Customer Churn Prediction and Analysis

This project aims to predict which customers are more likely to discontinue their subscription service, also known as churn prediction. Using the Telco Customer Churn dataset from Kaggle, I will apply data analysis techniques to classify customers as “returned” or “churned”. The dataset includes information regarding the customers’ demographics, the services they subscribed to, whether the customer left within the last month, and account information. The goal is to compare simple machine learning models with a deep learning approach to see which provides better predictions and business insights.

In [20]:
```
# import libraries
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
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score, classification
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.callbacks import EarlyStopping
```

In [2]:
```
# 1. Loading the Dataset
df = pd.read_csv('dataset/Telco-Customer-Churn.csv')
df.head()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 100 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   rev_Mean          99643 non-null   float64
 1   mou_Mean          99643 non-null   float64
 2   totmrc_Mean       99643 non-null   float64
 3   da_Mean           99643 non-null   float64
 4   ovrmou_Mean       99643 non-null   float64
 5   ovrrev_Mean       99643 non-null   float64
 6   vceovr_Mean       99643 non-null   float64
 7   datovr_Mean       99643 non-null   float64
 8   roam_Mean         99643 non-null   float64
 9   change_mou        99109 non-null   float64
 10  change_rev        99109 non-null   float64
 11  drop_vce_Mean     100000 non-null  float64
 12  drop_dat_Mean     100000 non-null  float64
 13  blck_vce_Mean     100000 non-null  float64
 14  blck_dat_Mean     100000 non-null  float64
 15  unan_vce_Mean     100000 non-null  float64
 16  unan_dat_Mean     100000 non-null  float64
 17  plcd_vce_Mean     100000 non-null  float64
 18  plcd_dat_Mean     100000 non-null  float64
 19  recv_vce_Mean     100000 non-null  float64
 20  recv_sms_Mean     100000 non-null  float64
 21  comp_vce_Mean     100000 non-null  float64
 22  comp_dat_Mean     100000 non-null  float64
 23  custcare_Mean     100000 non-null  float64
 24  ccrndmou_Mean     100000 non-null  float64
 25  cc_mou_Mean       100000 non-null  float64
 26  inonemin_Mean     100000 non-null  float64
 27  threeway_Mean     100000 non-null  float64
 28  mou_cvce_Mean     100000 non-null  float64
 29  mou_cdat_Mean     100000 non-null  float64
 30  mou_rvce_Mean     100000 non-null  float64
 31  owylis_vce_Mean   100000 non-null  float64
 32  mouowylisv_Mean   100000 non-null  float64
 33  iwylis_vce_Mean   100000 non-null  float64
 34  mouiwylisv_Mean   100000 non-null  float64
 35  peak_vce_Mean     100000 non-null  float64
 36  peak_dat_Mean     100000 non-null  float64
 37  mou_peav_Mean     100000 non-null  float64
 38  mou_pead_Mean     100000 non-null  float64
 39  opk_vce_Mean      100000 non-null  float64
 40  opk_dat_Mean      100000 non-null  float64
 41  mou_opkv_Mean     100000 non-null  float64
 42  mou_opkd_Mean     100000 non-null  float64
 43  drop_blk_Mean     100000 non-null  float64
 44  attempt_Mean      100000 non-null  float64
 45  complete_Mean     100000 non-null  float64
 46  callfwdv_Mean     100000 non-null  float64
 47  callwait_Mean     100000 non-null  float64
 48  churn             100000 non-null  int64  
 49  months            100000 non-null  int64  
 50  uniqsubs          100000 non-null  int64  
```

```
 51  actvsubs         100000 non-null  int64
 52  new_cell         100000 non-null  object
 53  crclscod         100000 non-null  object
 54  asl_flag         100000 non-null  object
 55  totcalls         100000 non-null  int64
 56  totmou           100000 non-null  float64
 57  totrev           100000 non-null  float64
 58  adjrev           100000 non-null  float64
 59  adjmou           100000 non-null  float64
 60  adjqty           100000 non-null  int64
 61  avgrev           100000 non-null  float64
 62  avgmou           100000 non-null  float64
 63  avgqty           100000 non-null  float64
 64  avg3mou          100000 non-null  int64
 65  avg3qty          100000 non-null  int64
 66  avg3rev          100000 non-null  int64
 67  avg6mou          97161 non-null   float64
 68  avg6qty          97161 non-null   float64
 69  avg6rev          97161 non-null   float64
 70  prizm_social_one 92612 non-null   object
 71  area             99960 non-null   object
 72  dualband         99999 non-null   object
 73  refurb_new       99999 non-null   object
 74  hnd_price        99153 non-null   float64
 75  phones           99999 non-null   float64
 76  models           99999 non-null   float64
 77  hnd_webcap       89811 non-null   object
 78  truck            98268 non-null   float64
 79  rv               98268 non-null   float64
 80  ownrent          66294 non-null   object
 81  lor              69810 non-null   float64
 82  dwlltype         68091 non-null   object
 83  marital          98268 non-null   object
 84  adults           76981 non-null   float64
 85  infobase         77921 non-null   object
 86  income           74564 non-null   float64
 87  numbcars         50634 non-null   float64
 88  HHstatin         62077 non-null   object
 89  dwllsize         61692 non-null   object
 90  forgntvl         98268 non-null   float64
 91  ethnic           98268 non-null   object
 92  kid0_2           98268 non-null   object
 93  kid3_5           98268 non-null   object
 94  kid6_10          98268 non-null   object
 95  kid11_15         98268 non-null   object
 96  kid16_17         98268 non-null   object
 97  creditcd         98268 non-null   object
 98  eqpdays          99999 non-null   float64
 99  Customer_ID      100000 non-null  int64
dtypes: float64(69), int64(10), object(21)
memory usage: 76.3+ MB
```

In [3]:
```
# 2. Data preprocessing
df["churn"] = LabelEncoder().fit_transform(df["churn"])

# One-hot coding
```

```
df = pd.get_dummies(df, drop_first=True)

# Separate features and target
X = df.drop("churn", axis=1)
y = df["churn"]

# Create an imputer to replaces NaN with the column mean
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')
X = pd.DataFrame(imputer.fit_transform(X), columns=X.columns)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Features scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

print("Data preprocessing complete.")
print(f"Training set shape: {X_train.shape}")
print(f"Test set shape: {X_test.shape}")
print(f"NaN values? {pd.isna(X_train).any()}")
```

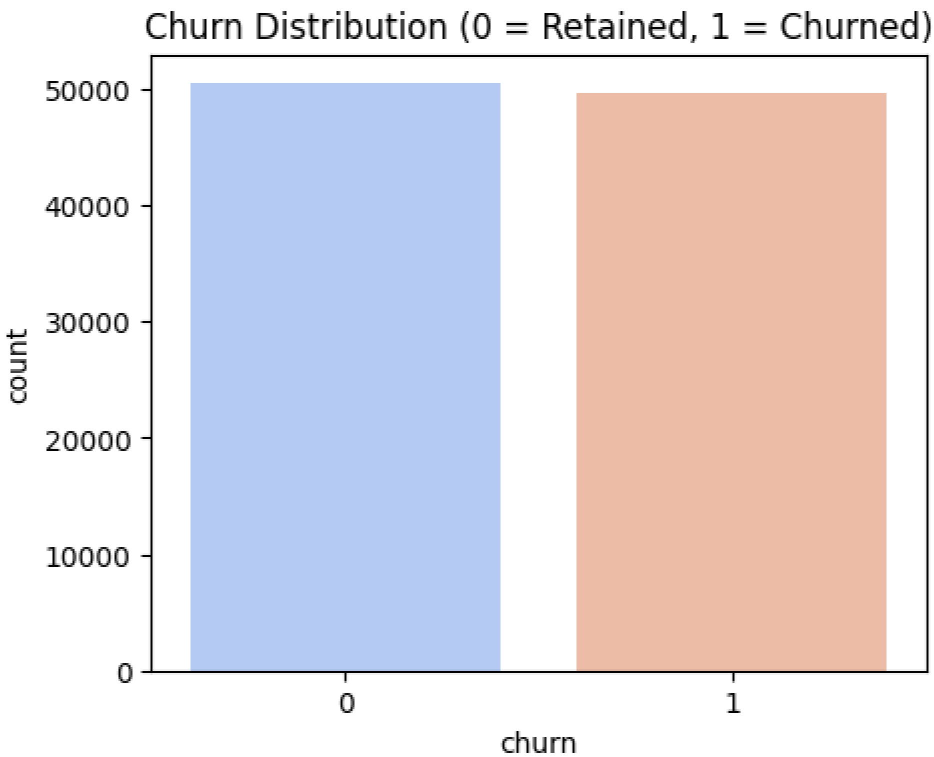
```
Data preprocessing complete.
Training set shape: (80000, 210)
Test set shape: (20000, 210)
NaN values? False
```

In [22]:

```
# 2.1. Data exploration
# Check dataset dimensions and types
print("Dataset shape:", df.shape)
print("\nData types:")
print(df.dtypes.head(10))

# Look at missing values
print("\nMissing values per column:")
print(df.isnull().sum().sort_values(ascending=False).head(15))

# Churn distribution
print(f"Churn Rate: {y.mean():.2%}")
plt.figure(figsize=(5,4))
sns.countplot(x="churn", data=df, palette="coolwarm")
plt.title("Churn Distribution (0 = Retained, 1 = Churned)")
plt.show()
```

```
Dataset shape: (100000, 211)

Data types:
rev_Mean        float64
mou_Mean        float64
totmrc_Mean     float64
da_Mean         float64
ovrmou_Mean     float64
ovrrev_Mean     float64
vceovr_Mean     float64
datovr_Mean     float64
roam_Mean       float64
change_mou      float64
dtype: object

Missing values per column:
numbcars        49366
lor             30190
income          25436
adults          23019
avg6rev          2839
avg6qty          2839
avg6mou          2839
rv               1732
forgntvl         1732
truck            1732
change_mou        891
change_rev        891
hnd_price         847
totmrc_Mean       357
ovrmou_Mean       357
dtype: int64
Churn Rate: 49.56%
```

```
C:\Users\anhth\AppData\Local\Temp\ipykernel_15504\3314583481.py:14: FutureWarning:
C:\Users\anhth\AppData\Local\Temp\ipykernel_22600\3314583481.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(x="churn", data=df, palette="coolwarm")
```

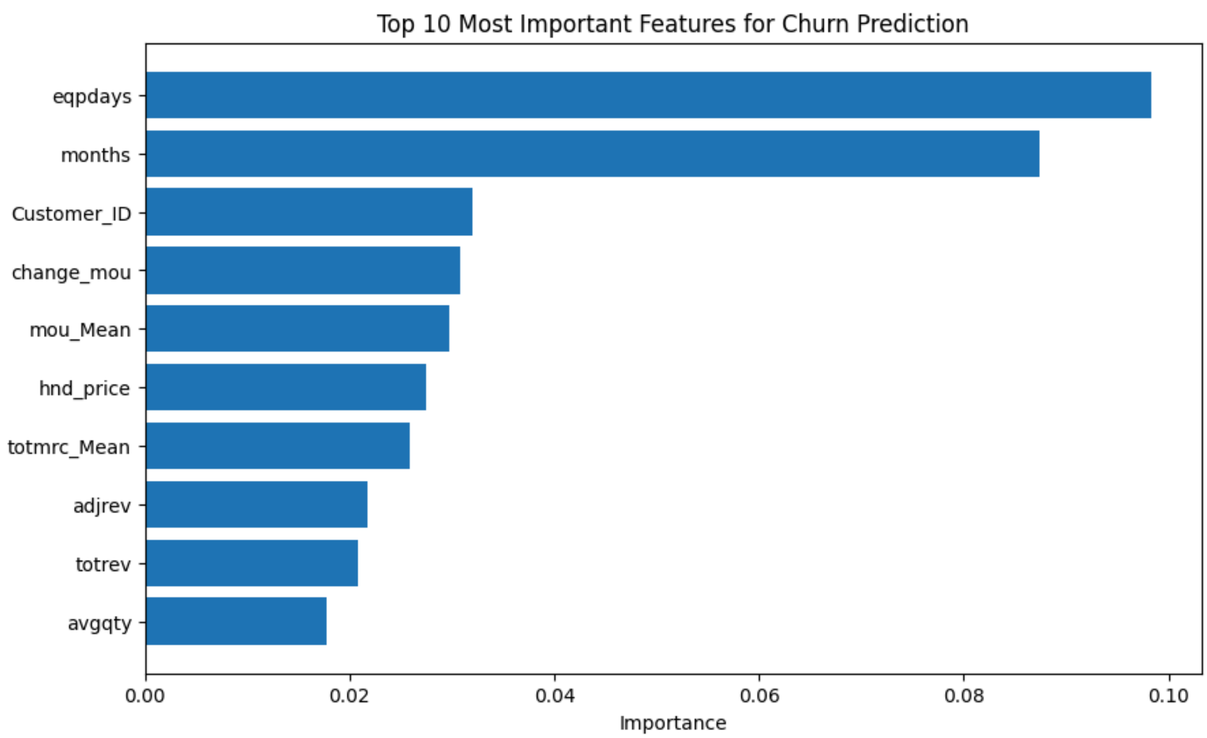


In [15]:

```
# 3. Baseline models
# Logistic Regression
lr = LogisticRegression(max_iter=1000, n_jobs=-1) #Use all CPU cores for parallel t
lr.fit(X_train, y_train)
lr_preds = lr.predict(X_test)

# Random Forest
rf = RandomForestClassifier(
    n_estimators=100,
    random_state=42,
    n_jobs=-1,       # use all CPU cores
    max_depth = 10) # limit tree depth to prevent overfitting
rf.fit(X_train, y_train)
rf_preds = rf.predict(X_test)

# 3.1. Model evaluation
for name, preds in [('Logistic Regression', lr_preds), ('Random Forest', rf_preds)]
    print(f"{name}")
    print(f"Accuracy: {accuracy_score(y_test, preds):.3f}")
    print(f"F1 Score: {f1_score(y_test, preds):.3f}")
    print(f"ROC AUC: {roc_auc_score(y_test, preds):.3f}\n")

# 3.2. Compare baseline models results
models_list = ['Logistic Regression', 'Random Forest']
metrics = {
    'Accuracy': [0.592, 0.617],
    'F1 Score': [0.590, 0.628],
    'ROC AUC': [0.592, 0.617]
}

x = np.arange(len(models_list))
width = 0.25
```

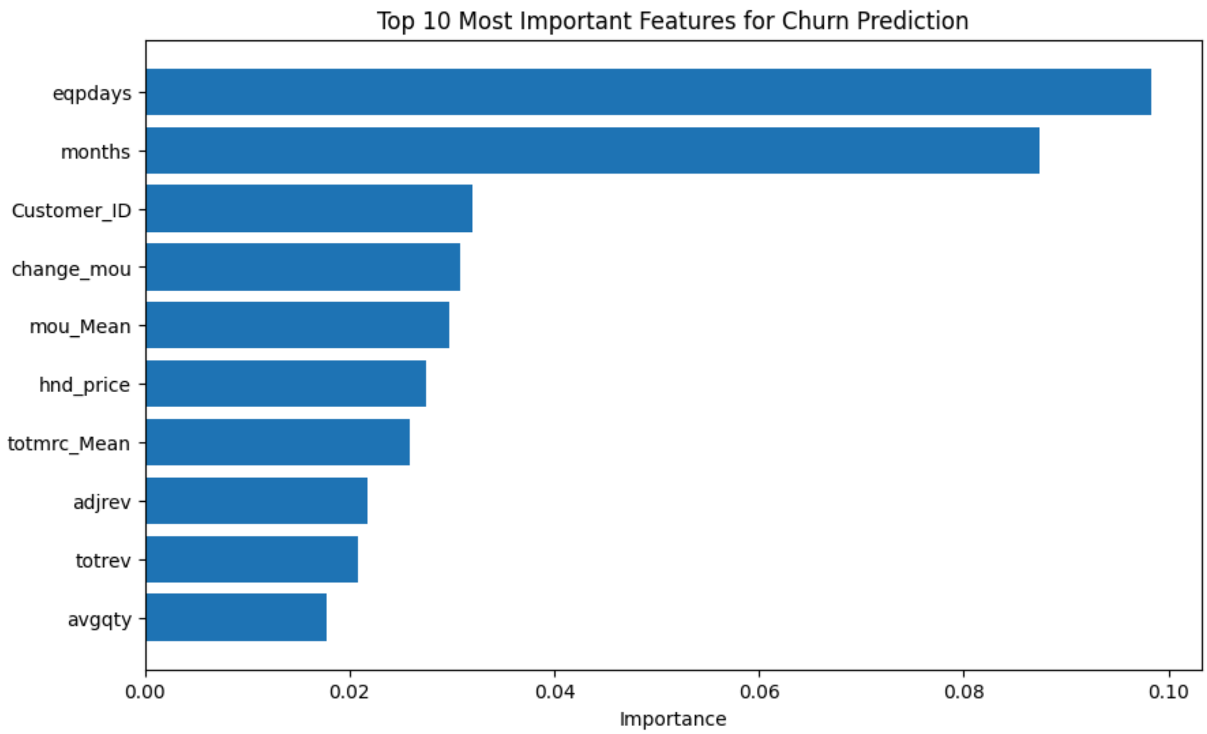
```
fig, ax = plt.subplots(figsize=(12, 6))
for i, (metric, values) in enumerate(metrics.items()):
    ax.bar(x + i*width, values, width, label=metric)

ax.set_xlabel('Models')
ax.set_ylabel('Score')
ax.set_title('Model Performance Comparison')
ax.set_xticks(x + width)
ax.set_xticklabels(models_list)
ax.legend()
ax.set_ylim(0.5, 0.7)
plt.tight_layout()
plt.show()
```

```
Logistic Regression
Accuracy: 0.592
F1 Score: 0.590
ROC AUC: 0.592

Random Forest
Accuracy: 0.617
F1 Score: 0.628
ROC AUC: 0.617
```



In [6]:
```
# 3.3. Feature importance from Random Forest
importances = rf.feature_importances_
feature_names = X.columns
importance_df = pd.DataFrame({
    'feature': feature_names,
    'importance': importances
}).sort_values('importance', ascending=False).head(10)
```

```
plt.figure(figsize=(10, 6))
plt.barh(importance_df['feature'], importance_df['importance'])
plt.xlabel('Importance')
plt.title('Top 10 Most Important Features for Churn Prediction')
plt.gca().invert_yaxis()
plt.show()
```



In [7]:

```
# 4. Deep Neural Network model
model = models.Sequential([
    # Input layer with more neurons for complex patterns
    layers.Input(shape=(X_train.shape[1],)),
    layers.Dense(128, activation='relu'),
    layers.BatchNormalization(),
    layers.Dropout(0.3),

    # hidden layer
    layers.Dense(64, activation='relu'),
    layers.BatchNormalization(),
    layers.Dropout(0.3),
    layers.Dense(32, activation='relu'),
    layers.BatchNormalization(),
    layers.Dropout(0.2),

    # Output layer
    layers.Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', tf.keras.metrics.AUC(name='auc')])

# add EarlyStopping for better training
callbacks = [
```

```
    # Stop training if validation loss doesn't improve for 5 epochs
    EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True,
        verbose=1
    )
]

# training
history = model.fit(
    X_train, y_train,
    epochs=30,
    batch_size=128,
    validation_split=0.2,
    callbacks=callbacks,
    verbose=1
)

loss, accuracy, auc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy:.3f}, Test AUC: {auc:.3f}")
```

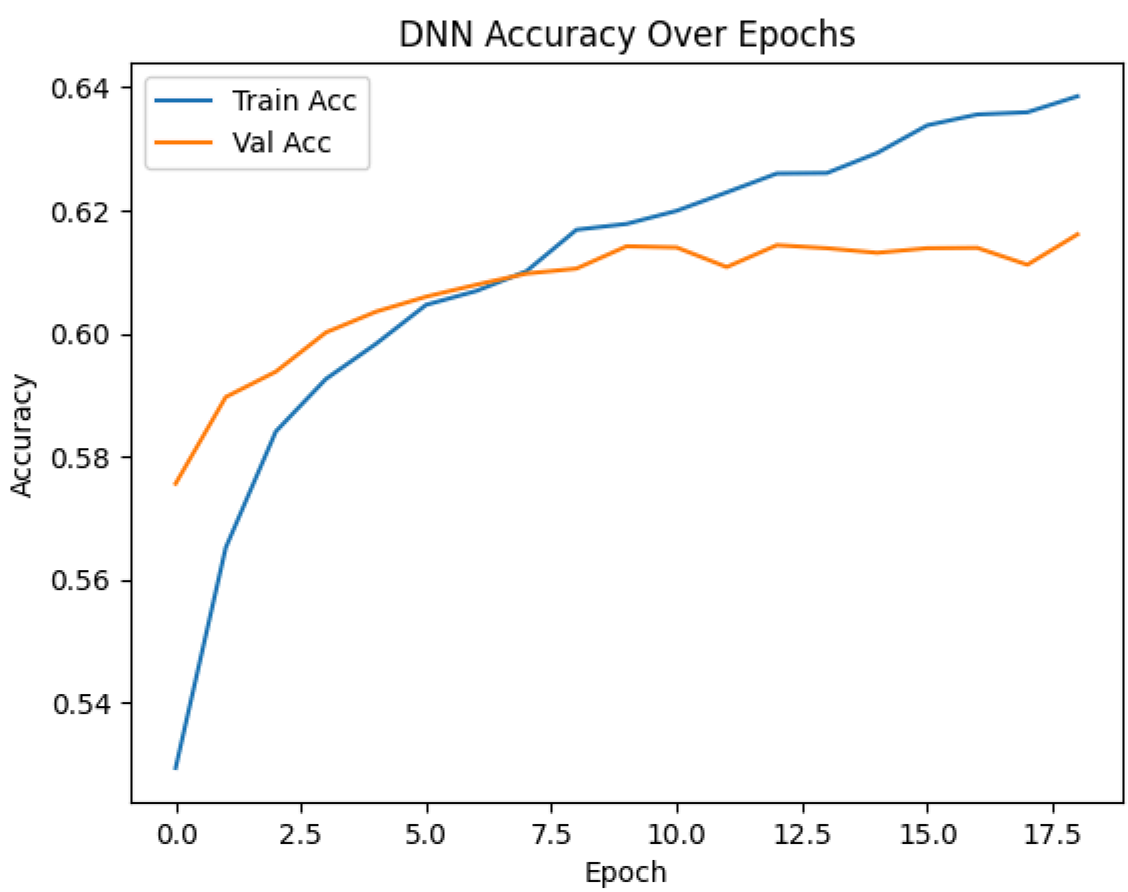
```
Epoch 1/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 8s 7ms/step - accuracy: 0.5294 - auc: 0.5399 - loss: 0.
7317 - val_accuracy: 0.5756 - val_auc: 0.6037 - val_loss: 0.6777
Epoch 2/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.5652 - auc: 0.5899 - loss: 0.
6831 - val_accuracy: 0.5897 - val_auc: 0.6222 - val_loss: 0.6707
Epoch 3/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.5841 - auc: 0.6165 - loss: 0.
6721 - val_accuracy: 0.5938 - val_auc: 0.6285 - val_loss: 0.6683
Epoch 4/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.5926 - auc: 0.6284 - loss: 0.
6676 - val_accuracy: 0.6002 - val_auc: 0.6370 - val_loss: 0.6643
Epoch 5/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.5983 - auc: 0.6358 - loss: 0.
6641 - val_accuracy: 0.6036 - val_auc: 0.6421 - val_loss: 0.6629
Epoch 6/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6047 - auc: 0.6430 - loss: 0.
6612 - val_accuracy: 0.6060 - val_auc: 0.6444 - val_loss: 0.6616
Epoch 7/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6069 - auc: 0.6489 - loss: 0.
6582 - val_accuracy: 0.6079 - val_auc: 0.6496 - val_loss: 0.6590
Epoch 8/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6101 - auc: 0.6529 - loss: 0.
6562 - val_accuracy: 0.6097 - val_auc: 0.6515 - val_loss: 0.6586
Epoch 9/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6169 - auc: 0.6592 - loss: 0.
6531 - val_accuracy: 0.6106 - val_auc: 0.6530 - val_loss: 0.6564
Epoch 10/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6178 - auc: 0.6622 - loss: 0.
6517 - val_accuracy: 0.6142 - val_auc: 0.6553 - val_loss: 0.6561
Epoch 11/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6200 - auc: 0.6659 - loss: 0.
6492 - val_accuracy: 0.6140 - val_auc: 0.6553 - val_loss: 0.6560
Epoch 12/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6230 - auc: 0.6705 - loss: 0.
6469 - val_accuracy: 0.6108 - val_auc: 0.6533 - val_loss: 0.6565
Epoch 13/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6260 - auc: 0.6743 - loss: 0.
6445 - val_accuracy: 0.6144 - val_auc: 0.6574 - val_loss: 0.6548
Epoch 14/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6261 - auc: 0.6746 - loss: 0.
6446 - val_accuracy: 0.6139 - val_auc: 0.6577 - val_loss: 0.6546
Epoch 15/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6293 - auc: 0.6789 - loss: 0.
6419 - val_accuracy: 0.6131 - val_auc: 0.6586 - val_loss: 0.6547
Epoch 16/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6338 - auc: 0.6847 - loss: 0.
6383 - val_accuracy: 0.6139 - val_auc: 0.6536 - val_loss: 0.6568
Epoch 17/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6356 - auc: 0.6874 - loss: 0.
6366 - val_accuracy: 0.6139 - val_auc: 0.6563 - val_loss: 0.6551
Epoch 18/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6360 - auc: 0.6892 - loss: 0.
6354 - val_accuracy: 0.6112 - val_auc: 0.6550 - val_loss: 0.6561
Epoch 19/30
500/500 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.6386 - auc: 0.6923 - loss: 0.
```

```
6334 - val_accuracy: 0.6161 - val_auc: 0.6576 - val_loss: 0.6560
Epoch 19: early stopping
Restoring model weights from the end of the best epoch: 14.
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6090 - auc: 0.6527 - loss: 0.
6569
Test Accuracy: 0.609, Test AUC: 0.653
```

In [8]:

```python
# 4.1. Model Evaluation
loss, accuracy, auc = model.evaluate(X_test, y_test, verbose=0)
print(f"\nTest Results:")
print(f"  Loss:          {loss:.4f}")
print(f"  Accuracy:      {accuracy:.3f}")
print(f"  ROC AUC:       {auc:.3f}")

# Visualization
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.title('DNN Accuracy Over Epochs')
plt.show()
```

```
Test Results:
  Loss:          0.6569
  Accuracy:      0.609
  ROC AUC:       0.653
```



In [9]:
```python
# 4.2. Evaluate Recall and Precision of DNN
dnn_preds = (model.predict(X_test, verbose=0) > 0.5).astype(int).flatten()
# Get predictions
dnn_preds = (model.predict(X_test, verbose=0) > 0.5).astype(int).flatten()

print("DNN Classification Report")
print("="*60)
print(classification_report(y_test, dnn_preds))
```

```
DNN Classification Report
============================================================
              precision    recall  f1-score   support

           0       0.61      0.62      0.62     10021
           1       0.61      0.59      0.60      9979
           0       0.62      0.60      0.61     10021
           1       0.61      0.63      0.62      9979

    accuracy                           0.61     20000
   macro avg       0.61      0.61      0.61     20000
weighted avg       0.61      0.61      0.61     20000
```

Deep Neural Network Architecture Tuning

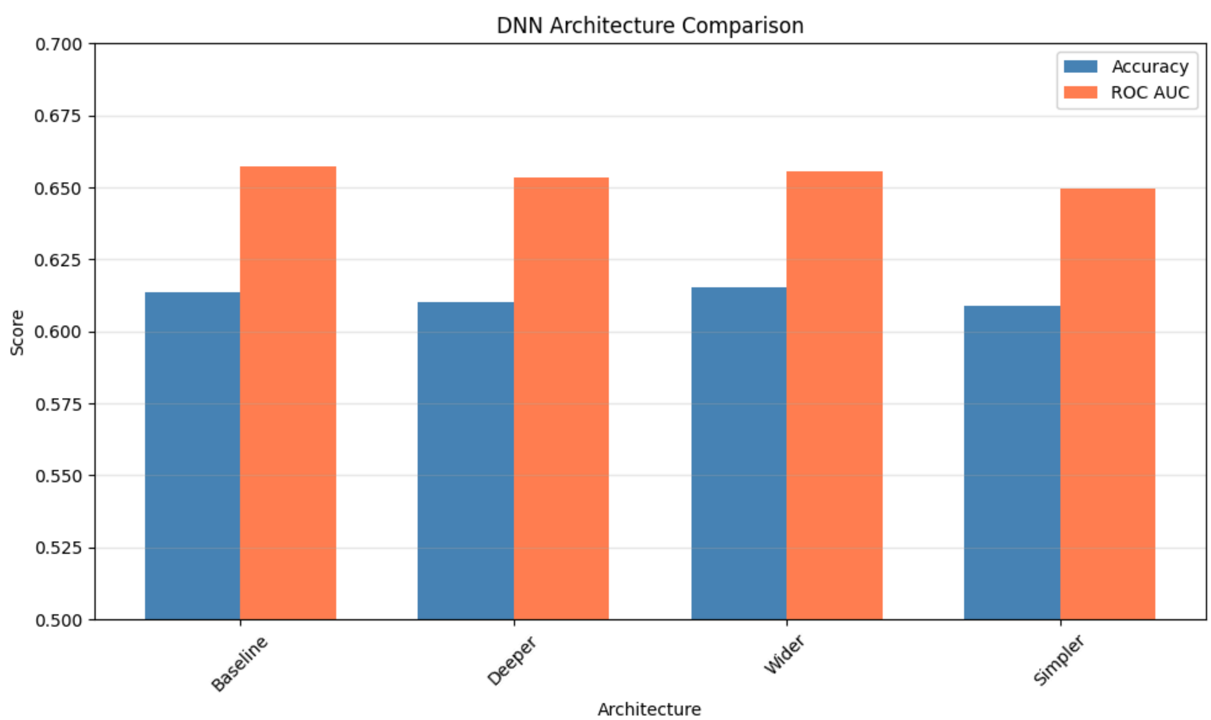
After exploring the basic DNN architecture, I want to test different network architectures to find the optimal configuration:

- Varying number of layers
- Different layer sizes
- Different dropout rates

In [10]:
```python
# 5.1. DNN Architecture Tuning
print("Testing different DNN architectures...\n")

tuning_results = []

# Define architectures to test
architectures = [
    {'name': 'Baseline', 'layers': [128, 64, 32], 'dropout': 0.3},
    {'name': 'Deeper', 'layers': [256, 128, 64, 32], 'dropout': 0.3},
    {'name': 'Wider', 'layers': [256, 128, 64], 'dropout': 0.4},
    {'name': 'Simpler', 'layers': [128, 64], 'dropout': 0.2},
]

for arch in architectures:
    print(f"Training {arch['name']} architecture: {arch['layers']}")

    # Build model
    model_test = models.Sequential()
    model_test.add(layers.Input(shape=(X_train.shape[1],)))

    # Add layers
```

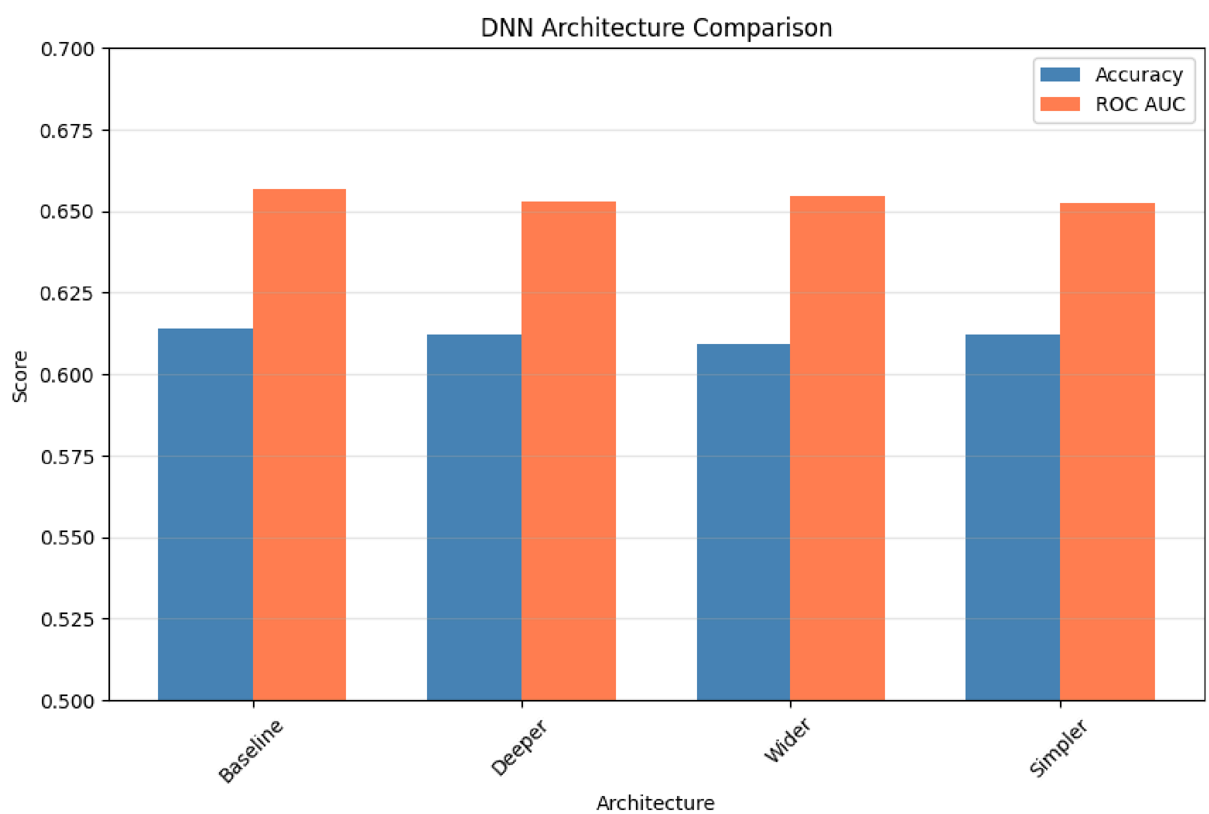
```python
    for units in arch['layers']:
        model_test.add(layers.Dense(units, activation='relu'))
        model_test.add(layers.BatchNormalization())
        model_test.add(layers.Dropout(arch['dropout']))

    # Output layer
    model_test.add(layers.Dense(1, activation='sigmoid'))

    # Compile
    model_test.compile(
        optimizer='adam',
        loss='binary_crossentropy',
        metrics=['accuracy', tf.keras.metrics.AUC(name='auc')]
    )

    # Train with early stopping
    history = model_test.fit(
        X_train, y_train,
        epochs=20,
        batch_size=128,
        validation_split=0.2,
        callbacks=[EarlyStopping(monitor='val_loss', patience=3, restore_best_weigh
        verbose=0
    )

    # Evaluate
    loss, acc, auc = model_test.evaluate(X_test, y_test, verbose=0)

    tuning_results.append({
        'name': arch['name'],
        'architecture': str(arch['layers']),
        'dropout': arch['dropout'],
        'accuracy': acc,
        'auc': auc
    })

    print(f"  Test Accuracy: {acc:.3f}, Test AUC: {auc:.3f}\n")

# Display results
print("\n" + "="*60)
print("DNN Architecture Tuning Results")
print("="*60)
tuning_df = pd.DataFrame(tuning_results)
print(tuning_df.to_string(index=False))

# Find best architecture
best_arch = tuning_df.loc[tuning_df['auc'].idxmax()]
print(f"\nBest Architecture: {best_arch['name']}")
print(f"  Architecture: {best_arch['architecture']}")
print(f"  Dropout: {best_arch['dropout']}")
print(f"  Accuracy: {best_arch['accuracy']:.3f}")
print(f"  ROC AUC: {best_arch['auc']:.3f}")

# 5.2. Visualize tuning results
print(f"  ROC AUC: {best_arch['auc']:.3f}")
```

```
Testing different DNN architectures...

Training Baseline architecture: [128, 64, 32]
  Test Accuracy: 0.614, Test AUC: 0.657

Training Deeper architecture: [256, 128, 64, 32]
  Test Accuracy: 0.610, Test AUC: 0.653

Training Wider architecture: [256, 128, 64]
  Test Accuracy: 0.615, Test AUC: 0.656

Training Simpler architecture: [128, 64]
  Test Accuracy: 0.609, Test AUC: 0.650


============================================================
DNN Architecture Tuning Results
============================================================
    name       architecture  dropout  accuracy      auc
Baseline      [128, 64, 32]      0.3   0.61355 0.657162
  Deeper [256, 128, 64, 32]      0.3   0.61020 0.653437
   Wider     [256, 128, 64]      0.4   0.61530 0.655563
 Simpler          [128, 64]      0.2   0.60870 0.649687

Best Architecture: Baseline
  Architecture: [128, 64, 32]
  Dropout: 0.3
  Accuracy: 0.614
  ROC AUC: 0.657
```



In [13]:
```python
# 4.2. Visualize tuning results
fig, ax = plt.subplots(figsize=(10, 6))

# Bar chart of architectures
```

```
arch_names = [r['name'] for r in tuning_results]
accuracies = [r['accuracy'] for r in tuning_results]
aucs = [r['auc'] for r in tuning_results]

x = np.arange(len(arch_names))
width = 0.35

ax.bar(x - width/2, accuracies, width, label='Accuracy', color='steelblue')
ax.bar(x + width/2, aucs, width, label='ROC AUC', color='coral')
ax.set_xlabel('Architecture')
ax.set_ylabel('Score')
ax.set_title('DNN Architecture Comparison')
ax.set_xticks(x)
ax.set_xticklabels(arch_names, rotation=45)
ax.legend()
ax.set_ylim(0.5, 0.7)
ax.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show()
ax.grid(axis='y', alpha=0.3)
```



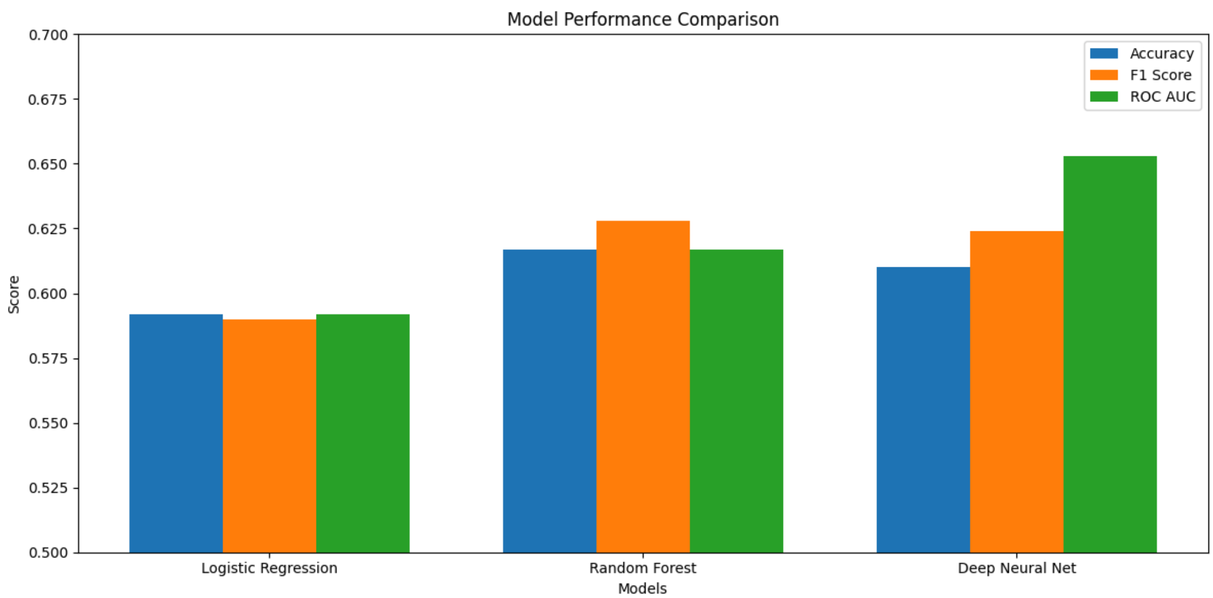
Comparing all models: DNN, Logistic Regression, Random Forest

This section evaluates and compares the performance of DNN against LR and RF.

In [16]:
```
# 6. Compare DNN with baseline models
print("Models Comparison")
print("="*60)
```

```python
# 6.1. Overall performance comparison
# Get predictions for fair comparison
dnn_preds = (model.predict(X_test, verbose=0) > 0.5).astype(int).flatten()

print(f"\nLogistic Regression:")
print(f"  Accuracy: {accuracy_score(y_test, lr_preds):.3f}")
print(f"  F1 Score: {f1_score(y_test, lr_preds):.3f}")
print(f"  ROC AUC:  {roc_auc_score(y_test, lr_preds):.3f}")

print(f"\nRandom Forest:")
print(f"  Accuracy: {accuracy_score(y_test, rf_preds):.3f}")
print(f"  F1 Score: {f1_score(y_test, rf_preds):.3f}")
print(f"  ROC AUC:  {roc_auc_score(y_test, rf_preds):.3f}")

print(f"\nDeep Neural Network:")
print(f"  Accuracy: {accuracy_score(y_test, dnn_preds):.3f}")
print(f"  F1 Score: {f1_score(y_test, dnn_preds):.3f}")
print(f"  ROC AUC:  {auc:.3f}")

models_list = ['Logistic Regression', 'Random Forest', 'Deep Neural Net']
metrics = {
    'Accuracy': [0.592, 0.617, 0.610],
    'F1 Score': [0.590, 0.628, 0.624],
    'ROC AUC': [0.592, 0.617, 0.653]
}

x = np.arange(len(models_list))
width = 0.25

fig, ax = plt.subplots(figsize=(12, 6))
for i, (metric, values) in enumerate(metrics.items()):
    ax.bar(x + i*width, values, width, label=metric)

ax.set_xlabel('Models')
ax.set_ylabel('Score')
ax.set_title('Model Performance Comparison')
ax.set_xticks(x + width)
ax.set_xticklabels(models_list)
ax.legend()
ax.set_ylim(0.5, 0.7)
plt.tight_layout()
plt.show()
```

```
Models Comparison
============================================================

Logistic Regression:
  Accuracy: 0.592
  F1 Score: 0.590
  ROC AUC:  0.592

Random Forest:
  Accuracy: 0.617
  F1 Score: 0.628
  ROC AUC:  0.617

Deep Neural Network:
  Accuracy: 0.609
  F1 Score: 0.603
  ROC AUC:  0.650
  Accuracy: 0.611
  F1 Score: 0.617
  ROC AUC:  0.653
```



In [12]:
```
# 6.2. Individual customer prediction breakdown to see how each model produces a pr
# generate sample customer data
customer_idx = 0
customer_features = X_test[customer_idx]
actual_churn = y_test.iloc[customer_idx]

print("="*80)
print("CUSTOMER PREDICTION BREAKDOWN")
print("="*80)

print(f"\n INPUT FEATURES")
print(f"  Number of features: {len(customer_features)}")
print(f"  Sample values: {customer_features[:10]}")

print(f"\n ACTUAL OUTCOME:")
print(f"  churn = {actual_churn} ({'CHURNED' if actual_churn == 1 else 'STAYED'})")
```

```python
print(f"\n MODEL PREDICTIONS:")

# Logistic Regression
lr_pred = lr.predict([customer_features])[0]
lr_prob = lr.predict_proba([customer_features])[0]
print(f"  Logistic Regression:")
print(f"    Prediction: {lr_pred} ({'CHURN' if lr_pred == 1 else 'STAY'})")
print(f"    Probabilities: [Stay: {lr_prob[0]:.1%}, Churn: {lr_prob[1]:.1%}]")

# Random Forest
rf_pred = rf.predict([customer_features])[0]
rf_prob = rf.predict_proba([customer_features])[0]
print(f"  Random Forest:")
print(f"    Prediction: {rf_pred} ({'CHURN' if rf_pred == 1 else 'STAY'})")
print(f"    Probabilities: [Stay: {rf_prob[0]:.1%}, Churn: {rf_prob[1]:.1%}]")

# Deep Neural Network
dnn_prob = model.predict(np.array([customer_features]), verbose=0)[0][0]
dnn_pred = 1 if dnn_prob > 0.5 else 0
print(f"  Deep Neural Network:")
print(f"   Prediction: {'Churn' if dnn_pred == 1 else 'Stay'}")
print(f"   Churn Probability: {dnn_prob:.1%}")

print("="*80)
```

```
================================================================================
CUSTOMER PREDICTION BREAKDOWN
================================================================================

 INPUT FEATURES
  Number of features: 210
  Sample values: [-0.32711824  0.34981012 -0.05048493 -0.40527053 -0.17198534 -0.164
82292
 -0.15809594 -0.08688812 -0.08107395  0.11658782]

 ACTUAL OUTCOME:
  churn = 1 (CHURNED)

 MODEL PREDICTIONS:
  Logistic Regression:
    Prediction: 1 (CHURN)
    Probabilities: [Stay: 44.1%, Churn: 55.9%]
  Random Forest:
    Prediction: 1 (CHURN)
    Probabilities: [Stay: 39.5%, Churn: 60.5%]
  Deep Neural Network:
   Prediction: Stay
   Churn Probability: 41.6%
================================================================================
```

In [ ]:

```python
# 6.2. View sample predictions from all models
# Get predictions and churn probabilities from all models
lr_preds = lr.predict(X_test)
lr_probs = lr.predict_proba(X_test)[:, 1]

rf_preds = rf.predict(X_test)
```

```python
rf_probs = rf.predict_proba(X_test)[:, 1]

dnn_probs = model.predict(X_test, verbose=0).flatten()
dnn_preds = (dnn_probs > 0.5).astype(int)

# Create comparison DataFrame
predictions_df = pd.DataFrame({
    'Actual': y_test.values,
    'LR_Pred': lr_preds,
    'LR_Prob': lr_probs,
    'RF_Pred': rf_preds,
    'RF_Prob': rf_probs,
    'DNN_Pred': dnn_preds,
    'DNN_Prob': dnn_probs
})

# View first 20 predictions
print("Sample Predictions:")
print("=" * 80)
print(predictions_df.head(20).to_string(index=False))
```

```
Sample Predictions:
================================================================================
 Actual  LR_Pred  LR_Prob  RF_Pred  RF_Prob  DNN_Pred  DNN_Prob
      1        1 0.558936        1 0.604994         0  0.415715
      0        0 0.479679        1 0.521751         1  0.671899
      0        0 0.310861        0 0.441351         0  0.286902
      1        1 0.507620        1 0.657821         1  0.585613
      0        1 0.586324        1 0.520562         1  0.679461
      1        0 0.483201        0 0.308577         1  0.501587
      0        0 0.395235        0 0.197001         0  0.222004
      1        0 0.421257        1 0.555085         0  0.343363
      0        1 0.513560        1 0.509744         1  0.532644
      0        0 0.300240        0 0.399589         0  0.288548
      0        1 0.599736        1 0.599173         1  0.685539
      0        0 0.397359        0 0.439991         0  0.374813
      1        0 0.492876        1 0.502165         1  0.562245
      1        0 0.422962        1 0.675033         1  0.597472
      1        0 0.349140        0 0.387403         0  0.229550
      1        1 0.682840        0 0.382601         1  0.680490
      0        0 0.289784        0 0.375985         0  0.245283
      0        1 0.664613        1 0.535018         1  0.596997
      1        0 0.437240        0 0.410950         0  0.483759
      0        0 0.471336        1 0.613439         1  0.532856
```

In [14]:

```python
# 6.3. Cases where models agree or differ
print("\n" + "="*80)
print("DETAILED PREDICTION ANALYSIS")
print("="*80)

# Case 1: All models agree - correct
correct_agreement = predictions_df[
    (predictions_df['Actual'] == predictions_df['LR_Pred']) &
    (predictions_df['LR_Pred'] == predictions_df['RF_Pred']) &
    (predictions_df['RF_Pred'] == predictions_df['DNN_Pred'])
]
```

```
print(f"\n All models agree AND correct: {len(correct_agreement)} cases")
print(correct_agreement.head(3))

# Case 2: All models agree - wrong
wrong_agreement = predictions_df[
    (predictions_df['Actual'] != predictions_df['LR_Pred']) &
    (predictions_df['LR_Pred'] == predictions_df['RF_Pred']) &
    (predictions_df['RF_Pred'] == predictions_df['DNN_Pred'])
]
print(f"\n All models agree BUT wrong: {len(wrong_agreement)} cases")
print(wrong_agreement.head(3))

# Case 3: DNN correct when others wrong
dnn_saves = predictions_df[
    (predictions_df['Actual'] == predictions_df['DNN_Pred']) &
    (predictions_df['LR_Pred'] != predictions_df['Actual']) &
    (predictions_df['RF_Pred'] != predictions_df['Actual'])
]
print(f"\n DNN correct when LR & RF wrong: {len(dnn_saves)} cases")
print(dnn_saves.head(3))
```

```
================================================================================
DETAILED PREDICTION ANALYSIS
================================================================================

 All models agree AND correct: 8336 cases
   Actual  LR_Pred   LR_Prob  RF_Pred   RF_Prob  DNN_Pred  DNN_Prob
2       0        0  0.310861        0  0.441351         0  0.286902
3       1        1  0.507620        1  0.657821         1  0.585613
6       0        0  0.395235        0  0.197001         0  0.222004

 All models agree BUT wrong: 4240 cases
    Actual  LR_Pred   LR_Prob  RF_Pred   RF_Prob  DNN_Pred  DNN_Prob
4        0        1  0.586324        1  0.520562         1  0.679461
8        0        1  0.513560        1  0.509744         1  0.532644
10       0        1  0.599736        1  0.599173         1  0.685539

 DNN correct when LR & RF wrong: 802 cases
    Actual  LR_Pred   LR_Prob  RF_Pred   RF_Prob  DNN_Pred  DNN_Prob
5        1        0  0.483201        0  0.308577         1  0.501587
22       0        1  0.513963        1  0.574623         0  0.481774
66       1        0  0.465984        0  0.495227         1  0.509838
```

In [15]:

```
# 6.4. Compare training times
import time

# Train baseline
start = time.time()
lr.fit(X_train, y_train)
lr_time = time.time() - start

start = time.time()
rf.fit(X_train, y_train)
rf_time = time.time() - start

# Train DNN
```

```python
start = time.time()
model.fit(X_train, y_train, epochs=20, verbose=0)
dnn_time = time.time() - start

print(f"Logistic Regression: {lr_time:.2f}s")
print(f"Random Forest: {rf_time:.2f}s")
print(f"DNN: {dnn_time:.2f}s ({dnn_time/lr_time:.1f}x slower than LR, {dnn_time/rf_
print(f"\nPerformance gain - DNN vs. Logistic Regression: {(auc - roc_auc_score(y_t
print(f"\nPerformance gain - DNN vs. Random Forest: {(auc - roc_auc_score(y_test, r
```

```
Logistic Regression: 8.15s
Random Forest: 3.97s
DNN: 207.72s (25.5x slower than LR, 52.3x slower than RF)

Performance gain - DNN vs. Logistic Regression: 5.8% improvement

Performance gain - DNN vs. Random Forest: 3.3% improvement
```