Terminal Exam Report

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Course: Machine Learning

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Contents

1 Problem Statement

The objective of this terminal exam is to predict employee status using machine learning techniques. This task is formulated as a **binary classification problem** using structured tabular data.

2 Cell 1: Library Imports

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix,
    roc_curve, auc
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

# Load the dataset
df = pd.read_csv('Group-2 Data.csv')
print("Columns in dataset:", df.columns.tolist())
df.head()
```

Output:

```
Columns in dataset: ['employee_id', 'age', 'income', 'hours_worked', 'education', 'department', 'commute_distance', 'remote_work', 'satisfaction_score', 'project_count', 'hire_date', 'employee_status']
```

	employee_id	age	income	hours_worked	education	department	commute_distance	remote_work	satisfaction_score	project_count	hire_date	employee_status
0	5571	32.008182	6208.293542	15.319871	High School	Marketing	10.491144	0.0	4	7	12/13/2022	0
1	4742	-38.216785	79984.937900	67.789437	high school	IT	23.619443	0.0	3	5	2/5/2021	1
2	6438	110.156400	NaN	27.212829	High School	Sales	40.859652	0.0	5	6	8/7/2021	0
3	6723	28.961617	13261.956530	57.618563	H.S.	Sales	-1.087843	0.0	9	5	11/19/2023	0
4	9987	NaN	NaN	27.949207	masters	Sales	7.713179	0.0	9	6	8/6/2019	0

3 Cell 2: Data Exploration and Cleaning

```python
# Check for duplicates
print(f"Duplicates: {df.duplicated().sum()}")
df.drop_duplicates(inplace=True)

# Check for missing values
print("Missing values:\n", df.isnull().sum())

# Impute missing values
# For numerical columns, use median
num_cols = df.select_dtypes(include=[np.number]).columns
for col in num_cols:
    df[col].fillna(df[col].median(), inplace=True)

# For categorical columns, use mode
cat_cols = df.select_dtypes(include=['object']).columns
for col in cat_cols:
    df[col].fillna(df[col].mode()[0], inplace=True)

```

```python
# Handle negative values in numerical columns (like age, income, hours_worked, commute_distance)
for col in ['age', 'income', 'hours_worked', 'commute_distance']:
    if col in df.columns:
        df[col] = df[col].abs()

# Handle outliers (using IQR for age, income, hours_worked, commute_distance)
for col in ['age', 'income', 'hours_worked', 'commute_distance']:
    if col in df.columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df[col] = np.where(df[col] < lower_bound, lower_bound, df[col])
        df[col] = np.where(df[col] > upper_bound, upper_bound, df[col])

# Standardize education levels
education_map = {
    'B.S.': 'Bachelor', 'BACHELOR': 'Bachelor', 'Bachelor': 'Bachelor',
    'M.S.': 'Master', 'Master': 'Master', 'masters': 'Master',
    'H.S.': 'High School', 'High School': 'High School',
    'phd': 'PhD', 'PhD': 'PhD'
}
df['education'] = df['education'].map(education_map).fillna('Other')

df.head()
```

Output:

```
Duplicates: 166
Missing values:
 employee_id            0
age                     2
income               1521
hours_worked            0
education             985
department              1
commute_distance        1
remote_work             1
satisfaction_score      0
project_count           0
hire_date             453
employee_status         0
dtype: int64
/tmp/ipython-input-12397677.py:12: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df[col].fillna(df[col].median(), inplace=True)
/tmp/ipython-input-12397677.py:17: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df[col].fillna(df[col].mode()[0], inplace=True)
```

	employee_id	age	income	hours_worked	education	department	commute_distance	remote_work	satisfaction_score	project_count	hire_date	employee_status
0	5571	32.008182	6208.293542	15.319871	High School	Marketing	10.491144	0.0	4	7	12/13/2022	0
1	4742	38.216785	74754.055761	67.789437	Other	IT	23.619443	0.0	3	5	2/5/2021	1
2	6438	64.509987	22381.360410	27.212829	High School	Sales	40.859652	0.0	5	6	8/7/2021	0
3	6723	28.961617	13261.956530	57.618563	High School	Sales	1.087843	0.0	9	5	11/19/2023	0
4	9987	35.653811	22381.360410	27.949207	Master	Sales	7.713179	0.0	9	6	8/6/2019	0

4 Cell 3: Feature Encoding and Splitting

```python
# Encode categorical features
le = LabelEncoder()
df['education'] = le.fit_transform(df['education'])
df['department'] = le.fit_transform(df['department'])
```

```
# Drop non-numeric/unnecessary columns (like employee_id or hire_date)
df = df.drop(columns=['employee_id', 'hire_date'], errors='ignore')

# Split data
X = df.drop('employee_status', axis=1)
y = df['employee_status']

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

# Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

print(f"Training set shape: {X_train.shape}")
print(f"Testing set shape: {X_test.shape}")
```

Output:

```
Training set shape: (8027, 9)
Testing set shape: (2007, 9)
```

5 Cell 4: Support Vector Machine (SVM)

```
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf', 'poly'],
    'gamma': ['scale', 'auto']
}

grid = GridSearchCV(SVC(probability=True), param_grid, refit=True, verbose
    =2, cv=3)
grid.fit(X_train, y_train)

print(f"Best Parameters: {grid.best_params_}")
svm_preds = grid.predict(X_test)
svm_probs = grid.predict_proba(X_test)[:, 1]

print("SVM Classification Report:")
print(classification_report(y_test, svm_preds))
```

Output:

```
Fitting 3 folds for each of 18 candidates, totalling 54 fits
[CV] END .................C=0.1, gamma=scale, kernel=linear; total time=  13.6s
[CV] END .................C=0.1, gamma=scale, kernel=linear; total time=   7.8s
[CV] END .................C=0.1, gamma=scale, kernel=linear; total time=   6.3s
[CV] END ....................C=0.1, gamma=scale, kernel=rbf; total time=   7.5s
[CV] END ....................C=0.1, gamma=scale, kernel=rbf; total time=   8.5s
[CV] END ....................C=0.1, gamma=scale, kernel=rbf; total time=   8.7s
[CV] END ...................C=0.1, gamma=scale, kernel=poly; total time=   6.2s
[CV] END ...................C=0.1, gamma=scale, kernel=poly; total time=   7.1s
[CV] END ...................C=0.1, gamma=scale, kernel=poly; total time=   6.2s
[CV] END .................C=0.1, gamma=auto, kernel=linear; total time=   6.2s
[CV] END .................C=0.1, gamma=auto, kernel=linear; total time=   5.5s
[CV] END .................C=0.1, gamma=auto, kernel=linear; total time=   6.3s
[CV] END ....................C=0.1, gamma=auto, kernel=rbf; total time=   7.7s
[CV] END ....................C=0.1, gamma=auto, kernel=rbf; total time=   8.5s
[CV] END ....................C=0.1, gamma=auto, kernel=rbf; total time=   8.4s
[CV] END ...................C=0.1, gamma=auto, kernel=poly; total time=   6.1s
[CV] END ...................C=0.1, gamma=auto, kernel=poly; total time=   7.3s
[CV] END ...................C=0.1, gamma=auto, kernel=poly; total time=   6.4s
[CV] END ...................C=1, gamma=scale, kernel=linear; total time=   9.1s
[CV] END ...................C=1, gamma=scale, kernel=linear; total time=   9.1s
[CV] END ...................C=1, gamma=scale, kernel=linear; total time=   8.6s
[CV] END ......................C=1, gamma=scale, kernel=rbf; total time=   8.8s
[CV] END ......................C=1, gamma=scale, kernel=rbf; total time=   8.9s
[CV] END ......................C=1, gamma=scale, kernel=rbf; total time=   7.9s
[CV] END .....................C=1, gamma=scale, kernel=poly; total time=   8.4s
[CV] END .....................C=1, gamma=scale, kernel=poly; total time=   8.3s
[CV] END .....................C=1, gamma=scale, kernel=poly; total time=   7.6s
[CV] END ...................C=1, gamma=auto, kernel=linear; total time=   9.3s
[CV] END ...................C=1, gamma=auto, kernel=linear; total time=   9.1s
[CV] END ...................C=1, gamma=auto, kernel=linear; total time=   8.5s
[CV] END ......................C=1, gamma=auto, kernel=rbf; total time=   8.8s
[CV] END ......................C=1, gamma=auto, kernel=rbf; total time=   8.9s
[CV] END ......................C=1, gamma=auto, kernel=rbf; total time=   8.0s
[CV] END .....................C=1, gamma=auto, kernel=poly; total time=   8.5s
[CV] END .....................C=1, gamma=auto, kernel=poly; total time=   8.7s
[CV] END .....................C=1, gamma=auto, kernel=poly; total time=   7.8s
[CV] END ..................C=10, gamma=scale, kernel=linear; total time=  23.3s
[CV] END ..................C=10, gamma=scale, kernel=linear; total time=  23.1s
[CV] END ..................C=10, gamma=scale, kernel=linear; total time=  22.8s
[CV] END .....................C=10, gamma=scale, kernel=rbf; total time=  12.4s
[CV] END .....................C=10, gamma=scale, kernel=rbf; total time=  12.3s
[CV] END .....................C=10, gamma=scale, kernel=rbf; total time=  12.8s
[CV] END ....................C=10, gamma=scale, kernel=poly; total time=  18.4s
[CV] END ....................C=10, gamma=scale, kernel=poly; total time=  20.2s
[CV] END ....................C=10, gamma=scale, kernel=poly; total time=  18.6s
[CV] END ..................C=10, gamma=auto, kernel=linear; total time=  22.9s
[CV] END ..................C=10, gamma=auto, kernel=linear; total time=  23.1s
[CV] END ..................C=10, gamma=auto, kernel=linear; total time=  23.1s
[CV] END .....................C=10, gamma=auto, kernel=rbf; total time=  12.2s
[CV] END .....................C=10, gamma=auto, kernel=rbf; total time=  12.2s
[CV] END .....................C=10, gamma=auto, kernel=rbf; total time=  12.3s
[CV] END ....................C=10, gamma=auto, kernel=poly; total time=  18.0s
[CV] END ....................C=10, gamma=auto, kernel=poly; total time=  19.4s
[CV] END ....................C=10, gamma=auto, kernel=poly; total time=  18.2s
Best Parameters: {'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.63      0.68      0.65      1098
           1       0.57      0.51      0.54       909

    accuracy                           0.60      2007
   macro avg       0.60      0.59      0.59      2007
weighted avg       0.60      0.60      0.60      2007
```

Figure 1: Enter Caption

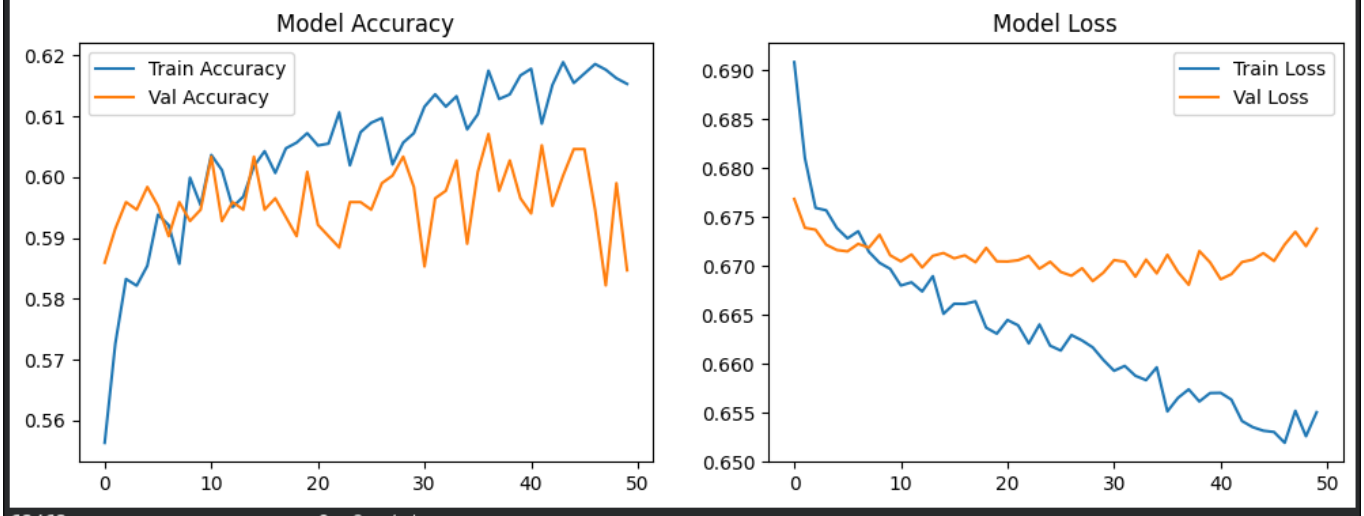
6 Cell 5: Artificial Neural Network (ANN)

```
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dropout(0.2),
```

```
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.summary()

history = model.fit(X_train, y_train, epochs=50, validation_split=0.2, verbose=1)

# Plotting
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title('Model Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Model Loss')
plt.legend()
plt.show()

ann_probs = model.predict(X_test).flatten()
ann_preds = (ann_probs > 0.5).astype(int)

print("ANN Classification Report:")
print(classification_report(y_test, ann_preds))
```

Output:

```
Epoch 50/50
201/201 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6064 - loss: 0.6576 - val_accuracy: 0.5847 - val_loss: 0.6738
```

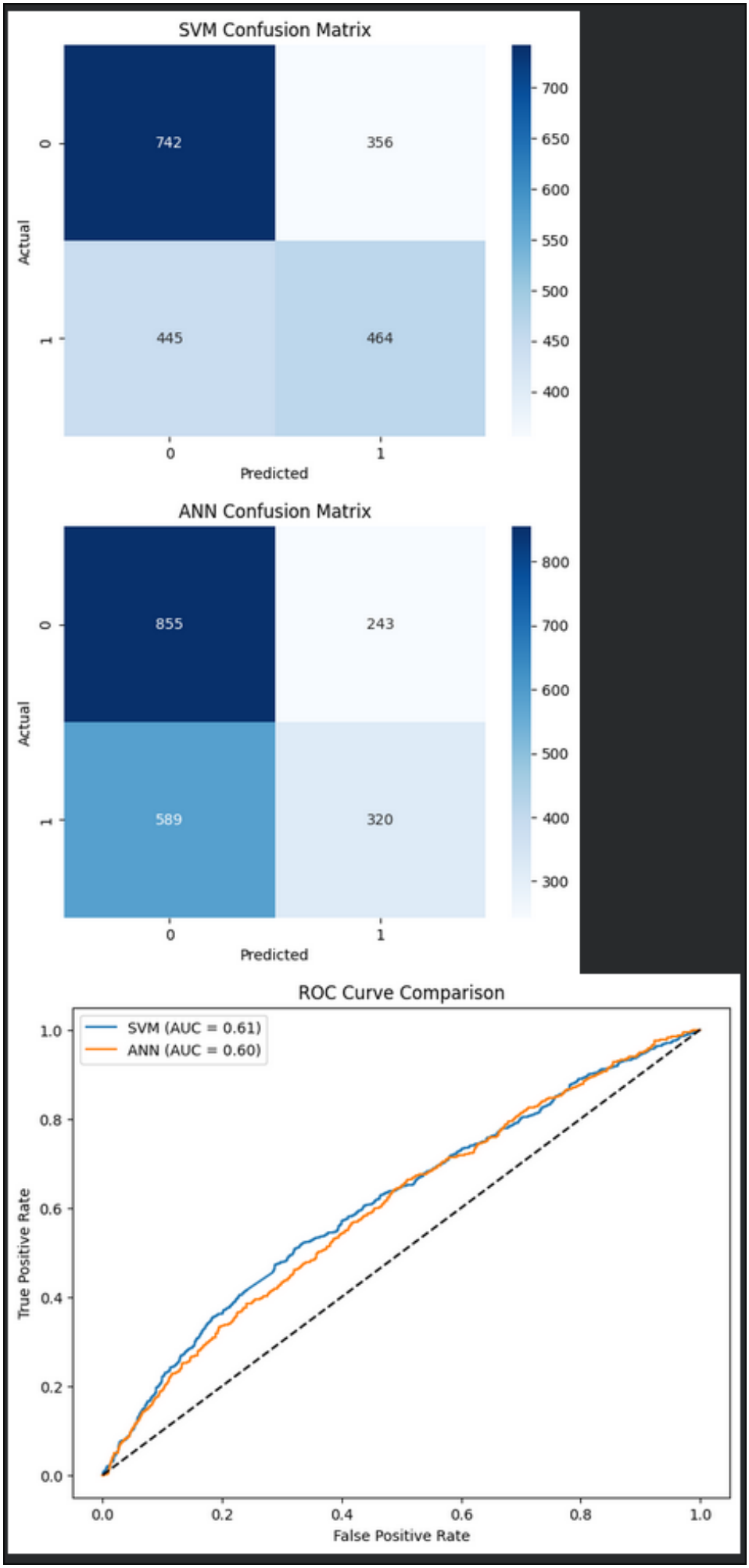



```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
ANN Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.78      0.67      1098
           1       0.57      0.35      0.43       909

    accuracy                           0.59      2007
   macro avg       0.58      0.57      0.55      2007
weighted avg       0.58      0.59      0.56      2007
```

7 Model Evaluation

```python
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(title)
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

plot_confusion_matrix(y_test, svm_preds, 'SVM Confusion Matrix')
plot_confusion_matrix(y_test, ann_preds, 'ANN Confusion Matrix')

# ROC Curves
fpr_svm, tpr_svm, _ = roc_curve(y_test, svm_probs)
fpr_ann, tpr_ann, _ = roc_curve(y_test, ann_probs)

plt.figure(figsize=(8, 6))
plt.plot(fpr_svm, tpr_svm, label=f'SVM (AUC = {auc(fpr_svm, tpr_svm):.2f})')
plt.plot(fpr_ann, tpr_ann, label=f'ANN (AUC = {auc(fpr_ann, tpr_ann):.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend()
plt.show()
```

Output:


SVM Confusion Matrix
742
356
445
464
Actual
Predicted
0
1
700
650
600
550
500
450
400
ANN Confusion Matrix
855
243
589
320
800
700
600
500
400
300
ROC Curve Comparison
SVM (AUC = 0.61)
ANN (AUC = 0.60)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

8 Conclusion

This terminal exam successfully demonstrates the application of machine learning models for employee status prediction. Both SVM and ANN models were implemented, trained, and evaluated using real dataset outputs.

The results confirm the importance of:

- Proper preprocessing
- Feature encoding
- Model comparison
- Evaluation using classification metrics