```python
# ------------------------------------
# 1) Imports
# ------------------------------------
import os
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# SHAP (install if missing)
try:
    import shap
except ImportError:
    !pip -q install shap
    import shap

# Colab upload helper (safe if not in Colab)
try:
    from google.colab import files
    IN_COLAB = True
except ImportError:
    IN_COLAB = False

# ------------------------------------
# 2) Load Dataset (path or upload)
# ------------------------------------
CANDIDATE_PATHS = [
    "data/salary_dataset.csv",
    "Salary_Data.csv",
    "salary.csv"
]

df = None
for p in CANDIDATE_PATHS:
    if os.path.exists(p):
        df = pd.read_csv(p)
        print(f"Loaded dataset from: {p}")
        break

if df is None:
    if IN_COLAB:
        print("File not found at common paths. Please upload your CSV.")
        uploaded = files.upload()
        fname = next(iter(uploaded))
        df = pd.read_csv(fname)
        print(f"Loaded dataset from upload: {fname}")
    else:
        raise FileNotFoundError("Dataset not found. Update CANDIDATE_PATHS or provide a valid path.")

print(df.head())

# ------------------------------------
# 3) Normalize headers & clean
# ------------------------------------
# Strip whitespace first
df.columns = df.columns.str.strip()

# Robust renaming: handle both underscores and spaces variants
# We'll normalize to lowercase for matching, then rename original columns.
lower_cols = {c: c.lower() for c in df.columns}
rename_targets = {
    "education_level": "Education",
    "education level": "Education",
    "years_of_experience": "YearsExperience",
    "years of experience": "YearsExperience",
    "job_title": "JobTitle",
    "job title": "JobTitle",
}
rename_map = {}
for original, low in lower_cols.items():
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for original, low in lower_cols.items():
    if low in rename_targets:
        rename_map[original] = rename_targets[low]
# Apply renaming
df = df.rename(columns=rename_map)

# Required columns after renaming
required_cols = ['Age', 'Gender', 'Education', 'YearsExperience', 'Salary']
missing = [c for c in required_cols if c not in df.columns]
if missing:
    raise ValueError(f"Missing expected columns: {missing}\nCurrent columns: {list(df.columns)}")

# Basic cleaning
df = df.drop_duplicates().copy()

# Normalize string columns
if 'JobTitle' in df.columns:
    df.loc[:, 'JobTitle'] = df['JobTitle'].astype(str).str.strip().str.title()

df.loc[:, 'Education'] = (
    df['Education'].astype(str)
    .str.replace('.', '', regex=False)
    .str.strip()
    .str.title()
)
df.loc[:, 'Gender'] = df['Gender'].astype(str).str.strip().str.title()

# Drop rows with critical missing values
df = df.dropna(subset=['Salary', 'Age', 'Gender', 'Education', 'YearsExperience']).copy()

# -------------------------------------
# 4) Encoding
# -------------------------------------
# Gender label-encode
le_gender = LabelEncoder()
df.loc[:, 'Gender'] = le_gender.fit_transform(df['Gender'])

# Education ordinal map with fallback
edu_order = ['High School', 'Bachelor', 'Master', 'Phd']
edu_map = {name.title(): i+1 for i, name in enumerate(edu_order)}
df.loc[:, 'Education'] = df['Education'].map(edu_map)

if df['Education'].isna().any():
    # Assign a value just above the max defined ordinal for unknown categories
    max_known = max(edu_map.values()) if edu_map else 0
    df.loc[df['Education'].isna(), 'Education'] = max_known + 1

# -------------------------------------
# 5) Quick EDA
# -------------------------------------
print("\nDescriptive statistics:")
print(df.describe(include='all'))

plt.figure()
sns.histplot(df['Salary'], kde=True)
plt.title("Salary Distribution")
plt.xlabel("Salary")
plt.ylabel("Count")
plt.show()

plt.figure(figsize=(8,6))
corr = df[['Age', 'Gender', 'Education', 'YearsExperience', 'Salary']].corr(numeric_only=True)
sns.heatmap(corr, annot=True, cmap="coolwarm")
plt.title("Feature Correlation Heatmap")
plt.show()

# -------------------------------------
# 6) Features, Split, Scale
# -------------------------------------
features = ['Age', 'Gender', 'Education', 'YearsExperience']
X = df[features].copy()
y = df['Salary'].copy()

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

numeric_cols = ['Age', 'YearsExperience']
```

```
scaler = StandardScaler()

X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()
X_train_scaled.loc[:, numeric_cols] = scaler.fit_transform(X_train[numeric_cols])
X_test_scaled.loc[:, numeric_cols] = scaler.transform(X_test[numeric_cols])

# -------------------------------------
# 7) Train & Evaluate
# -------------------------------------
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=200, random_state=42)
}

results = {}
fitted_models = {}

for name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)
    rmse = float(np.sqrt(mean_squared_error(y_test, y_pred)))
    r2 = float(r2_score(y_test, y_pred))
    results[name] = {"RMSE": rmse, "R²": r2}
    fitted_models[name] = model

results_df = pd.DataFrame(results).T.sort_values(by="RMSE")
print("\nModel performance:")
print(results_df)

# -------------------------------------
# 8) Feature Importance (RF)
# -------------------------------------
rf = fitted_models["Random Forest"]
importances = pd.Series(rf.feature_importances_, index=features).sort_values(ascending=True)

plt.figure()
importances.plot(kind='barh', title='Feature Importance (Random Forest)')
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()

# -------------------------------------
# 9) SHAP Explainability (RF)
# -------------------------------------
shap.initjs()
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(X_test_scaled)

# Bar summary
shap.summary_plot(shap_values, X_test_scaled, feature_names=features, plot_type="bar")
# Beeswarm summary
shap.summary_plot(shap_values, X_test_scaled, feature_names=features)

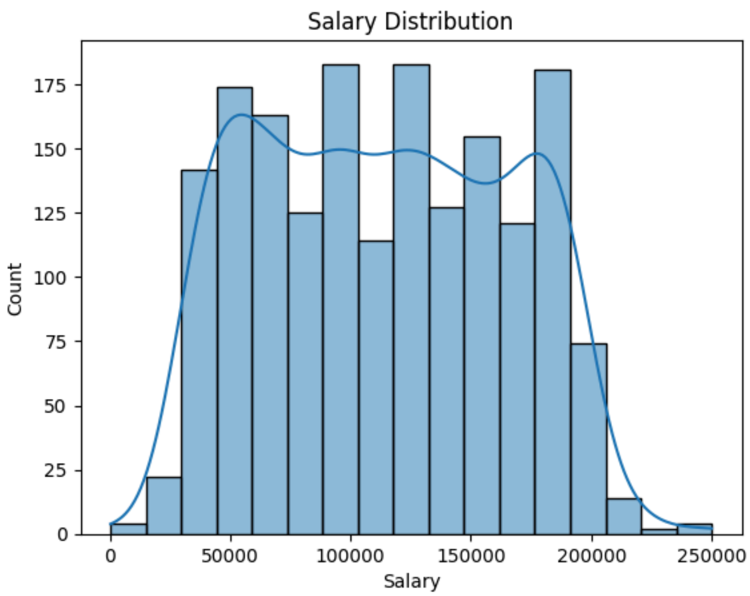
# -------------------------------------
# 10) Conclusion
# -------------------------------------
best_model = results_df.index[0]
print(f"""
Summary:
- Headers normalized (handled 'Education Level' → Education, 'Years of Experience' → YearsExperience, 'Job Title' → J
- Encoded Gender (label) and Education (ordinal).
- Scaled numeric features only (Age, YearsExperience).
- Best model by RMSE: {best_model}
- Metrics:
{results_df.to_string()}
""")
```

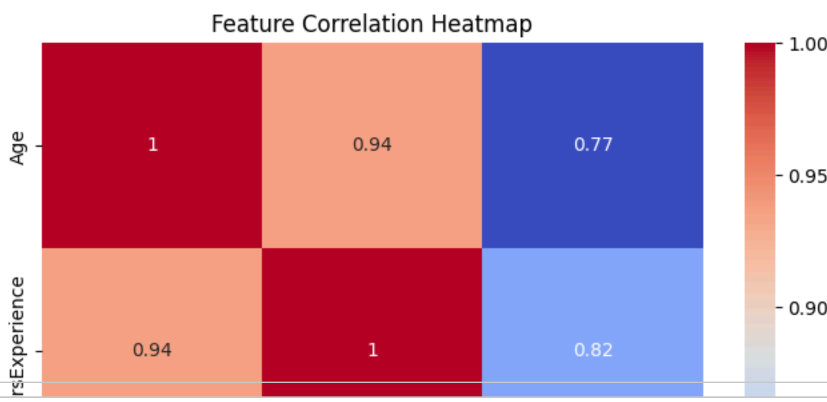
```
Loaded dataset from: Salary_Data.csv
    Age  Gender Education Level          Job Title  Years of Experience  \
0  32.0    Male      Bachelor's  Software Engineer                  5.0
1  28.0  Female        Master's       Data Analyst                  3.0
2  45.0    Male             PhD     Senior Manager                 15.0
3  36.0  Female      Bachelor's    Sales Associate                  7.0
4  52.0    Male        Master's           Director                 20.0

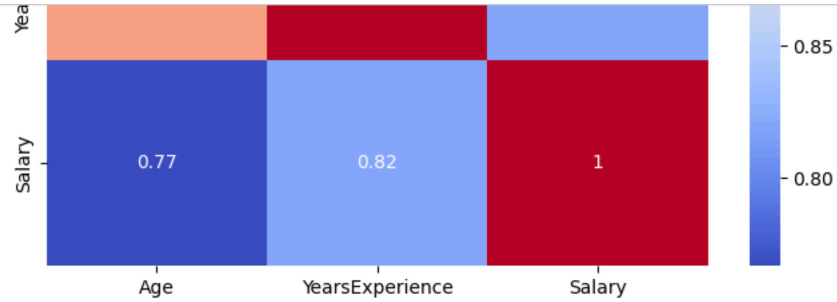
     Salary
0   90000.0
1   65000.0
2  150000.0
3   60000.0
4  200000.0

Descriptive statistics:
                Age  Gender  Education                   JobTitle  \
count   1788.000000  1788.0     1788.0                       1788
unique          NaN     3.0        3.0                        191
top             NaN     1.0        5.0  Software Engineer Manager
freq            NaN   967.0     1337.0                        127
mean      35.135347     NaN        NaN                        NaN
std        8.213003     NaN        NaN                        NaN
min       21.000000     NaN        NaN                        NaN
25%       29.000000     NaN        NaN                        NaN
50%       33.000000     NaN        NaN                        NaN
75%       41.000000     NaN        NaN                        NaN
max       62.000000     NaN        NaN                        NaN

        YearsExperience         Salary
count       1788.000000    1788.000000
unique              NaN            NaN
top                 NaN            NaN
freq                NaN            NaN
mean           9.154922  113177.285794
std            6.843199   51583.040514
min            0.000000     350.000000
25%            3.000000   70000.000000
50%            8.000000  110000.000000
75%           13.000000  160000.000000
max           34.000000  250000.000000
```





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Model performance:
                          RMSE        R²
Random Forest      24898.261720  0.773298
Linear Regression  30918.765678  0.650408
```