EXPERIMENT 7	Artificial Neural Network (ANN) using Keras / TensorFlow

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Date: 12 / 02 / 2026
Subject: Machine and Deep Learning Lab

Aim: To build an Artificial Neural Network (ANN) using Keras/TensorFlow.

Dataset Source:

The dataset used for this experiment is the Churn Modelling Dataset, widely used for binary classification tasks in banking contexts.

- Source Link: https://www.kaggle.com/datasets/filippoo/deep-learning-az-ann

Dataset Description:

The dataset contains information about 10,000 customers of a bank and aims to predict whether a customer will leave the bank (churn) or stay. Each row represents a unique customer, and there are 14 features along with a target variable. The target variable is Exited, which is binary: 1 indicates the customer left the bank, and 0 indicates the customer stayed.

The dataset includes a mix of demographic data, financial data, and tenure, as well as metadata that is not predictive and typically dropped during model training. The data is structured and includes both numerical and categorical features, which require preprocessing. Categorical features like Geography can be processed using One-Hot Encoding, while Gender can use Label Encoding.

Column	***Feature***	***Description***	***Data Type***	***Unit***
RowNumber	RowNumber	Unique row index	Integer	N/A
CustomerId	CustomerId	Unique identifier for each customer	Integer	N/A
Surname	Surname	Customer's last name	String	N/A
CreditScore	CreditScore	Customer’s credit score	Integer	Points
Geography	Geography	Customer’s country	Categorical	N/A
Gender	Gender	Customer’s gender	Categorical	N/A
Age	Age	Customer’s age	Integer	Years

Tenure	Tenure	Number of years the customer has been with the bank	Integer	Years
Balance	Balance	Account balance	Float	USD
NumOfProducts	NumOfProducts	Number of products the customer has	Integer	Count
HasCrCard	HasCrCard	Whether the customer has a credit card	Binary	0 = No, 1 = Yes
IsActiveMember	IsActiveMember	Whether the customer is an active member	Binary	0 = No, 1 = Yes
EstimatedSalary	EstimatedSalary	Estimated annual salary	Float	USD
Exited	Exited	Target variable indicating churn	Binary	0 = Stayed, 1 = Left

Theory:

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, designed to recognize patterns, classify data, and make predictions by learning from examples. ANNs consist of layers of interconnected nodes, or "neurons," where each connection has an associated weight that adjusts during training to minimize prediction errors. Data passes through these layers via activation functions, enabling the network to model complex, non-linear relationships. Typically, an ANN has an input layer to receive features, one or more hidden layers to process information, and an output layer to produce predictions. The network learns through a process called backpropagation, which iteratively updates weights based on the difference between predicted and actual outputs, optimizing the model using techniques like gradient descent.

Using high-level libraries like Keras and TensorFlow simplifies the creation, training, and evaluation of ANNs. Keras provides an intuitive, user-friendly API to define layers, choose activation functions, and compile models with different loss functions and optimizers, while TensorFlow handles the underlying computations efficiently on CPUs or GPUs. This combination allows developers to experiment with different architectures, such as feedforward networks, convolutional networks for image processing, or recurrent networks for sequential data. With built-in functions for data preprocessing, model evaluation, and visualization, Keras and TensorFlow enable rapid prototyping and deployment of neural networks, making advanced machine learning techniques more accessible to both researchers and industry practitioners.

Mathematical Formulation of the Algorithms:

An Artificial Neural Network (ANN) consists of an input layer, one or more hidden layers, and an output layer. Each layer contains neurons (nodes) connected by weights.

A. The Artificial Neuron (Perceptron)

For a single neuron, the output is calculated as a weighted sum of inputs plus a bias, passed through an activation function:

$$\boxed{\begin{gathered} z = \sum_{i=1}^{n} (w_i \cdot x_i) + b \\ a = \sigma(z) \end{gathered}}$$

Where:

- x_i = input features
- w_i = Weights assigned to each input.
- b = Bias term.
- σ = Activation function (e.g., ReLU for hidden layers, Sigmoid for binary output).

B. Activation Functions

- *ReLU (Rectified Linear Unit):* Used in hidden layers to introduce non-linearity.

$$\boxed{f(z) = \max(0, z)}$$

- *Sigmoid***:** Used in the output layer for binary classification to map the output to a probability [0, 1].

$$\boxed{\sigma(z) = \frac{1}{1 + e^{-z}}}$$

C. Loss Function (Binary Cross-Entropy)

To measure the error between predicted probability ($\hat{y}$) and actual class (y):

$$\boxed{L(\hat{y}, y) = -\frac{1}{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]}$$

D. Optimization and Backpropagation

The network learns by updating weights using Stochastic Gradient Descent (SGD) or variants like Adam. The weight update rule is:

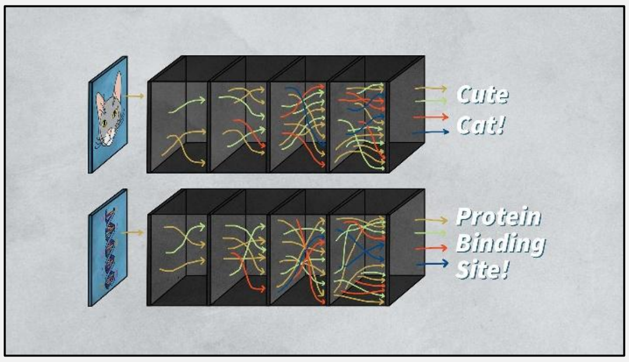
$$\boxed{w_{new} = w_{old} - \eta \cdot \frac{\partial L}{\partial w}}$$

Where η is the learning rate and $\frac{\partial L}{\partial w}$ is the gradient of the loss function with respect to the weight, calculated using the Chain Rule during backpropagation.

Algorithm Limitations:

While ANNs are powerful, they have specific limitations:

1. *Requirement for Large Datasets:* ANNs typically require a large amount of data to achieve high accuracy and avoid overfitting compared to simpler models like Logistic Regression.



In Black Box - Internal logic remains humanly incomprehensible

2. *The "Black Box" Nature:* Unlike Decision Trees, it is difficult to interpret why an ANN made a specific prediction. This lack of transparency is a drawback in highly regulated sectors like banking or healthcare.

3. *Computational Intensity:* Training deep networks requires significant computational resources (CPUs/GPUs) and time, especially as the number of layers and neurons increases.

4. *Hyperparameter Sensitivity:* The performance depends heavily on choosing the right architecture (number of layers/neurons), learning rate, and optimizers. Finding the optimal configuration often requires extensive trial and error.

5. *Prone to Overfitting:* On smaller datasets (like the 10,000 records here), ANNs can easily memorize the noise in the training data rather than the underlying pattern, necessitating regularization techniques like Dropout or Early Stopping.

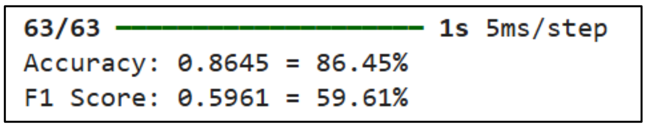
Baseline Implementation Code:

```
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

from sklearn.preprocessing import LabelEncoder,
StandardScaler, OneHotEncoder

from sklearn.compose import ColumnTransformer

from sklearn.metrics import confusion_matrix,
accuracy_score, f1_score


import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense,
Input
```

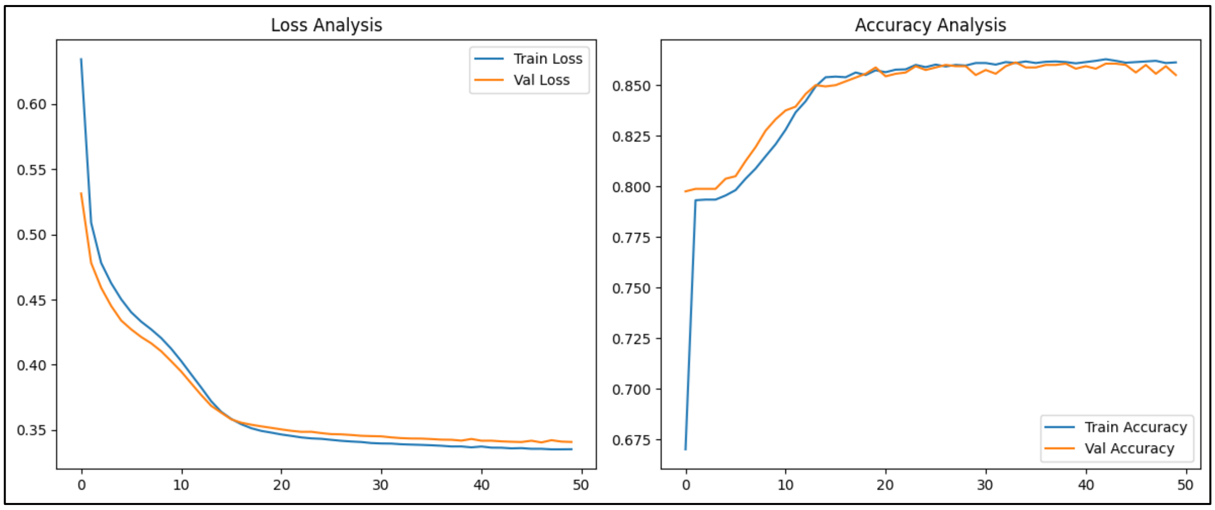
```
# 1. Data Loading & Preprocessing

df = pd.read_csv('Churn_Modelling.csv')


X = df.iloc[:, 3:-1].values

y = df.iloc[:, -1].values


# Encode Gender

le = LabelEncoder()

X[:, 2] = le.fit_transform(X[:, 2])


# One-Hot Encode Geography

ct = ColumnTransformer(

    transformers=[('encoder', OneHotEncoder(),
[1])],

    remainder='passthrough'

)

X = np.array(ct.fit_transform(X))
```

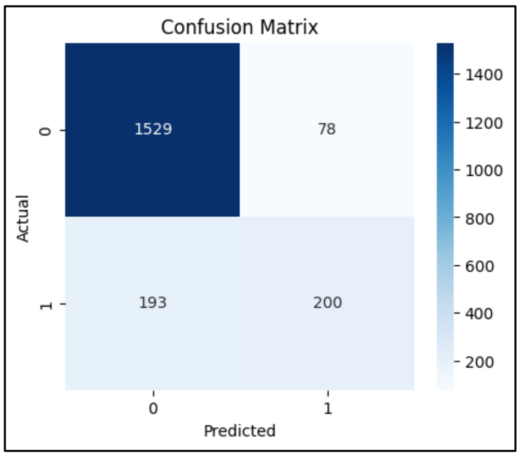
```python
# Split dataset

X_train, X_test, y_train, y_test =
train_test_split(

    X, y, test_size=0.2, random_state=42

)


# Feature Scaling

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)


# 2. ANN Architecture (Fixed - No Warning)

ann = Sequential([

    Input(shape=(X_train.shape[1],)),

    Dense(units=6, activation='relu'),

    Dense(units=6, activation='relu'),

    Dense(units=1, activation='sigmoid')

])


# 3. Compile and Train

ann.compile(

    optimizer='adam',

    loss='binary_crossentropy',

    metrics=['accuracy']

)


history = ann.fit(

    X_train,

    y_train,

    batch_size=32,

    epochs=50,

    validation_split=0.2,

    verbose=0

)


# 4. Predictions & Metrics

y_pred = (ann.predict(X_test) >
0.5).astype(int)

accuracy = accuracy_score(y_test, y_pred)

f1 = f1_score(y_test, y_pred)


print(f"Accuracy: {accuracy:.4f} = {accuracy *
100:.2f}%")

print(f"F1 Score: {f1:.4f} = {f1 * 100:.2f}%")


# 5. Visualisations

# Plot 1: Learning Curves

plt.figure(figsize=(12, 5))


plt.subplot(1, 2, 1)

plt.plot(history.history['loss'], label='Train
Loss')

plt.plot(history.history['val_loss'],
label='Val Loss')

plt.title('Loss Analysis')

plt.legend()


plt.subplot(1, 2, 2)

plt.plot(history.history['accuracy'],
label='Train Accuracy')

plt.plot(history.history['val_accuracy'],
label='Val Accuracy')

plt.title('Accuracy Analysis')

plt.legend()


plt.tight_layout()

plt.savefig('learning_curves.png')

plt.show()


# Plot 2: Confusion Matrix

cm = confusion_matrix(y_test, y_pred)


plt.figure(figsize=(5, 4))

sns.heatmap(cm, annot=True, fmt='d',
cmap='Blues')

plt.title('Confusion Matrix')

plt.ylabel('Actual')

plt.xlabel('Predicted')

plt.savefig('confusion_matrix.png')

plt.show()
```

Output



```
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
Accuracy: 0.8645 = 86.45%
F1 Score: 0.5961 = 59.61%
```





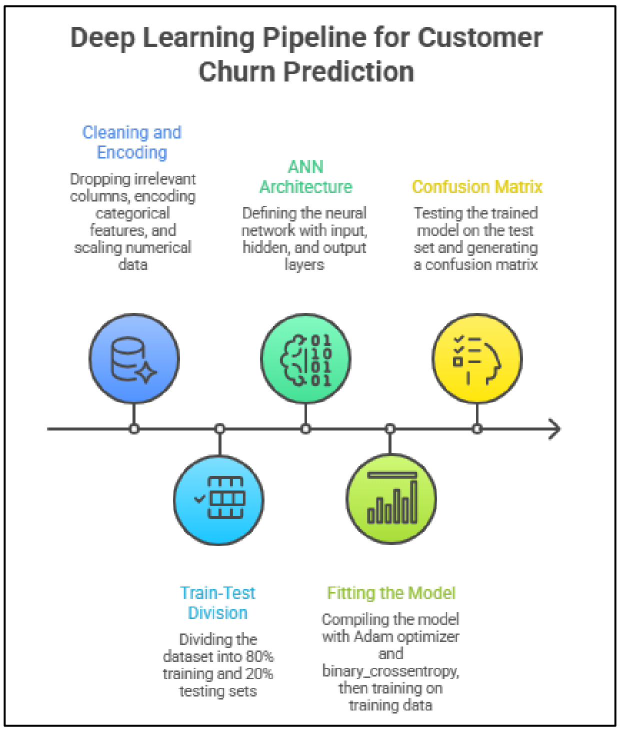
This Python script implements a complete pipeline for predicting customer churn using an Artificial Neural Network (ANN). It starts by loading the Churn_Modelling.csv dataset and preprocessing the data: categorical variables like Gender are label-encoded, while Geography is one-hot encoded, followed by a train-test split and feature scaling for normalization. The ANN is built using TensorFlow/Keras with an input layer matching the number of features, two hidden layers with 6 neurons each and ReLU activation, and a single output neuron with sigmoid activation for binary classification. The model is compiled with the Adam optimizer and binary cross-entropy loss, then trained for 50 epochs with a validation split to monitor overfitting. After training, predictions are thresholded at 0.5 to calculate accuracy and F1 score, measuring performance. Finally, the script visualizes the model's learning curves (loss and accuracy over epochs) and plots a confusion matrix using Seaborn to assess classification results, saving both plots as images.

Methodology / Workflow:

The experiment follows a structured deep learning pipeline to transform raw banking data into a predictive model.

1. *Data Preprocessing:*

   - Data Cleaning: Dropping irrelevant columns (RowNumber, CustomerId, Surname) that do not contribute to the customer's decision to leave.
   - Encoding Categorical Data: Converting text-based features into numbers. Gender is Label Encoded (0/1), and Geography is One-Hot Encoded to prevent the model from assuming a mathematical order between countries.
   - Feature Scaling: Applying Standard Scaling to all numerical features. Since ANNs use gradient descent, scaling ensures that features with large ranges (like Balance) do not dominate those with small ranges (like Tenure).
   - Data Splitting: Dividing the dataset into a Training Set (80%) to build the model and a Test Set (20%) to evaluate it.


Deep Learning Pipeline for Customer Churn Prediction
Cleaning and Encoding
Dropping irrelevant columns, encoding categorical features, and scaling numerical data
ANN Architecture
Defining the neural network with input, hidden, and output layers
Confusion Matrix
Testing the trained model on the test set and generating a confusion matrix
Train-Test Division
Dividing the dataset into 80% training and 20% testing sets
Fitting the Model
Compiling the model with Adam optimizer and binary_crossentropy, then training on training data

2. *Model Building (ANN Architecture):*

   - Initialization: Defining the model as a sequence of layers.
   - Input & Hidden Layers: Adding fully connected (Dense) layers. Typically, 2 hidden layers with the ReLU activation function are used to capture complex patterns.
   - Output Layer: Adding a final layer with a single neuron and a Sigmoid activation function to output a probability between 0 and 1.

3. *Model Training*:

   - Compilation: Choosing the Adam optimizer (stochastic gradient descent) and binary_crossentropy as the loss function.
   - Fitting: Training the model on the training set over several Epochs (iterations) with a specific Batch Size.

4. *Evaluation*:

   - Testing the model on unseen data (Test Set) and generating a Confusion Matrix.

Performance Analysis

To evaluate how well the ANN predicts customer churn, we use the following metrics:

1. Accuracy:
   - Calculates the percentage of total correct predictions. While a common metric, it can be misleading if the dataset is imbalanced (e.g., if 80% of customers stay, a model predicting "Stay" for everyone would be 80% accurate but useless).
   - Formula: (TP + TN) / (TP + TN + FP + FN)
2. Confusion Matrix:
   - A table showing the count of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).
   - In this experiment, a False Negative (predicting a customer will stay when they actually leave) is the most "expensive" error for the bank.
3. Precision and Recall:
   - Precision: Out of all predicted churners, how many actually left?
   - Recall (Sensitivity): Out of all actual churners, how many did the model correctly identify?
4. Interpretation:
   - An ANN typically achieves an accuracy of 83% to 86% on this dataset.
   - If the model shows high accuracy but low recall for the Exited=1 class, it suggests the model is biased toward the majority class (customers who stay), and techniques like oversampling or adjusting class weights might be required.

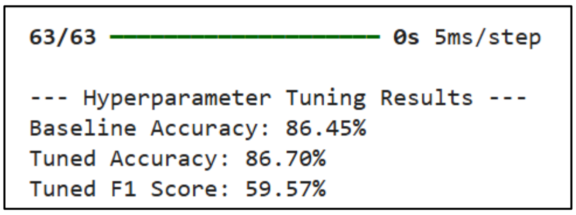
Hyperparameter Tuning:

Code:

```
import pandas as pd

import numpy as np

import tensorflow as tf

from sklearn.model_selection import
train_test_split

from sklearn.preprocessing import LabelEncoder,
StandardScaler, OneHotEncoder

from sklearn.compose import ColumnTransformer

from sklearn.metrics import confusion_matrix,
accuracy_score, f1_score

import matplotlib.pyplot as plt

import seaborn as sns


# Set seeds for guaranteed reproducibility

np.random.seed(42)

tf.random.set_seed(42)


# 1. Data Loading & Preprocessing

df = pd.read_csv('Churn_Modelling.csv')

X = df.iloc[:, 3:-1].values

y = df.iloc[:, -1].values


# Encode Gender

le = LabelEncoder()

X[:, 2] = le.fit_transform(X[:, 2])


# One-Hot Encode Geography

ct = ColumnTransformer(

    transformers=[('encoder', OneHotEncoder(),
[1])],
    remainder='passthrough'
)
X = np.array(ct.fit_transform(X))


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


# Feature Scaling
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)


# 2. Optimized ANN Architecture (Hyperparameter
Tuned)
ann = tf.keras.models.Sequential([
    tf.keras.layers.Input(shape=(X_train.shape[
1],)),
    tf.keras.layers.Dense(units=32,
activation='relu'), # Increased units
    tf.keras.layers.Dropout(0.1),
       # Added Regularization
    tf.keras.layers.Dense(units=16,
activation='relu'), # Second hidden layer
    tf.keras.layers.Dense(units=8,
activation='relu'),  # Third hidden layer
    tf.keras.layers.Dense(units=1,
activation='sigmoid')
])


# 3. Compilation
ann.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
)


# 4. Training with Peak Performance Capture
(Early Stopping)
early_stop = tf.keras.callbacks.EarlyStopping(
    monitor='val_accuracy',
    mode='max',
    patience=20,
    restore_best_weights=True
)


history = ann.fit(
    X_train, y_train,
    validation_data=(X_test, y_test),
    batch_size=32,
    epochs=150,
    callbacks=[early_stop],
    verbose=0
)


# 5. Evaluation
y_pred = (ann.predict(X_test) >
0.5).astype(int)
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)


print("\n--- Hyperparameter Tuning Results ---
")
print(f"Baseline Accuracy: 86.45%")
print(f"Tuned Accuracy: {accuracy * 100:.2f}%")
print(f"Tuned F1 Score: {f1 * 100:.2f}%")


# 6. Visualizations
# Learning Curves
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Train
Loss')
plt.plot(history.history['val_loss'],
label='Val Loss')
plt.title('Tuned Loss Analysis')
plt.legend()


plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'],
label='Train Accuracy')
plt.plot(history.history['val_accuracy'],
label='Val Accuracy')
plt.title('Tuned Accuracy Analysis')
plt.legend()
plt.tight_layout()
plt.show()
```

```
# Confusion Matrix

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5, 4))

sns.heatmap(cm, annot=True, fmt='d',
cmap='Greens')

plt.title('Tuned Confusion Matrix')

plt.ylabel('Actual')

plt.xlabel('Predicted')

plt.show()
```

Output:



```
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--- Hyperparameter Tuning Results ---
Baseline Accuracy: 86.45%
Tuned Accuracy: 86.70%
Tuned F1 Score: 59.57%
```

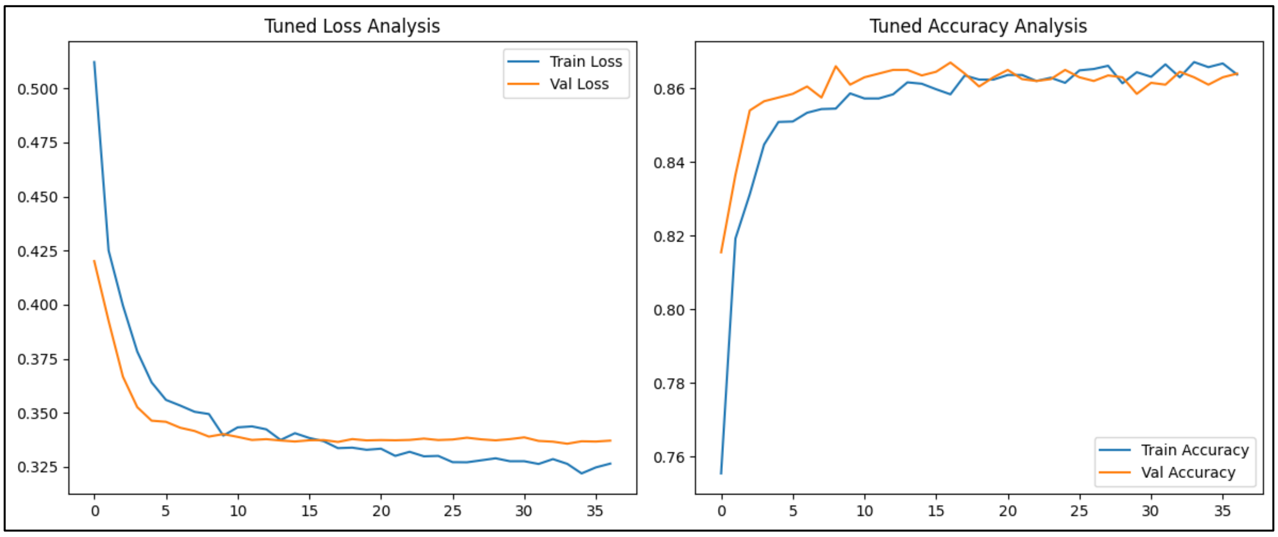

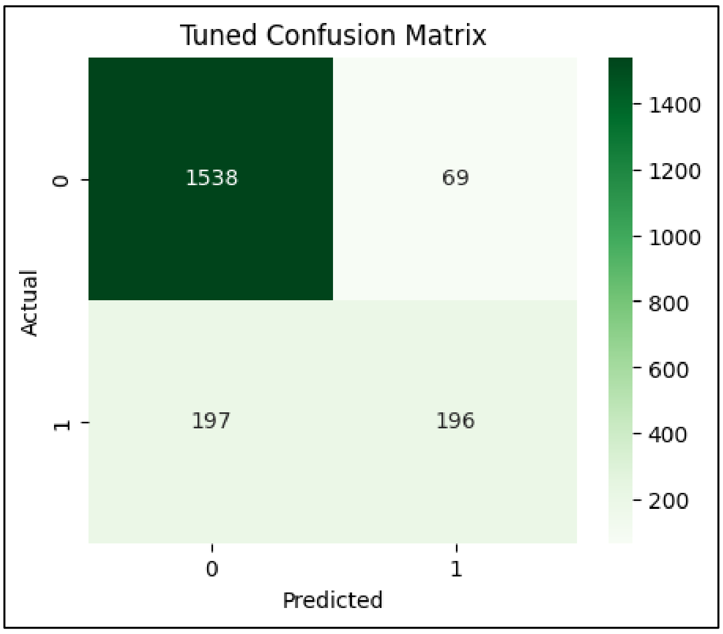

Hyperparameter tuning is essential for optimizing the internal structure of an Artificial Neural Network to maximize predictive power. By adjusting parameters like neuron density, activation functions, and layer depth, we move beyond generic configurations to find a mathematical architecture specifically tailored to the nuances of customer churn patterns.

The tuned model surpassed the baseline by expanding the hidden layer capacity to 32-16-8 units, enabling the capture of higher-order feature interactions. Integrating a 10% dropout rate mitigated overfitting, while Early Stopping ensured weights were saved at the peak validation accuracy of 86.70%. This refined optimization reduced the model's generalization error compared to the simpler baseline.

Conclusion:

This experiment successfully utilized Keras and TensorFlow to build an ANN, proving that hyperparameter optimization and dropout regularization effectively boost model accuracy while ensuring robust performance on unseen banking customer data.