'device_type_2': 0, 'device_type_3': 0,
    'device_type_4': 0, 'device_type_5': 0, 'device_type_6': 0,
    'device_type_7': 0, 'device_type_8': 0
}
```

```
df_new = pd.DataFrame([nuevo_registro])

# Ensure the new dataframe has the same columns as X, in the same order
# This is crucial because the scaler was fitted on X
missing_cols = set(X.columns) - set(df_new.columns)
for c in missing_cols:
    df_new[c] = 0  # Add missing columns with a default value (e.g., 0 for one-hot encoded)

# Reorder columns to match the order of X
df_new = df_new[X.columns]

# Escalar con el mismo StandardScaler
df_scaled = scaler.transform(df_new)
```

```
# Predicción
prediccion = model.predict(df_scaled)
probabilidad = model.predict_proba(df_scaled)

# Interpretar el resultado
estado = "🟢 Normal (0)" if int(prediccion[0]) == 0 else "🔴 Abnormal (1)"

print(f"Predicción: {estado}")
print(f"Probabilidad de anomalía: {probabilidad[0][1]*100:.2f}%")
```

```
Predicción: 🔴 Abnormal (1)
Probabilidad de anomalía: 98.00%
```

```
!pip install lazypredict
```

```
Requirement already satisfied: lazypredict in /usr/local/lib/python3.12/dist-packages (0.2.16)
Requirement already satisfied: click in /usr/local/lib/python3.12/dist-packages (from lazypredict) (8.3.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.12/dist-packages (from lazypredict) (1.6.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-packages (from lazypredict) (2.2.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-packages (from lazypredict) (4.67.1)
Requirement already satisfied: joblib in /usr/local/lib/python3.12/dist-packages (from lazypredict) (1.5.2)
Requirement already satisfied: lightgbm in /usr/local/lib/python3.12/dist-packages (from lazypredict) (4.6.0)
Requirement already satisfied: xgboost in /usr/local/lib/python3.12/dist-packages (from lazypredict) (3.0.5)
Requirement already satisfied: pytest-runner in /usr/local/lib/python3.12/dist-packages (from lazypredict) (6.0.1)
Requirement already satisfied: mlflow>=2.0.0 in /usr/local/lib/python3.12/dist-packages (from lazypredict) (3.5.0)
Requirement already satisfied: mlflow-skinny==3.5.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (3.5.0)
Requirement already satisfied: mlflow-tracing==3.5.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (3.5.0)
Requirement already satisfied: Flask-CORS<7 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (6.0.1)
Requirement already satisfied: Flask<4 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (3.1.2)
Requirement already satisfied: alembic!=1.10.0,<2 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (1.16.5)
Requirement already satisfied: cryptography<47,>=43.0.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (43.0.3)
Requirement already satisfied: docker<8,>=4.0.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (7.1.0)
Requirement already satisfied: fastmcp<3,>=2.0.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (2.12.4)
Requirement already satisfied: graphene<4 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (3.4.3)
Requirement already satisfied: gunicorn<24 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (23.0.0)
Requirement already satisfied: matplotlib<4 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (3.10.0)
Requirement already satisfied: numpy<3 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (2.0.2)
Requirement already satisfied: pyarrow<22,>=4.0.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (18.1.0)
Requirement already satisfied: scipy<2 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (1.16.2)
Requirement already satisfied: sqlalchemy<3,>=1.4.0 in /usr/local/lib/python3.12/dist-packages (from mlflow>=2.0.0->lazypredict) (2.0.43)
Requirement already satisfied: cachetools<7,>=5.0.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (5.5.2)
Requirement already satisfied: cloudpickle<4 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (3.1.1)
Requirement already satisfied: databricks-sdk<1,>=0.20.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (0.68.0)
Requirement already satisfied: fastapi<1 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (0.118.2)
Requirement already satisfied: gitpython<4,>=3.1.9 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (3.1.45)
```

```
Requirement already satisfied: importlib_metadata!=4.7.0,<9,>=3.7.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (8.7.0)
Requirement already satisfied: opentelemetry-api<3,>=1.9.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (1.37.0)
Requirement already satisfied: opentelemetry-proto<3,>=1.9.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (1.38.0)
Requirement already satisfied: opentelemetry-sdk<3,>=1.9.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (1.37.0)
Requirement already satisfied: packaging<26 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (25.0)
Requirement already satisfied: protobuf<7,>=3.12.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (5.29.5)
Requirement already satisfied: pydantic<3,>=1.10.8 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (2.11.10)
Requirement already satisfied: python-dotenv<2,>=0.19.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (1.1.1)
Requirement already satisfied: pyyaml<7,>=5.1 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (6.0.3)
Requirement already satisfied: requests<3,>=2.17.3 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (2.32.4)
Requirement already satisfied: sqlparse<1,>=0.4.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (0.5.3)
Requirement already satisfied: typing-extensions<5,>=4.0.0 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (4.15.0)
Requirement already satisfied: uvicorn<1 in /usr/local/lib/python3.12/dist-packages (from mlflow-skinny==3.5.0->mlflow>=2.0.0->lazypredict) (0.37.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas->lazypredict) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas->lazypredict) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas->lazypredict) (2025.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn->lazypredict) (3.6.0)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.12/dist-packages (from xgboost->lazypredict) (2.27.3)
Requirement already satisfied: Mako in /usr/local/lib/python3.12/dist-packages (from alembic!=1.10.0,<2->mlflow>=2.0.0->lazypredict) (1.3.10)
Requirement already satisfied: cffi>=1.12 in /usr/local/lib/python3.12/dist-packages (from cryptography<47,>=43.0.0->mlflow>=2.0.0->lazypredict) (2.0.0)
Requirement already satisfied: urllib3>=1.26.0 in /usr/local/lib/python3.12/dist-packages (from docker<8,>=4.0.0->mlflow>=2.0.0->lazypredict) (2.5.0)
Requirement already satisfied: authlib>=1.5.2 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (1.6.5)
Requirement already satisfied: cyclopts>=3.0.0 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (3.24.0)
Requirement already satisfied: exceptiongroup>=1.2.2 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (1.3.0)
Requirement already satisfied: httpx>=0.28.1 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (0.28.1)
Requirement already satisfied: mcp<2.0.0,>=1.12.4 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (1.16.0)
Requirement already satisfied: openapi-core>=0.19.5 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (0.19.5)
Requirement already satisfied: openapi-pydantic>=0.5.1 in /usr/local/lib/python3.12/dist-packages (from fastmcp<3,>=2.0.0->mlflow>=2.0.0->lazypredict) (0.5.1)
```

```python
import gc, numpy as np, pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score
from sklearn.feature_selection import mutual_info_classif
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier, GradientBoostingClassifier
from sklearn.svm import LinearSVC

# 1) Carga
df = pd.read_csv('/content/T_ML_Dataset151025.csv')

assert 'is_anomaly' in df.columns, "Falta is_anomaly"
y = df['is_anomaly'].astype(int)

# Quita columnas no predictivas / textuales
drop_cols = [c for c in ['device_id','ts','Hostname','firmware','vendor','location','model'] if c in df.columns]
X = df.drop(columns=drop_cols + ['is_anomaly'], errors='ignore')

# Normaliza voltage_type si quedó como texto
if 'voltage_type' in X.columns and X['voltage_type'].dtype == 'object':
    X['voltage_type'] = X['voltage_type'].replace({'110V':0, '220V':1})

# Elimina no numéricas y NaN/Inf
X = X.select_dtypes(include=[np.number]).replace([np.inf, -np.inf], np.nan).fillna(0)

# 2) Muestreo estratificado: máx 15k por clase (ajusta si necesitas)
max_per_class = 15000
idx_keep = []
for c, idx in y.groupby(y).groups.items():
    take = np.random.RandomState(42).choice(idx, size=min(len(idx), max_per_class), replace=False)
    idx_keep.append(take)
idx_keep = np.concatenate(idx_keep)
X_s = X.iloc[idx_keep].astype('float32')
y_s = y.iloc[idx_keep].astype('int8')

print("Tamaño tras muestreo:", X_s.shape, dict(pd.Series(y_s).value_counts()))

# 3) Split antes del escalado
X_train, X_test, y_train, y_test = train_test_split(
    X_s, y_s, test_size=0.2, stratify=y_s, random_state=42
)

# 4) Selección de features (quedarse con las K mejores)
K = min(60, X_train.shape[1])  # hasta 60, ajusta según RAM
mi = mutual_info_classif(X_train, y_train, random_state=42)
topk_idx = np.argsort(mi)[-K:]
cols_k = X_train.columns[topk_idx]
X_train = X_train[cols_k].copy()
X_test  = X_test[cols_k].copy()

# 5) Escalado
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test  = scaler.transform(X_test)

# 6) Benchmark ligero de modelos
models = {
    "LogReg": LogisticRegression(max_iter=1000, class_weight='balanced', n_jobs=None),
    "SGD": SGDClassifier(loss='log_loss', class_weight='balanced', random_state=42),
    "RF": RandomForestClassifier(n_estimators=200, max_depth=16, class_weight='balanced', random_state=42),
    "ET": ExtraTreesClassifier(n_estimators=300, max_depth=16, random_state=42),
    "GB": GradientBoostingClassifier(random_state=42),
    "LinSVC": LinearSVC(dual='auto', random_state=42)
}
```

```python
rows = []
for name, m in models.items():
    try:
        m.fit(X_train, y_train)
        y_pred = m.predict(X_test)
        rows.append({
            "Model": name,
            "Accuracy": accuracy_score(y_test, y_pred),
            "F1": f1_score(y_test, y_pred, zero_division=0),
            "Recall": recall_score(y_test, y_pred, zero_division=0),
            "Precision": precision_score(y_test, y_pred, zero_division=0)
        })
    except Exception as e:
        rows.append({"Model": name, "Accuracy": np.nan, "F1": np.nan, "Recall": np.nan, "Precision": np.nan})
        print(f"❌ {name} falló:", repr(e))
    finally:
        gc.collect()

bench = pd.DataFrame(rows).sort_values('F1', ascending=False)
print(bench)
bench.to_csv('/content/model_benchmark_manual.csv', index=False)
print("✅ Ranking guardado en /content/model_benchmark_manual.csv")
```

```
/tmp/ipython-input-3277236342.py:11: DtypeWarning: Columns (15) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('/content/T_ML_Dataset151025.csv')
Tamaño tras muestreo: (30000, 20) {0: np.int64(15000), 1: np.int64(15000)}
    Model  Accuracy        F1    Recall  Precision
4      GB  1.000000  1.000000  1.000000   1.000000
2      RF  1.000000  1.000000  1.000000   1.000000
3      ET  0.993500  0.993457  0.987000   1.000000
0  LogReg  0.983000  0.982706  0.966000   1.000000
1     SGD  0.981667  0.981375  0.966000   0.997247
5  LinSVC  0.978167  0.977679  0.956333   1.000000
✅ Ranking guardado en /content/model_benchmark_manual.csv
```

| Model | Accuracy | F1 | Recall | Precision |
|---|---|---|---|---|
| RF (RandomForest) | **1.000** | **1.000** | **1.000** | **1.000** |
| GB (GradientBoosting) | **1.000** | **1.000** | **1.000** | **1.000** |
| ET (ExtraTrees) | 0.993 | 0.993 | 0.987 | **1.000** |
| LogReg | 0.983 | 0.983 | 0.966 | **1.000** |
| SGD | 0.982 | 0.981 | 0.966 | 0.997 |
| LinSVC | 0.978 | 0.978 | 0.956 | **1.000** |

```python
from sklearn.model_selection import cross_val_score
for name, model in [("RF", RandomForestClassifier(n_estimators=200, max_depth=16, random_state=42)),
                    ("ET", ExtraTreesClassifier(n_estimators=300, max_depth=16, random_state=42)),
                    ("GB", GradientBoostingClassifier(random_state=42))]:
    scores = cross_val_score(model, X_train, y_train, cv=5, scoring='f1')
    print(f"{name}: mean F1={scores.mean():.3f} ± {scores.std():.3f}")
```

```
RF: mean F1=1.000 ± 0.000
ET: mean F1=0.993 ± 0.001
GB: mean F1=1.000 ± 0.000
```

```python
import joblib
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Assuming X and y are already defined and preprocessed from previous steps
# If not, you would need to include the data loading and preprocessing here
# For demonstration, let's use the sampled and scaled data from the previous benchmark cell
# You might want to adjust this based on which data you want to use for the final model

# Re-split the sampled data to ensure X_train, X_test, y_train, y_test are available
```