Project

September 18, 2025

0.1 Importing All The Important Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,␣
↪auc, precision_recall_curve
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
import warnings
warnings.filterwarnings('ignore')
```

0.2 1. Data Exploration and Visualization

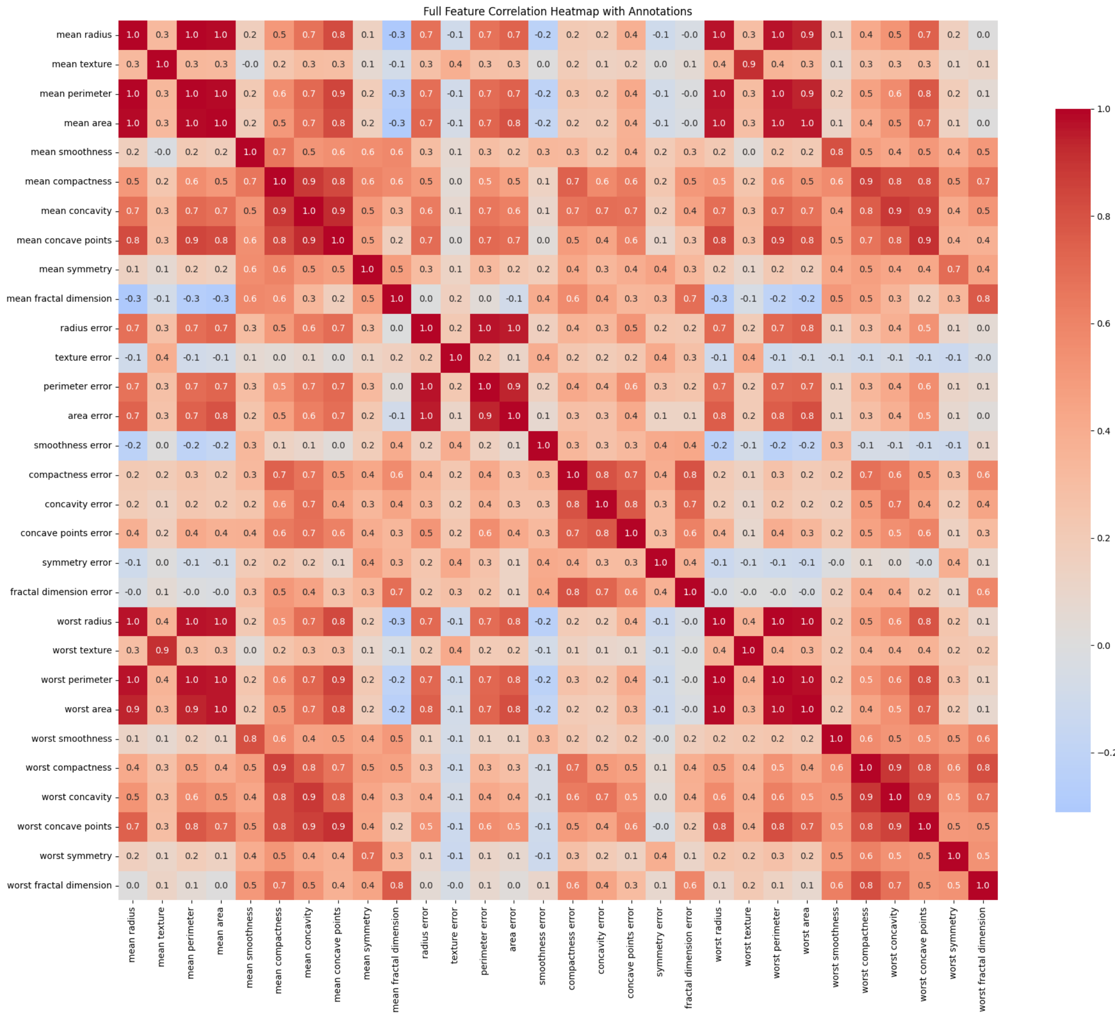
[2]:
```
# Set random seeds for reproducibility
np.random.seed(42)
tf.random.set_seed(42)

# Load the dataset
data = load_breast_cancer()
X = data.data
y = data.target
feature_names = data.feature_names
target_names = data.target_names

# Create DataFrame for better visualization
df = pd.DataFrame(X, columns=feature_names)
df['target'] = y
df['diagnosis'] = df['target'].map({0: 'Malignant', 1: 'Benign'})

print("Dataset Shape:", X.shape)
```

```python
print("Target Distribution:")
print(df['diagnosis'].value_counts())
print("\nFeature Names:")
print(feature_names)
```

```
Dataset Shape: (569, 30)
Target Distribution:
diagnosis
Benign       357
Malignant    212
Name: count, dtype: int64

Feature Names:
['mean radius' 'mean texture' 'mean perimeter' 'mean area'
 'mean smoothness' 'mean compactness' 'mean concavity'
 'mean concave points' 'mean symmetry' 'mean fractal dimension'
 'radius error' 'texture error' 'perimeter error' 'area error'
 'smoothness error' 'compactness error' 'concavity error'
 'concave points error' 'symmetry error' 'fractal dimension error'
 'worst radius' 'worst texture' 'worst perimeter' 'worst area'
 'worst smoothness' 'worst compactness' 'worst concavity'
 'worst concave points' 'worst symmetry' 'worst fractal dimension']
```

0.3 1.2 Correlation Between the Features

[3]:
```python
## 1.2 Correlation Between the Features
# Correlation Heatmap with Annotations
plt.figure(figsize=(20, 16)) # Increased figure size for better annotation␣
↪visibility
correlation_matrix = df.drop(['target', 'diagnosis'], axis=1).corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0,
            square=True, cbar_kws={"shrink": .8}, fmt='.1f') # annot=True,␣
↪removed mask, added fmt for annotation format
plt.title('Full Feature Correlation Heatmap with Annotations')
plt.tight_layout()
plt.show()
```



0.4 1.3 Top 5 Most Important Features

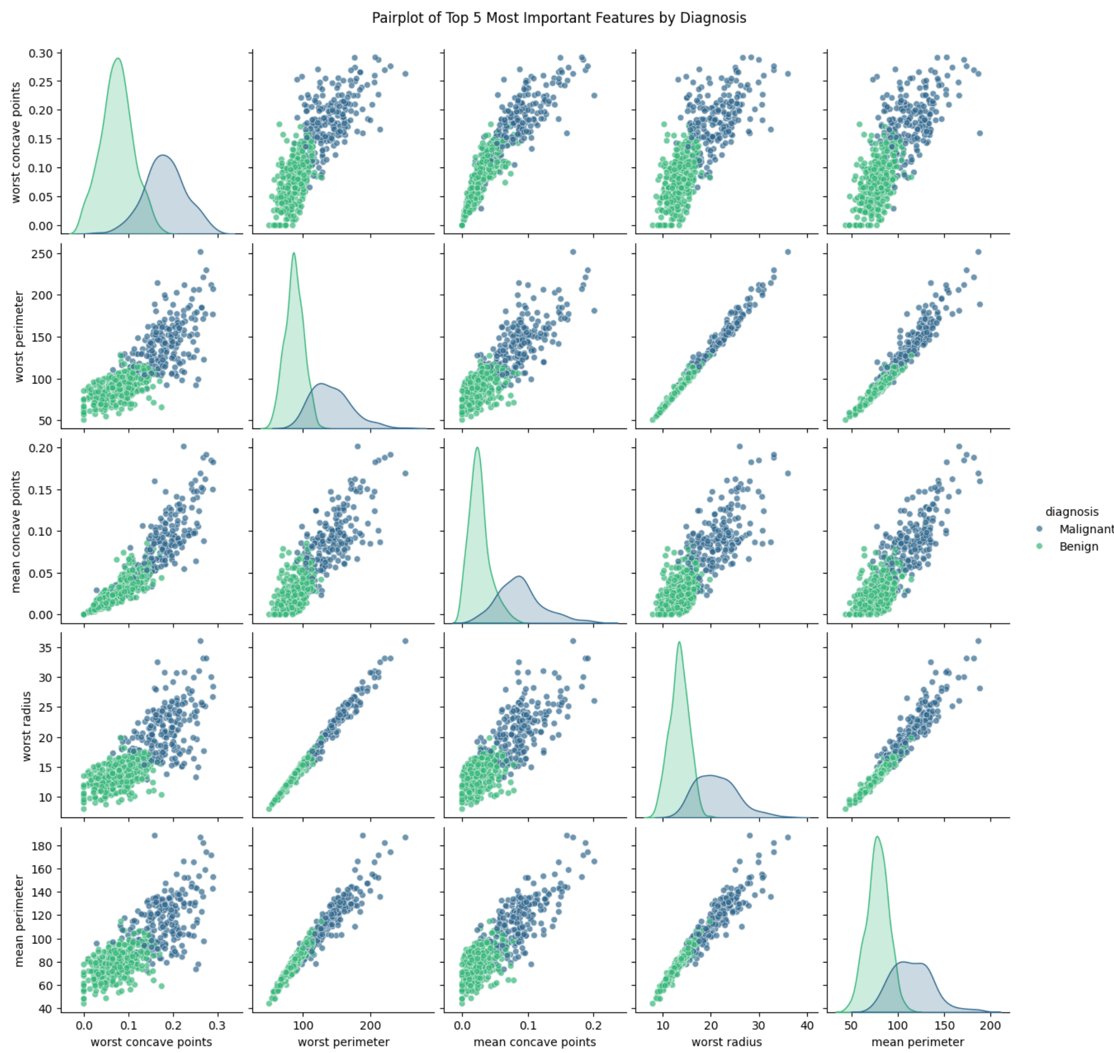
[4]:
```python
correlation_with_target = df.drop('diagnosis', axis=1).corr()['target'].abs().
↪sort_values(ascending=False)
top_5_features = correlation_with_target.index[1:6]  # Exclude target itself

print("Top 5 Most Important Features:")
for i, feature in enumerate(top_5_features, 1):
    print(f"{i}. {feature}: {correlation_with_target[feature]:.4f}")
```

```
Top 5 Most Important Features:
1. worst concave points: 0.7936
2. worst perimeter: 0.7829
3. mean concave points: 0.7766
4. worst radius: 0.7765
5. mean perimeter: 0.7426
```

0.5 1.4 Pairplot of Top 5 Features

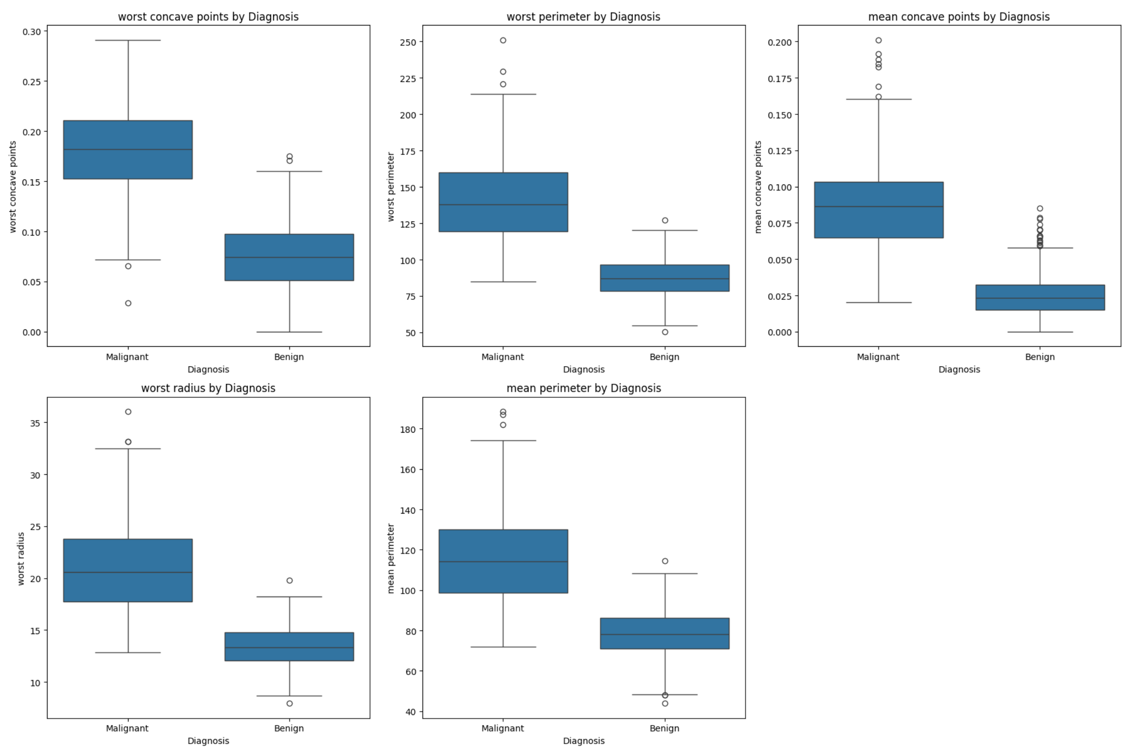
[5]:
```
plt.figure(figsize=(15, 12))
pairplot_df = df[list(top_5_features) + ['diagnosis']]
sns.pairplot(pairplot_df, hue='diagnosis', palette='viridis',
             plot_kws={'alpha': 0.7, 's': 30})
plt.suptitle('Pairplot of Top 5 Most Important Features by Diagnosis', y=1.02)
plt.show()
```

```
<Figure size 1500x1200 with 0 Axes>
```



0.6 1.5 Boxplots for Top 5 Features

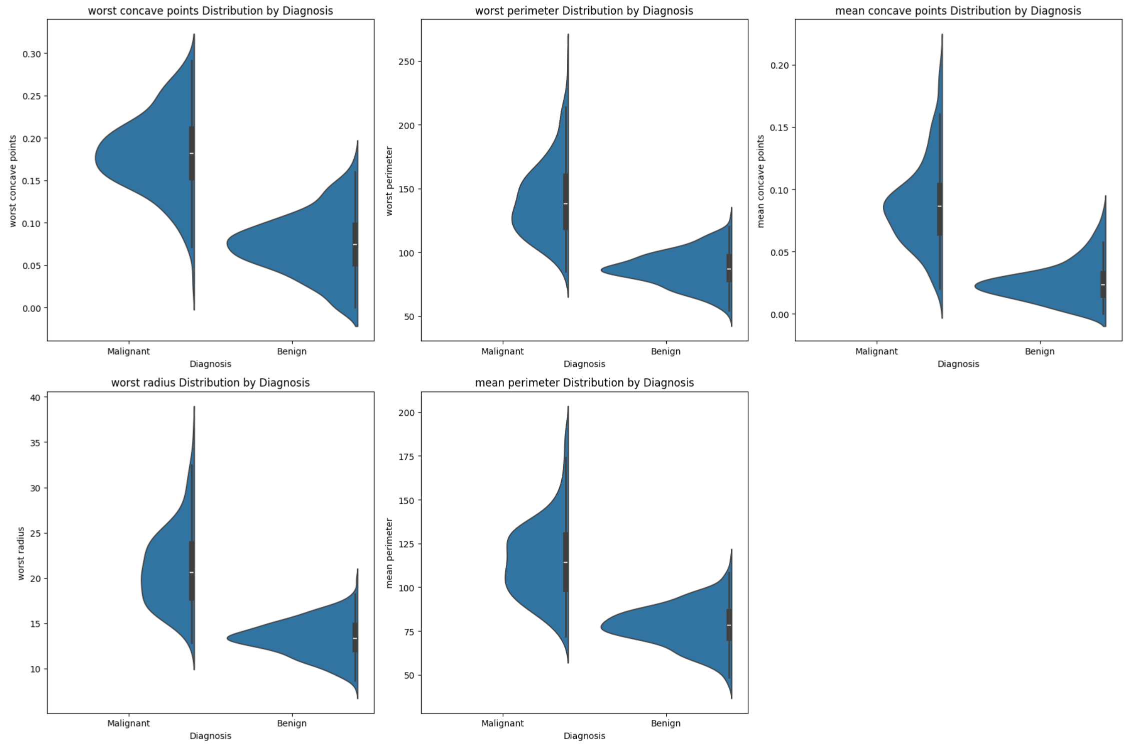
[6]:
```
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
axes = axes.ravel()

for i, feature in enumerate(top_5_features):
    sns.boxplot(x='diagnosis', y=feature, data=df, ax=axes[i])
    axes[i].set_title(f'{feature} by Diagnosis')
    axes[i].set_xlabel('Diagnosis')
    axes[i].set_ylabel(feature)

# Remove empty subplot
fig.delaxes(axes[5])
plt.tight_layout()
plt.show()
```



0.7 1.6 Violin Plots for Top Features

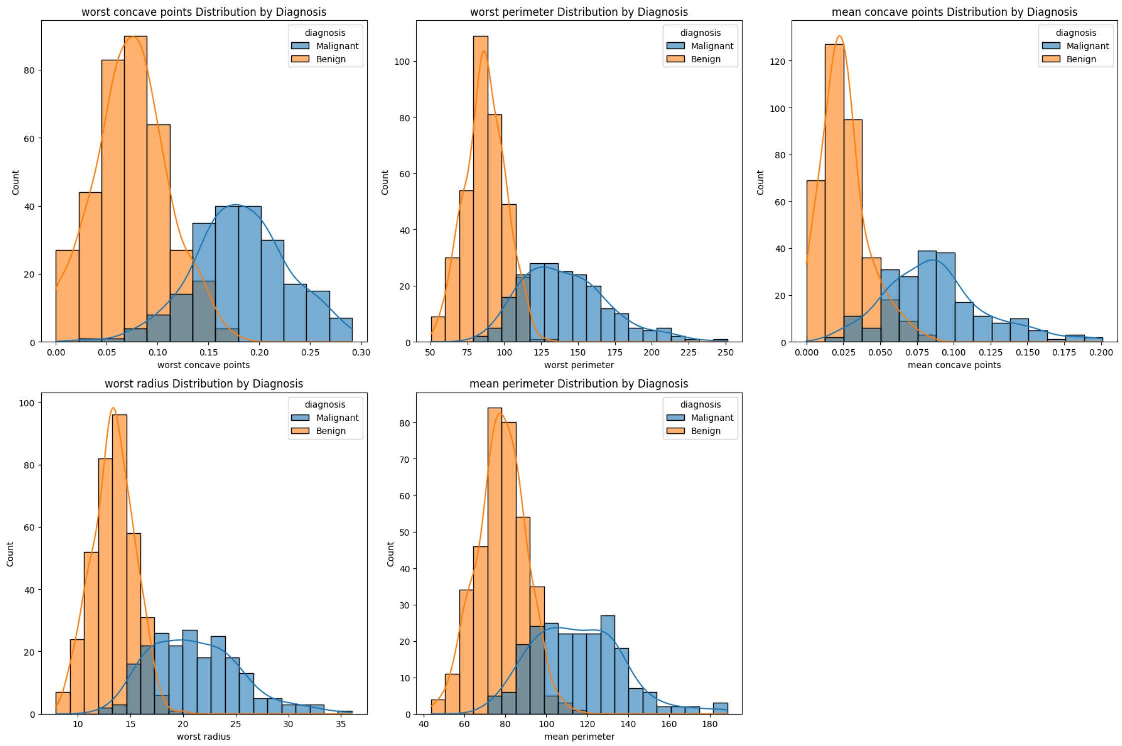
[7]:
```
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
axes = axes.ravel()

for i, feature in enumerate(top_5_features):
    sns.violinplot(x='diagnosis', y=feature, data=df, ax=axes[i], split=True)
```

```
    axes[i].set_title(f'{feature} Distribution by Diagnosis')
    axes[i].set_xlabel('Diagnosis')
    axes[i].set_ylabel(feature)

fig.delaxes(axes[5])
plt.tight_layout()
plt.show()
```



0.8 1.7 Distribution Plots for Top Features

[8]:
```
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
axes = axes.ravel()

for i, feature in enumerate(top_5_features):
    sns.histplot(data=df, x=feature, hue='diagnosis', kde=True, ax=axes[i],␣
 ↪alpha=0.6)
    axes[i].set_title(f'{feature} Distribution by Diagnosis')
    axes[i].set_xlabel(feature)

fig.delaxes(axes[5])
plt.tight_layout()
plt.show()
```



1 2 Data preprocessing

[9]:
```python
# Split the data
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print(f"Training set shape: {X_train_scaled.shape}")
print(f"Test set shape: {X_test_scaled.shape}")
print(f"Training target distribution: {np.bincount(y_train)}")
print(f"Test target distribution: {np.bincount(y_test)}")
```

```
Training set shape: (455, 30)
Test set shape: (114, 30)
Training target distribution: [170 285]
Test target distribution: [42 72]
```

2 3. Deep Learning Model

[10]:
```
# Build the model
model = Sequential([
    Dense(256, activation='relu', input_shape=(X_train_scaled.shape[1],),␣
 ↪name="Input_layer"),
    BatchNormalization(),
    Dropout(0.1),

    Dense(128, activation='relu', name="First_hidden_layer"),
    BatchNormalization(),
    Dropout(0.2),

    Dense(64, activation='relu', name="Second_hidden_layer"),
    BatchNormalization(),
    Dropout(0.3),

    Dense(32, activation='relu', name="Third_hidden_layer"),
    BatchNormalization(),
    Dropout(0.2),

    Dense(16, activation='relu', name="Fourth_hidden_layer"),
    BatchNormalization(),
    Dropout(0.1),

    Dense(1, activation='sigmoid', name="Output_layer")
])

# Compile the model
model.compile(
    optimizer=Adam(learning_rate=0.001),
    loss='binary_crossentropy',
    metrics=['accuracy', 'precision', 'recall']
)

# Callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=15,␣
 ↪restore_best_weights=True, verbose=1)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5,␣
 ↪min_lr=0.0001, verbose=1)
```

[11]:
```
model.summary()
```

```
Model: "sequential"


 Layer (type)                      Output Shape                   Param #
```

Input_layer (Dense)	(None, 256)	7,936
batch_normalization (BatchNormalization)	(None, 256)	1,024
dropout (Dropout)	(None, 256)	0
First_hidden_layer (Dense)	(None, 128)	32,896
batch_normalization_1 (BatchNormalization)	(None, 128)	512
dropout_1 (Dropout)	(None, 128)	0
Second_hidden_layer (Dense)	(None, 64)	8,256
batch_normalization_2 (BatchNormalization)	(None, 64)	256
dropout_2 (Dropout)	(None, 64)	0
Third_hidden_layer (Dense)	(None, 32)	2,080
batch_normalization_3 (BatchNormalization)	(None, 32)	128
dropout_3 (Dropout)	(None, 32)	0
Fourth_hidden_layer (Dense)	(None, 16)	528
batch_normalization_4 (BatchNormalization)	(None, 16)	64
dropout_4 (Dropout)	(None, 16)	0
Output_layer (Dense)	(None, 1)	17

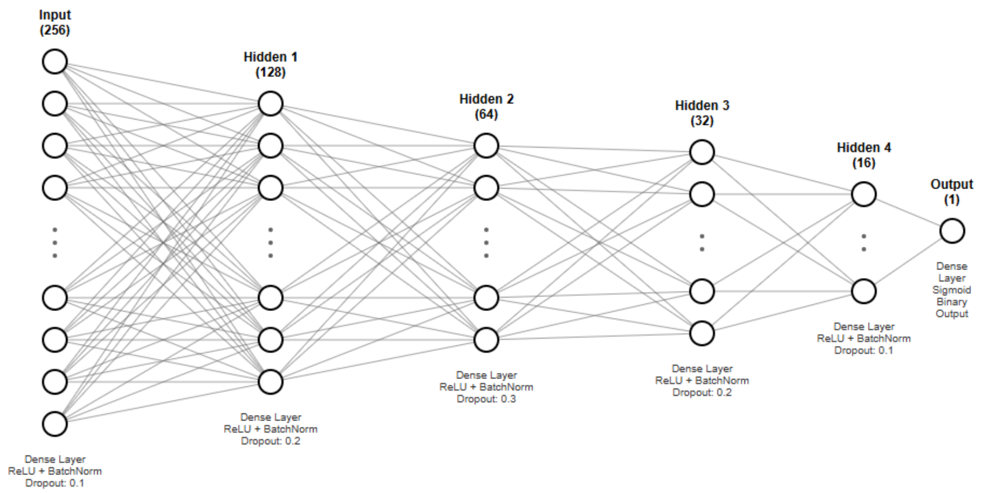
Total params: 53,697 (209.75 KB)

Trainable params: 52,705 (205.88 KB)

Non-trainable params: 992 (3.88 KB)

```
[27]: from IPython.display import Image, display

display(Image(filename='Model.png'))
```

Architecture of Deep Neural Network



Network Type:	Deep Feedforward Neural Network
Total Layers:	6 (1 Input + 4 Hidden + 1 Output)
Total Parameters:	44,033 trainable parameters
Activation Functions:	ReLU (Hidden Layers), Sigmoid (Output Layer)
Regularization:	Batch Normalization + Progressive Dropout (0.1→0.2→0.3→0.2→0.1)
Optimizer:	Adam (learning rate = 0.001)
Loss Function:	Binary Crossentropy
Evaluation Metrics:	Accuracy, Precision, Recall

3 4 Model Training

```
[12]: # Train the model
history = model.fit(
    X_train_scaled, y_train,
    validation_data=(X_test_scaled, y_test),
    epochs=100,
    batch_size=32,
    callbacks=[early_stopping, reduce_lr],
    verbose=1
)
```

```
Epoch 1/100
15/15                11s 118ms/step -
```

```
accuracy: 0.4867 - loss: 0.8246 - precision: 0.6362 - recall: 0.4410 -
val_accuracy: 0.8772 - val_loss: 0.6376 - val_precision: 0.9394 - val_recall:
0.8611 - learning_rate: 0.0010
Epoch 2/100
15/15            0s 18ms/step -
accuracy: 0.7607 - loss: 0.4856 - precision: 0.9100 - recall: 0.6911 -
val_accuracy: 0.8772 - val_loss: 0.5908 - val_precision: 0.9833 - val_recall:
0.8194 - learning_rate: 0.0010
Epoch 3/100
15/15            0s 16ms/step -
accuracy: 0.8051 - loss: 0.4082 - precision: 0.9282 - recall: 0.7495 -
val_accuracy: 0.8772 - val_loss: 0.5505 - val_precision: 0.9833 - val_recall:
0.8194 - learning_rate: 0.0010
Epoch 4/100
15/15            1s 32ms/step -
accuracy: 0.8674 - loss: 0.3610 - precision: 0.9529 - recall: 0.8307 -
val_accuracy: 0.9035 - val_loss: 0.5024 - val_precision: 0.9692 - val_recall:
0.8750 - learning_rate: 0.0010
Epoch 5/100
15/15            0s 26ms/step -
accuracy: 0.9008 - loss: 0.3182 - precision: 0.9714 - recall: 0.8694 -
val_accuracy: 0.9386 - val_loss: 0.4357 - val_precision: 0.9710 - val_recall:
0.9306 - learning_rate: 0.0010
Epoch 6/100
15/15            0s 19ms/step -
accuracy: 0.9147 - loss: 0.2525 - precision: 0.9492 - recall: 0.9160 -
val_accuracy: 0.9737 - val_loss: 0.3694 - val_precision: 0.9859 - val_recall:
0.9722 - learning_rate: 0.0010
Epoch 7/100
15/15            1s 22ms/step -
accuracy: 0.9381 - loss: 0.2285 - precision: 0.9631 - recall: 0.9390 -
val_accuracy: 0.9737 - val_loss: 0.3074 - val_precision: 0.9726 - val_recall:
0.9861 - learning_rate: 0.0010
Epoch 8/100
15/15            0s 18ms/step -
accuracy: 0.9229 - loss: 0.1973 - precision: 0.9576 - recall: 0.9200 -
val_accuracy: 0.9825 - val_loss: 0.2620 - val_precision: 0.9861 - val_recall:
0.9861 - learning_rate: 0.0010
Epoch 9/100
15/15            0s 19ms/step -
accuracy: 0.9375 - loss: 0.1862 - precision: 0.9532 - recall: 0.9488 -
val_accuracy: 0.9825 - val_loss: 0.2239 - val_precision: 0.9861 - val_recall:
0.9861 - learning_rate: 0.0010
Epoch 10/100
15/15            0s 16ms/step -
accuracy: 0.9690 - loss: 0.1563 - precision: 0.9728 - recall: 0.9782 -
val_accuracy: 0.9825 - val_loss: 0.1974 - val_precision: 0.9861 - val_recall:
0.9861 - learning_rate: 0.0010
```

```
Epoch 11/100
15/15            0s 21ms/step -
accuracy: 0.9581 - loss: 0.1542 - precision: 0.9666 - recall: 0.9675 -
val_accuracy: 0.9649 - val_loss: 0.1724 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 12/100
15/15            0s 25ms/step -
accuracy: 0.9719 - loss: 0.1443 - precision: 0.9765 - recall: 0.9789 -
val_accuracy: 0.9649 - val_loss: 0.1526 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 13/100
15/15            0s 22ms/step -
accuracy: 0.9577 - loss: 0.1381 - precision: 0.9737 - recall: 0.9593 -
val_accuracy: 0.9649 - val_loss: 0.1356 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 14/100
15/15            1s 30ms/step -
accuracy: 0.9496 - loss: 0.1448 - precision: 0.9559 - recall: 0.9657 -
val_accuracy: 0.9649 - val_loss: 0.1259 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 15/100
15/15            1s 22ms/step -
accuracy: 0.9696 - loss: 0.1040 - precision: 0.9647 - recall: 0.9879 -
val_accuracy: 0.9649 - val_loss: 0.1254 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 16/100
15/15            1s 20ms/step -
accuracy: 0.9803 - loss: 0.0961 - precision: 0.9788 - recall: 0.9900 -
val_accuracy: 0.9649 - val_loss: 0.1194 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 17/100
15/15            0s 19ms/step -
accuracy: 0.9739 - loss: 0.0853 - precision: 0.9771 - recall: 0.9816 -
val_accuracy: 0.9649 - val_loss: 0.1054 - val_precision: 0.9722 - val_recall:
0.9722 - learning_rate: 0.0010
Epoch 18/100
15/15            0s 17ms/step -
accuracy: 0.9749 - loss: 0.1012 - precision: 0.9738 - recall: 0.9865 -
val_accuracy: 0.9649 - val_loss: 0.1077 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 19/100
15/15            0s 17ms/step -
accuracy: 0.9662 - loss: 0.1016 - precision: 0.9754 - recall: 0.9711 -
val_accuracy: 0.9561 - val_loss: 0.1136 - val_precision: 0.9855 - val_recall:
0.9444 - learning_rate: 0.0010
Epoch 20/100
15/15            0s 20ms/step -
accuracy: 0.9686 - loss: 0.0895 - precision: 0.9766 - recall: 0.9736 -
```

```
val_accuracy: 0.9737 - val_loss: 0.0915 - val_precision: 0.9859 - val_recall:
0.9722 - learning_rate: 0.0010
Epoch 21/100
15/15            0s 17ms/step -
accuracy: 0.9830 - loss: 0.0610 - precision: 0.9953 - recall: 0.9784 -
val_accuracy: 0.9649 - val_loss: 0.0933 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 22/100
15/15            0s 17ms/step -
accuracy: 0.9764 - loss: 0.0608 - precision: 0.9860 - recall: 0.9765 -
val_accuracy: 0.9561 - val_loss: 0.1146 - val_precision: 0.9855 - val_recall:
0.9444 - learning_rate: 0.0010
Epoch 23/100
15/15            0s 17ms/step -
accuracy: 0.9874 - loss: 0.0559 - precision: 0.9891 - recall: 0.9907 -
val_accuracy: 0.9737 - val_loss: 0.0851 - val_precision: 0.9859 - val_recall:
0.9722 - learning_rate: 0.0010
Epoch 24/100
15/15            0s 19ms/step -
accuracy: 0.9772 - loss: 0.0663 - precision: 0.9787 - recall: 0.9851 -
val_accuracy: 0.9649 - val_loss: 0.0959 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 25/100
15/15            1s 25ms/step -
accuracy: 0.9821 - loss: 0.0677 - precision: 0.9788 - recall: 0.9928 -
val_accuracy: 0.9649 - val_loss: 0.1109 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 26/100
15/15            1s 18ms/step -
accuracy: 0.9835 - loss: 0.0578 - precision: 0.9890 - recall: 0.9847 -
val_accuracy: 0.9649 - val_loss: 0.1178 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 0.0010
Epoch 27/100
15/15            0s 18ms/step -
accuracy: 0.9934 - loss: 0.0453 - precision: 0.9892 - recall: 1.0000 -
val_accuracy: 0.9561 - val_loss: 0.1183 - val_precision: 0.9855 - val_recall:
0.9444 - learning_rate: 0.0010
Epoch 28/100
11/15            0s 12ms/step -
accuracy: 0.9912 - loss: 0.0389 - precision: 0.9856 - recall: 1.0000
Epoch 28: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
15/15            1s 32ms/step -
accuracy: 0.9925 - loss: 0.0359 - precision: 0.9878 - recall: 1.0000 -
val_accuracy: 0.9561 - val_loss: 0.1259 - val_precision: 0.9855 - val_recall:
0.9444 - learning_rate: 0.0010
Epoch 29/100
15/15            0s 19ms/step -
accuracy: 0.9953 - loss: 0.0365 - precision: 1.0000 - recall: 0.9928 -
```

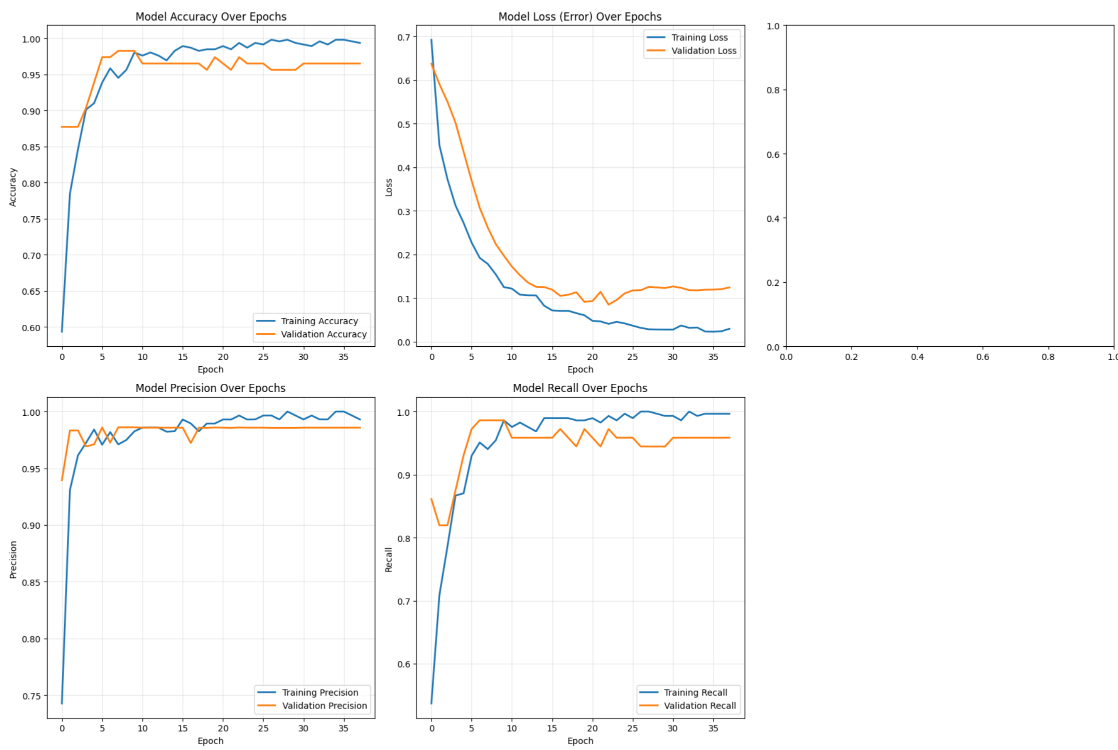
```
val_accuracy: 0.9561 - val_loss: 0.1246 - val_precision: 0.9855 - val_recall:
0.9444 - learning_rate: 2.0000e-04
Epoch 30/100
15/15            0s 18ms/step -
accuracy: 0.9850 - loss: 0.0416 - precision: 0.9891 - recall: 0.9871 -
val_accuracy: 0.9561 - val_loss: 0.1232 - val_precision: 0.9855 - val_recall:
0.9444 - learning_rate: 2.0000e-04
Epoch 31/100
15/15            0s 21ms/step -
accuracy: 0.9922 - loss: 0.0336 - precision: 0.9957 - recall: 0.9921 -
val_accuracy: 0.9649 - val_loss: 0.1269 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 2.0000e-04
Epoch 32/100
15/15            0s 18ms/step -
accuracy: 0.9786 - loss: 0.0561 - precision: 0.9889 - recall: 0.9772 -
val_accuracy: 0.9649 - val_loss: 0.1237 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 2.0000e-04
Epoch 33/100
 9/15            0s 8ms/step -
accuracy: 0.9902 - loss: 0.0585 - precision: 0.9839 - recall: 1.0000
Epoch 33: ReduceLROnPlateau reducing learning rate to 0.0001.
15/15            0s 18ms/step -
accuracy: 0.9925 - loss: 0.0477 - precision: 0.9878 - recall: 1.0000 -
val_accuracy: 0.9649 - val_loss: 0.1183 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 2.0000e-04
Epoch 34/100
15/15            0s 17ms/step -
accuracy: 0.9774 - loss: 0.0556 - precision: 0.9786 - recall: 0.9856 -
val_accuracy: 0.9649 - val_loss: 0.1180 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 1.0000e-04
Epoch 35/100
15/15            0s 20ms/step -
accuracy: 0.9953 - loss: 0.0332 - precision: 1.0000 - recall: 0.9928 -
val_accuracy: 0.9649 - val_loss: 0.1193 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 1.0000e-04
Epoch 36/100
15/15            0s 18ms/step -
accuracy: 0.9953 - loss: 0.0305 - precision: 1.0000 - recall: 0.9928 -
val_accuracy: 0.9649 - val_loss: 0.1195 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 1.0000e-04
Epoch 37/100
15/15            0s 17ms/step -
accuracy: 0.9897 - loss: 0.0369 - precision: 0.9891 - recall: 0.9943 -
val_accuracy: 0.9649 - val_loss: 0.1206 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 1.0000e-04
Epoch 38/100
15/15            0s 22ms/step -
accuracy: 0.9890 - loss: 0.0414 - precision: 0.9863 - recall: 0.9960 -
```

```
val_accuracy: 0.9649 - val_loss: 0.1246 - val_precision: 0.9857 - val_recall:
0.9583 - learning_rate: 1.0000e-04
Epoch 38: early stopping
Restoring model weights from the end of the best epoch: 23.
```

4 5. Model Evaluation and Advanced Plots

[13]:
```
# 5.1 Training History Plots
fig, axes = plt.subplots(2, 3, figsize=(18, 12))

# Accuracy plot
axes[0,0].plot(history.history['accuracy'], label='Training Accuracy',␣
↪linewidth=2)
axes[0,0].plot(history.history['val_accuracy'], label='Validation Accuracy',␣
↪linewidth=2)
axes[0,0].set_title('Model Accuracy Over Epochs')
axes[0,0].set_xlabel('Epoch')
axes[0,0].set_ylabel('Accuracy')
axes[0,0].legend()
axes[0,0].grid(True, alpha=0.3)

# Loss plot (Error reduction)
axes[0,1].plot(history.history['loss'], label='Training Loss', linewidth=2)
axes[0,1].plot(history.history['val_loss'], label='Validation Loss',␣
↪linewidth=2)
axes[0,1].set_title('Model Loss (Error) Over Epochs')
axes[0,1].set_xlabel('Epoch')
axes[0,1].set_ylabel('Loss')
axes[0,1].legend()
axes[0,1].grid(True, alpha=0.3)

# Learning rate decay
if 'lr' in history.history:
    axes[0,2].plot(history.history['lr'], label='Learning Rate', linewidth=2,␣
↪color='purple')
    axes[0,2].set_title('Learning Rate Decay Over Epochs')
    axes[0,2].set_xlabel('Epoch')
    axes[0,2].set_ylabel('Learning Rate')
    axes[0,2].set_yscale('log')
    axes[0,2].legend()
    axes[0,2].grid(True, alpha=0.3)

# Precision
axes[1,0].plot(history.history['precision'], label='Training Precision',␣
↪linewidth=2)
```

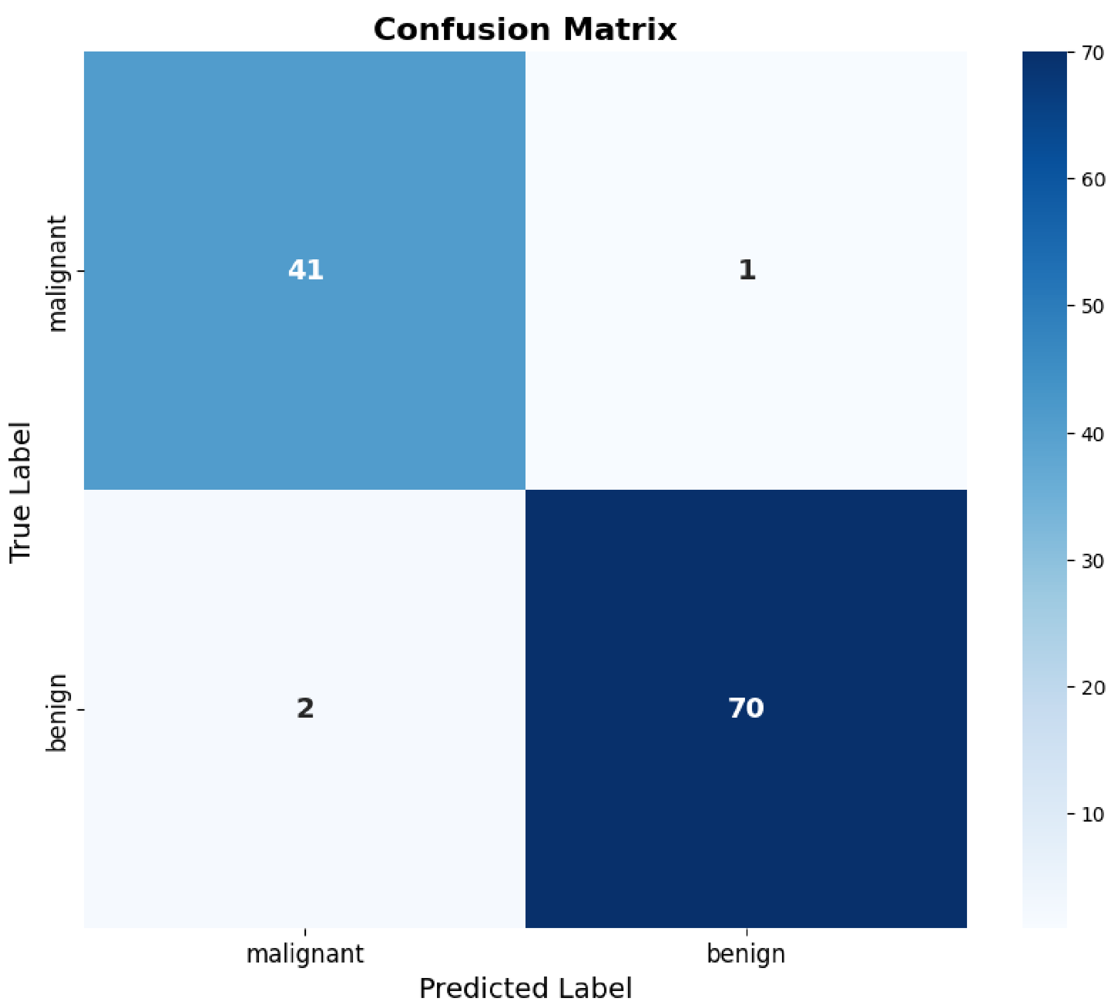
```python
axes[1,0].plot(history.history['val_precision'], label='Validation Precision', linewidth=2)
axes[1,0].set_title('Model Precision Over Epochs')
axes[1,0].set_xlabel('Epoch')
axes[1,0].set_ylabel('Precision')
axes[1,0].legend()
axes[1,0].grid(True, alpha=0.3)

# Recall
axes[1,1].plot(history.history['recall'], label='Training Recall', linewidth=2)
axes[1,1].plot(history.history['val_recall'], label='Validation Recall', linewidth=2)
axes[1,1].set_title('Model Recall Over Epochs')
axes[1,1].set_xlabel('Epoch')
axes[1,1].set_ylabel('Recall')
axes[1,1].legend()
axes[1,1].grid(True, alpha=0.3)

# Remove empty subplot
fig.delaxes(axes[1,2])
plt.tight_layout()
plt.show()
```



[14]:

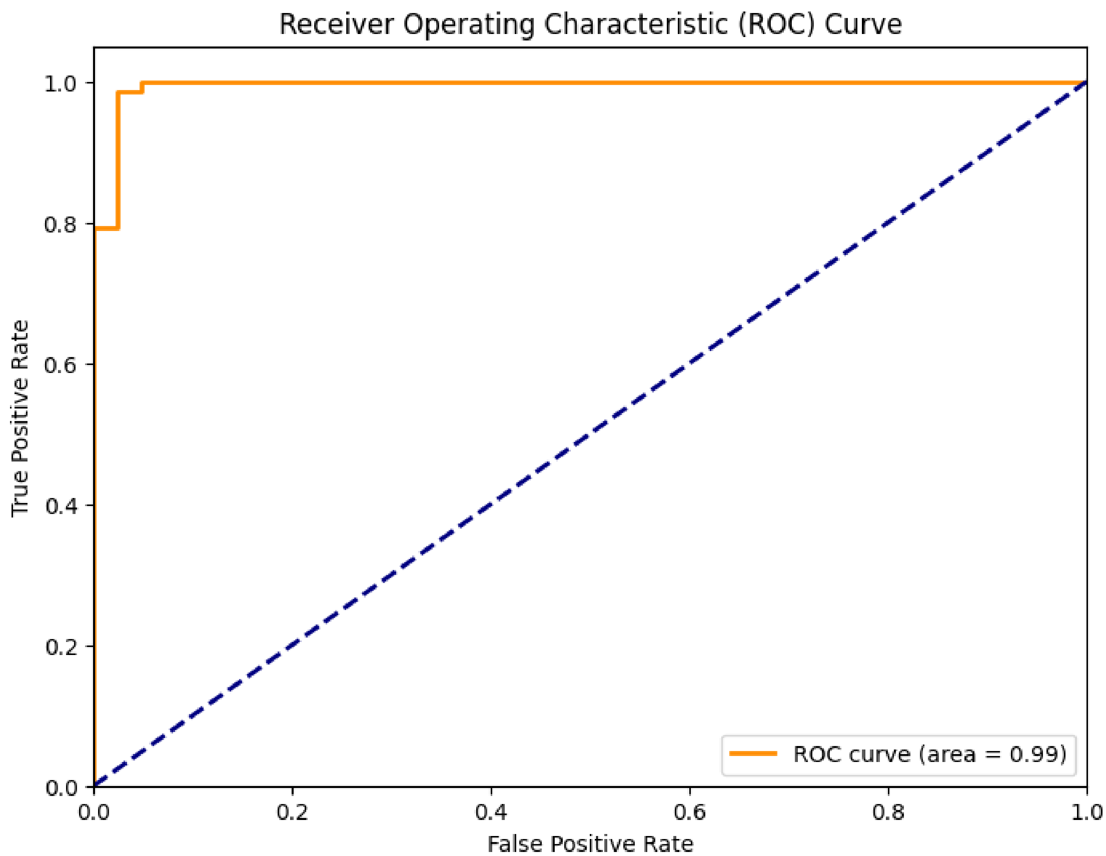
```
# 5.2 Make predictions
y_pred_proba = model.predict(X_test_scaled)
y_pred = (y_pred_proba > 0.5).astype(int)

# 5.3 Confusion Matrix
plt.figure(figsize=(10, 8))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=target_names, yticklabels=target_names,
            annot_kws={'size': 14, 'weight': 'bold'})
plt.title('Confusion Matrix', fontsize=16, fontweight='bold')
plt.ylabel('True Label', fontsize=14)
plt.xlabel('Predicted Label', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.show()
```

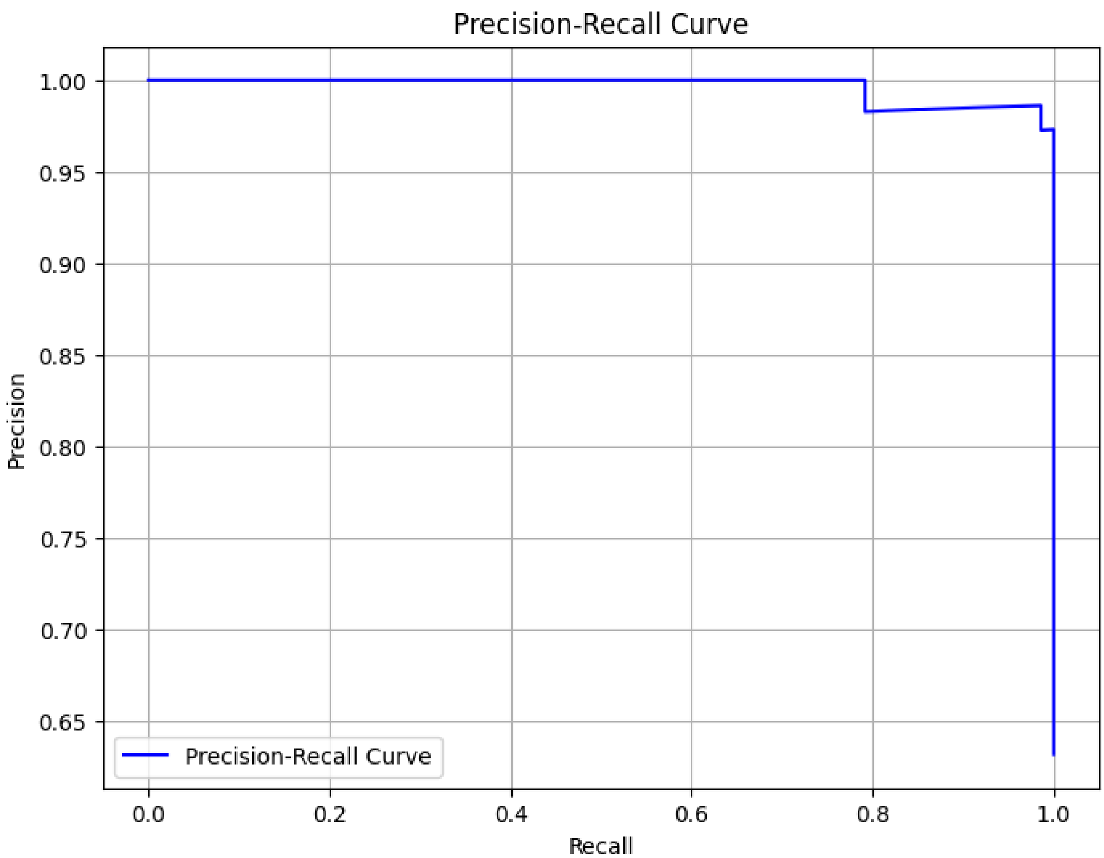
```
4/4               1s 98ms/step
```



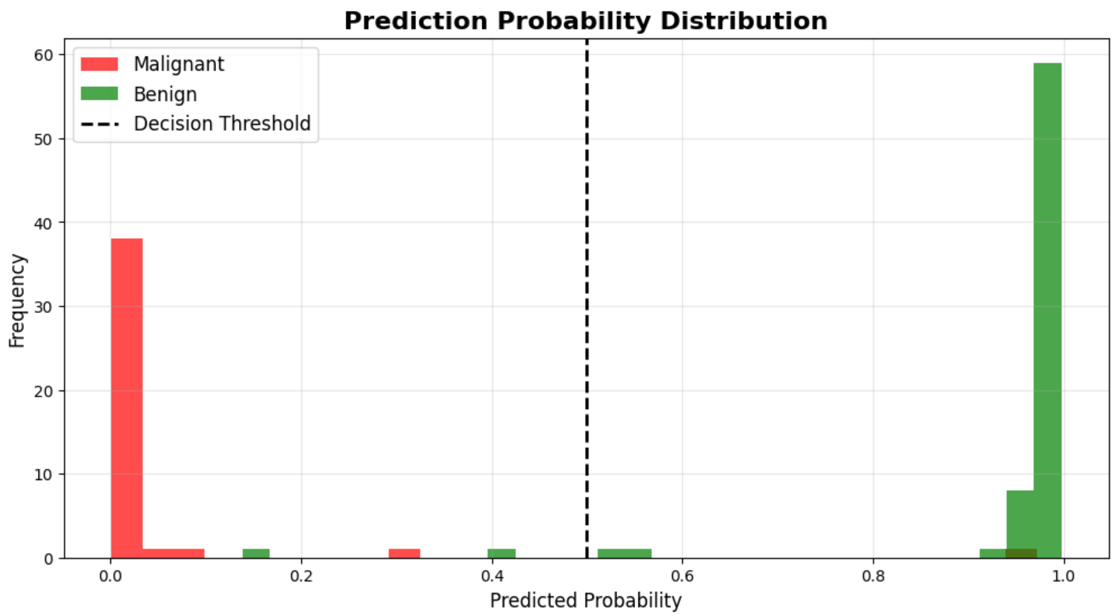
[15]:

```
# ROC Curve and AUC
fpr, tpr, thresholds_roc = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
↪.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

# Precision-Recall Curve
precision, recall, thresholds_pr = precision_recall_curve(y_test, y_pred_proba)
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, label='Precision-Recall Curve', color='blue')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='best')
plt.grid(True)
plt.show()
```


Receiver Operating Characteristic (ROC) Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
ROC curve (area = 0.99)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate



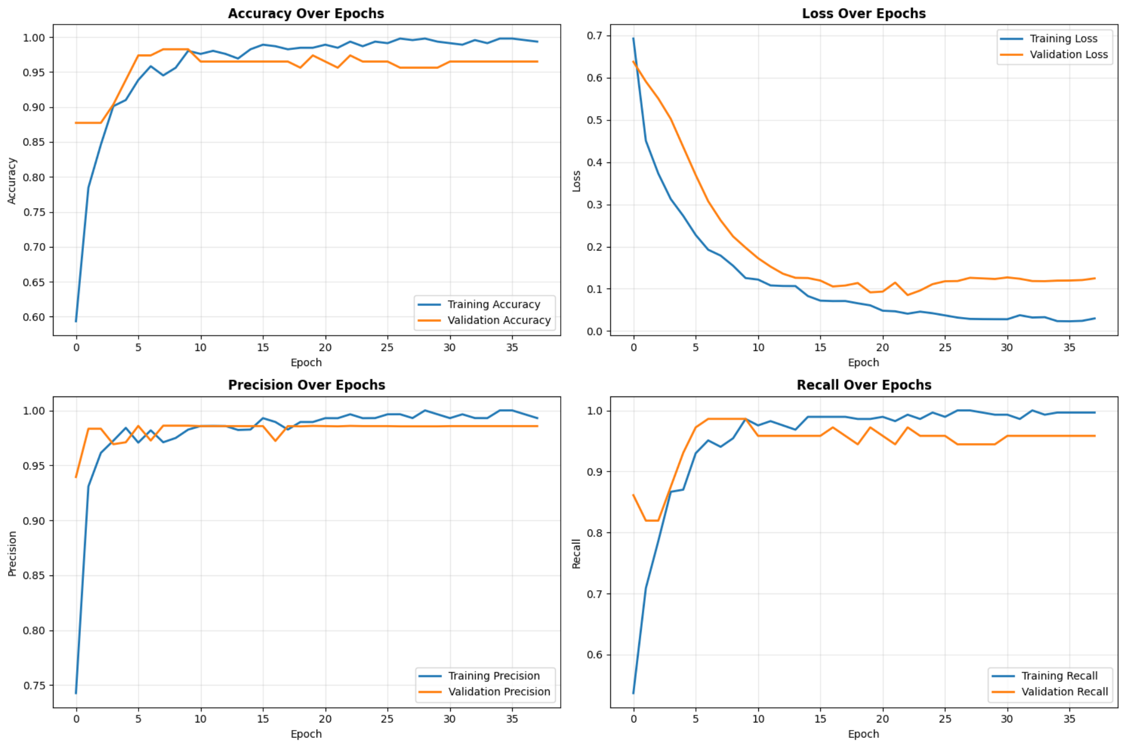
[16]:
```
# 5.7 Prediction Distribution
plt.figure(figsize=(12, 6))
plt.hist(y_pred_proba[y_test == 0], alpha=0.7, label='Malignant', bins=30,␣
    ↪color='red')
plt.hist(y_pred_proba[y_test == 1], alpha=0.7, label='Benign', bins=30,␣
    ↪color='green')
plt.axvline(0.5, color='black', linestyle='--', linewidth=2, label='Decision␣
    ↪Threshold')
plt.title('Prediction Probability Distribution', fontsize=16, fontweight='bold')
plt.xlabel('Predicted Probability', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.legend(fontsize=12)
plt.grid(True, alpha=0.3)
```



[17]:
```
#  Final Evaluation
print("\n" + "="*60)
print("FINAL MODEL EVALUATION")
print("="*60)

# Calculate final metrics
final_accuracy = history.history['val_accuracy'][-1]
final_loss = history.history['val_loss'][-1]

print(f"Final Validation Accuracy: {final_accuracy:.4f}")
print(f"Final Validation Loss: {final_loss:.4f}")
print(f"ROC AUC Score: {roc_auc:.4f}")

# Classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=target_names))


# Training vs Validation Metrics Comparison
metrics = ['accuracy', 'loss', 'precision', 'recall']
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
axes = axes.ravel()

for i, metric in enumerate(metrics):
    if metric in history.history:
```

```
        axes[i].plot(history.history[metric], label=f'Training {metric.
↪title()}', linewidth=2)
        axes[i].plot(history.history[f'val_{metric}'], label=f'Validation␣
↪{metric.title()}', linewidth=2)
        axes[i].set_title(f'{metric.title()} Over Epochs', fontsize=12,␣
↪fontweight='bold')
        axes[i].set_xlabel('Epoch')
        axes[i].set_ylabel(metric.title())
        axes[i].legend()
        axes[i].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("\n" + "="*60)
print("TRAINING SUMMARY")
print("="*60)
print(f"Total Epochs Trained: {len(history.history['loss'])}")
print(f"Best Validation Accuracy: {max(history.history['val_accuracy']):.4f}")
print(f"Best Validation Loss: {min(history.history['val_loss']):.4f}")
print(f"Final Learning Rate: {history.history.get('lr', [0.001])[-1]:.6f}")
```

```
============================================================
FINAL MODEL EVALUATION
============================================================
Final Validation Accuracy: 0.9649
Final Validation Loss: 0.1246
ROC AUC Score: 0.9947

Classification Report:
              precision    recall  f1-score   support

   malignant       0.95      0.98      0.96        42
      benign       0.99      0.97      0.98        72

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

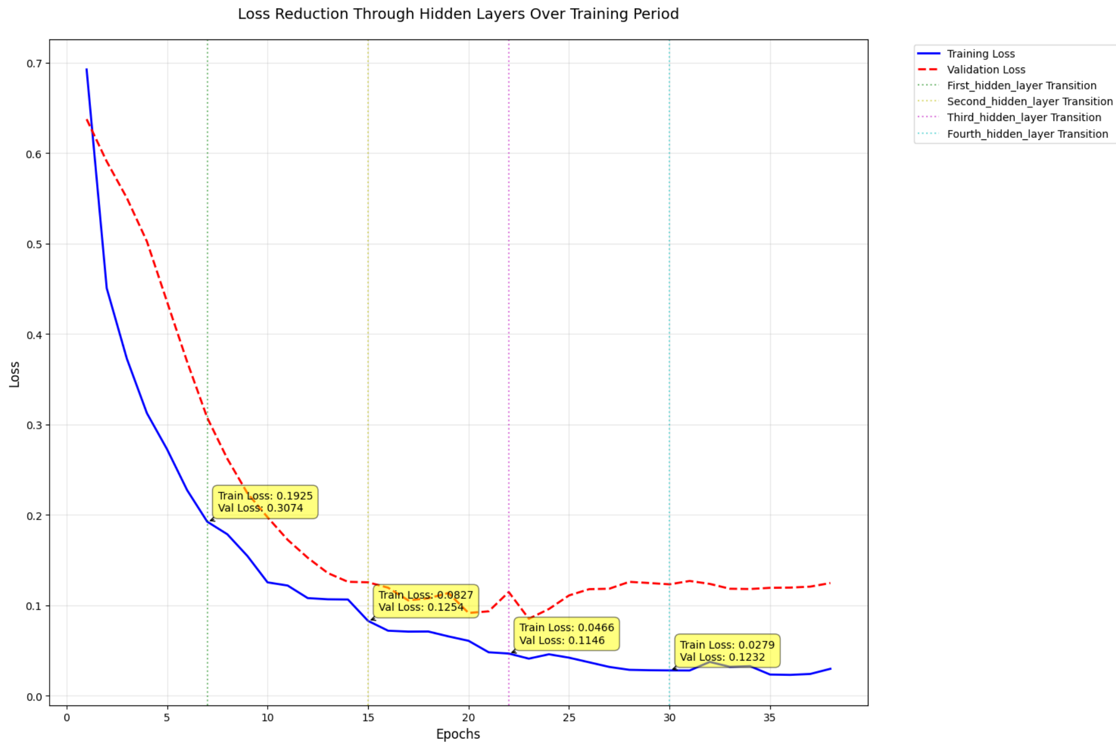



```
============================================================
TRAINING SUMMARY
============================================================
Total Epochs Trained: 38
Best Validation Accuracy: 0.9825
Best Validation Loss: 0.0851
Final Learning Rate: 0.001000
```

[18]:

```python
# Create a figure with a larger size
plt.figure(figsize=(15, 10))

# Get the layer names and their weights before and after training
layer_names = [layer.name for layer in model.layers if 'hidden' in layer.name.
↪lower()]

# Plot training loss
epochs = range(1, len(history.history['loss']) + 1)
plt.plot(epochs, history.history['loss'], 'b-', label='Training Loss',␣
↪linewidth=2)
plt.plot(epochs, history.history['val_loss'], 'r--', label='Validation Loss',␣
↪linewidth=2)
```

```python
# Add vertical lines to indicate layer transitions
colors = ['g', 'y', 'm', 'c']
for i, layer_name in enumerate(layer_names):
        transition_point = (i + 1) * len(epochs) // (len(layer_names) + 1)
        plt.axvline(x=transition_point, color=colors[i], linestyle=':',␣
 ↪label=f'{layer_name} Transition', alpha=0.5)

plt.title('Loss Reduction Through Hidden Layers Over Training Period',␣
 ↪fontsize=14, pad=20)
plt.xlabel('Epochs', fontsize=12)
plt.ylabel('Loss', fontsize=12)
plt.grid(True, alpha=0.3)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

# Add annotations for loss values at layer transitions
for i, layer_name in enumerate(layer_names):
        transition_point = (i + 1) * len(epochs) // (len(layer_names) + 1)
        train_loss = history.history['loss'][transition_point-1]
        val_loss = history.history['val_loss'][transition_point-1]
        plt.annotate(f'Train Loss: {train_loss:.4f}\nVal Loss: {val_loss:.4f}',
                                xy=(transition_point, train_loss),
                                xytext=(10, 10),
                                textcoords='offset points',
                                bbox=dict(boxstyle='round,pad=0.5',␣
 ↪fc='yellow', alpha=0.5),
                                arrowprops=dict(arrowstyle='->'))

plt.tight_layout()
plt.show()
```


Loss Reduction Through Hidden Layers Over Training Period
Training Loss
Validation Loss
First_hidden_layer Transition
Second_hidden_layer Transition
Third_hidden_layer Transition
Fourth_hidden_layer Transition
Train Loss: 0.1925
Val Loss: 0.3074
Train Loss: 0.0827
Val Loss: 0.1254
Train Loss: 0.0466
Val Loss: 0.1146
Train Loss: 0.0279
Val Loss: 0.1232
Loss
Epochs
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
5
10
15
20
25
30
35