```python
# -*- coding: utf-8 -*-
"""Lung_Cancer.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/17G23eTAyD9OXJ_qFDmGuyLECjPt51Fr9
"""

from google.colab import files
uploaded = files.upload()
print(f"dataset {uploaded} has been uploaded to this notebook")

from google.colab import drive
drive.mount('/content/drive')

import os
for filename in uploaded.keys():
  with open('/content/drive/My Drive/' + filename, 'wb') as f:
    f.write(uploaded[filename])
  print(f"dataset {filename} saved to Google Drive")

import pandas as pd
import matplotlib.pyplot as plt
import os

try:

    file_path = '/content/Lung Cancer/dataset_med.csv'
    df = pd.read_csv(file_path)
    print("DataFrame loaded successfully.")
    print(df.head())

    print("\nDataFrame Information:")
    print(f"Shape: {df.shape}")
    print(f"Columns: {df.columns.tolist()}")
    print(f"Data Types:\n{df.dtypes}")


    if df.select_dtypes(include=['number']).empty:
      print("No numerical columns found for plotting.")
    else:

      numerical_column = df.select_dtypes(include=['number']).columns[0]
      plt.figure(figsize=(10, 6))
      df[numerical_column].hist(bins=20)
      plt.title(f'Distribution of {numerical_column}')
      plt.xlabel(numerical_column)
      plt.ylabel('Frequency')
      plt.show()

except FileNotFoundError:
    print(f"Error: The file '{file_path}' was not found. Please ensure the zip file was extracted correctly and the path is correct.")
except Exception as e:
    print(f"An error occurred: {e}")

import zipfile
import os


zip_file_path = '/content/drive/My Drive/lung_cancer.zip'


extract_dir = '/content/'

os.makedirs(extract_dir, exist_ok=True)


with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

print(f"Files extracted to {extract_dir}")


extracted_files = os.listdir(extract_dir)
print("Files in extraction directory:", extracted_files)

df.info()
df.describe(include='all')

df.info()

df.head()

print(f"Rows: {df.shape[0]}, Columns: {df.shape[1]}")

"""visualizing distributions"""

import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(df['age'], kde=True)
plt.title('Age Distribution')
plt.show()

sns.countplot(data=df, x='cancer_stage', hue='survived')
plt.title('Cancer Stage vs Survival')
plt.show()

sns.countplot(data=df, x='cancer_stage', hue='survived')
plt.title('Cancer Stage vs Survival')
plt.show()

sns.countplot(data=df, x='smoking_status', hue='survived')
plt.title('Smoking Status vs Survival')
plt.show()

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Inspect
print(df.shape)
print(df.info())
print(df.isnull().sum())

# Stats
print(df.describe(include='all'))

# Visual
sns.countplot(data=df, x='cancer_stage', hue='survived')
plt.show()
```

```
!pip install torch torchvision scikit-learn

"""importing libraries"""

import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import pandas as pd
import numpy as np

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")

data = df.drop(['id', 'diagnosis_date', 'end_treatment_date'], axis=1)

cat_cols = data.select_dtypes(include='object').columns
for col in cat_cols:
    le = LabelEncoder()
    data[col] = le.fit_transform(data[col].astype(str))


X = data.drop("survived", axis=1).values
y = data["survived"].values

scaler = StandardScaler()
X = scaler.fit_transform(X)


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


X_train = torch.tensor(X_train, dtype=torch.float32)
X_test  = torch.tensor(X_test, dtype=torch.float32)
y_train = torch.tensor(y_train, dtype=torch.float32).unsqueeze(1)
y_test  = torch.tensor(y_test, dtype=torch.float32).unsqueeze(1)

class LungCancerNN(nn.Module):
    def __init__(self, input_dim):
        super(LungCancerNN, self).__init__()
        self.net = nn.Sequential(
            nn.Linear(input_dim, 64),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.net(x)

model = LungCancerNN(X_train.shape[1]).to(device)

"""defining loss and optimizer"""

criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

"""model training"""

epochs = 50
for epoch in range(epochs):
    model.train()

    # Move data to the same device as the model
    X_train_device = X_train.to(device)
    y_train_device = y_train.to(device)

    optimizer.zero_grad()
    outputs = model(X_train_device)
    loss = criterion(outputs, y_train_device)
    loss.backward()
    optimizer.step()

    if (epoch+1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

"""model evaluating"""

model.eval()
with torch.no_grad():
    # Move test data to the same device as the model
    X_test_device = X_test.to(device)
    y_test_device = y_test.to(device)

    y_pred = model(X_test_device)
    y_pred_class = (y_pred >= 0.5).float()
    accuracy = (y_pred_class == y_test_device).float().mean()
    print(f"Test Accuracy: {accuracy:.4f}")

learning_rates = [0.01, 0.001, 0.0001]
epochs_list = [50, 100, 150]

dropout_rates = [0.3, 0.4, 0.5]

best_accuracy = 0
best_hyperparameters = {}

for lr in learning_rates:
    for epochs in epochs_list:
        for dropout_rate in dropout_rates:
            print(f"Training with LR: {lr}, Epochs: {epochs}, Dropout: {dropout_rate}")

            model = LungCancerNN(X_train.shape[1]).to(device)
            criterion = nn.BCELoss()
            optimizer = optim.Adam(model.parameters(), lr=lr)

            for epoch in range(epochs):
                model.train()
                X_train_device = X_train.to(device)
                y_train_device = y_train.to(device)

                optimizer.zero_grad()
                outputs = model(X_train_device)
                loss = criterion(outputs, y_train_device)
                loss.backward()
                optimizer.step()

            model.eval()
            with torch.no_grad():
```

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                X_test_device = X_test.to(device)
                y_test_device = y_test.to(device)
                y_pred = model(X_test_device)
                y_pred_class = (y_pred >= 0.5).float()
                accuracy = (y_pred_class == y_test_device).float().mean()

                print(f"Test Accuracy: {accuracy:.4f}")

                if accuracy > best_accuracy:
                    best_accuracy = accuracy
                    best_hyperparameters = {
                        'learning_rate': lr,
                        'epochs': epochs,
                        'dropout_rate': dropout_rate
                    }

print("\nBest Hyperparameters:")
print(best_hyperparameters)
print(f"Best Test Accuracy: {best_accuracy:.4f}")

learning_rates = [0.01, 0.001, 0.0001]
epochs_list = [50, 100, 150]
dropout_rates = [0.3, 0.4, 0.5]

best_accuracy = 0
best_hyperparameters = {}

for lr in learning_rates:
    for epochs in epochs_list:
        for dropout_rate in dropout_rates:
            print(f"Training with LR: {lr}, Epochs: {epochs}, Dropout: {dropout_rate}")

            model = LungCancerNN(X_train.shape[1]).to(device)
            criterion = nn.BCELoss()
            optimizer = optim.Adam(model.parameters(), lr=lr)

            for epoch in range(epochs):
                model.train()
                X_train_device = X_train.to(device)
                y_train_device = y_train.to(device)

                optimizer.zero_grad()
                outputs = model(X_train_device)
                loss = criterion(outputs, y_train_device)
                loss.backward()
                optimizer.step()

            model.eval()
            with torch.no_grad():
                X_test_device = X_test.to(device)
                y_test_device = y_test.to(device)
                y_pred = model(X_test_device)
                y_pred_class = (y_pred >= 0.5).float()
                accuracy = (y_pred_class == y_test_device).float().mean()

                print(f"Test Accuracy: {accuracy:.4f}")

                if accuracy > best_accuracy:
                    best_accuracy = accuracy
                    best_hyperparameters = {
                        'learning_rate': lr,
                        'epochs': epochs,
                        'dropout_rate': dropout_rate
                    }

print("\nBest Hyperparameters:")
print(best_hyperparameters)
print(f"Best Test Accuracy: {best_accuracy:.4f}")

class EnhancedLungCancerNN(nn.Module):
    def __init__(self, input_dim):
        super(EnhancedLungCancerNN, self).__init__()
        self.net = nn.Sequential(
            nn.Linear(input_dim, 128),
            nn.ReLU(),
            nn.Dropout(0.4),
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Dropout(0.4),
            nn.Linear(32, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.net(x)

model_enhanced = EnhancedLungCancerNN(X_train.shape[1]).to(device)
criterion_enhanced = nn.BCELoss()
optimizer_enhanced = optim.Adam(model_enhanced.parameters(), lr=0.001)

epochs_enhanced = 50
for epoch in range(epochs_enhanced):
    model_enhanced.train()
    X_train_device = X_train.to(device)
    y_train_device = y_train.to(device)

    optimizer_enhanced.zero_grad()
    outputs = model_enhanced(X_train_device)
    loss = criterion_enhanced(outputs, y_train_device)
    loss.backward()
    optimizer_enhanced.step()

    if (epoch+1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs_enhanced}], Loss: {loss.item():.4f}")

model_enhanced.eval()
with torch.no_grad():
    X_test_device = X_test.to(device)
    y_test_device = y_test.to(device)
    y_pred_enhanced = model_enhanced(X_test_device)
    y_pred_class_enhanced = (y_pred_enhanced >= 0.5).float()
    accuracy_enhanced = (y_pred_class_enhanced == y_test_device).float().mean()
    print(f"Enhanced Model Test Accuracy: {accuracy_enhanced:.4f}")

optimizer_configs = [
    {'name': 'Adam', 'optimizer': optim.Adam, 'params': {'lr': best_hyperparameters['learning_rate']}},
    {'name': 'SGD', 'optimizer': optim.SGD, 'params': {'lr': best_hyperparameters['learning_rate'], 'momentum': 0.9}},
    {'name': 'RMSprop', 'optimizer': optim.RMSprop, 'params': {'lr': best_hyperparameters['learning_rate']}}
]

best_accuracy_optimizer = 0
```

```python
best_optimizer_name = None
best_optimizer_params = None

for config in optimizer_configs:
    print(f"Training with Optimizer: {config['name']} and parameters: {config['params']}")


    model = LungCancerNN(X_train.shape[1]).to(device)


    optimizer = config['optimizer'](model.parameters(), **config['params'])


    epochs = best_hyperparameters['epochs']

    # Training loop
    for epoch in range(epochs):
        model.train()
        X_train_device = X_train.to(device)
        y_train_device = y_train.to(device)

        optimizer.zero_grad()
        outputs = model(X_train_device)
        loss = criterion(outputs, y_train_device)
        loss.backward()
        optimizer.step()

    # Evaluation
    model.eval()
    with torch.no_grad():
        X_test_device = X_test.to(device)
        y_test_device = y_test.to(device)
        y_pred = model(X_test_device)
        y_pred_class = (y_pred >= 0.5).float()
        accuracy = (y_pred_class == y_test_device).float().mean()

        print(f"Test Accuracy with {config['name']}: {accuracy:.4f}")

        if accuracy > best_accuracy_optimizer:
            best_accuracy_optimizer = accuracy
            best_optimizer_name = config['name']
            best_optimizer_params = config['params']

print("\nBest Optimizer:")
print(f"Name: {best_optimizer_name}")
print(f"Parameters: {best_optimizer_params}")
print(f"Best Test Accuracy: {best_accuracy_optimizer:.4f}")

class LungCancerNN_L2(nn.Module):
    def __init__(self, input_dim):
        super(LungCancerNN_L2, self).__init__()
        self.net = nn.Sequential(
            nn.Linear(input_dim, 64),
            nn.ReLU(),
            nn.Dropout(best_hyperparameters['dropout_rate']),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.net(x)

model_l2 = LungCancerNN_L2(X_train.shape[1]).to(device)
criterion_l2 = nn.BCELoss()
optimizer_l2 = optim.RMSprop(model_l2.parameters(), lr=best_hyperparameters['learning_rate']) # Use the best optimizer and learning rate
lambda_l2 = 0.001

epochs_l2 = best_hyperparameters['epochs']

for epoch in range(epochs_l2):
    model_l2.train()
    X_train_device = X_train.to(device)
    y_train_device = y_train.to(device)

    optimizer_l2.zero_grad()
    outputs = model_l2(X_train_device)
    loss = criterion_l2(outputs, y_train_device)


    l2_reg = torch.tensor(0.).to(device)
    for param in model_l2.parameters():
        l2_reg += torch.norm(param, 2)
    loss += lambda_l2 * l2_reg

    loss.backward()
    optimizer_l2.step()

    if (epoch+1) % 10 == 0:
        print(f"Epoch [{epoch+1}/{epochs_l2}], Loss with L2: {loss.item():.4f}")

model_l2.eval()
with torch.no_grad():
    X_test_device = X_test.to(device)
    y_test_device = y_test.to(device)
    y_pred_l2 = model_l2(X_test_device)
    y_pred_class_l2 = (y_pred_l2 >= 0.5).float()
    accuracy_l2 = (y_pred_class_l2 == y_test_device).float().mean()
    print(f"Test Accuracy with L2 regularization: {accuracy_l2:.4f}")

from sklearn.model_selection import KFold

n_splits = 5
kf = KFold(n_splits=n_splits, shuffle=True, random_state=42)
fold_accuracies = []

# Combine X and y back for KFold splitting
X_np = X_train.cpu().numpy() if X_train.is_cuda else X_train.numpy()
y_np = y_train.cpu().numpy().squeeze() if y_train.is_cuda else y_train.numpy().squeeze()

for fold, (train_index, val_index) in enumerate(kf.split(X_np)):
    print(f"Fold {fold+1}/{n_splits}")

    X_train_fold, X_val_fold = X_np[train_index], X_np[val_index]
    y_train_fold, y_val_fold = y_np[train_index], y_np[val_index]

    X_train_fold = torch.tensor(X_train_fold, dtype=torch.float32).to(device)
    X_val_fold = torch.tensor(X_val_fold, dtype=torch.float32).to(device)
    y_train_fold = torch.tensor(y_train_fold, dtype=torch.float32).unsqueeze(1).to(device)
    y_val_fold = torch.tensor(y_val_fold, dtype=torch.float32).unsqueeze(1).to(device)

    # Instantiate a new model for each fold with best hyperparameters
```

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    model_cv = LungCancerNN(X_train_fold.shape[1]).to(device)


    criterion_cv = nn.BCELoss()
    optimizer_cv = optim.RMSprop(model_cv.parameters(), lr=best_hyperparameters['learning_rate'])

    # Train the model
    epochs_cv = best_hyperparameters['epochs']
    for epoch in range(epochs_cv):
        model_cv.train()
        optimizer_cv.zero_grad()
        outputs_cv = model_cv(X_train_fold)
        loss_cv = criterion_cv(outputs_cv, y_train_fold)
        loss_cv.backward()
        optimizer_cv.step()

    # Evaluate the model
    model_cv.eval()
    with torch.no_grad():
        y_pred_cv = model_cv(X_val_fold)
        y_pred_class_cv = (y_pred_cv >= 0.5).float()
        accuracy_cv = (y_pred_class_cv == y_val_fold).float().mean()
        fold_accuracies.append(accuracy_cv.item())
        print(f"Fold {fold+1} Accuracy: {accuracy_cv:.4f}")

average_accuracy = np.mean(fold_accuracies)
print("\nCross-validation Accuracies:")
for i, acc in enumerate(fold_accuracies):
    print(f"Fold {i+1}: {acc:.4f}")
print(f"\nAverage Cross-validation Accuracy: {average_accuracy:.4f}")

model.eval()
with torch.no_grad():
    # Move test data to the same device as the model
    X_test_device = X_test.to(device)
    y_test_device = y_test.to(device)

    y_pred = model(X_test_device)
    y_pred_class = (y_pred >= 0.5).float()
    accuracy = (y_pred_class == y_test_device).float().mean()
    print(f"Test Accuracy: {accuracy:.4f}")

# Instantiate the best model with the best hyperparameters and optimizer
best_model = LungCancerNN(X_train.shape[1]).to(device)

# Use the best optimizer and its parameters
best_optimizer_config = None
for config in optimizer_configs:
    if config['name'] == best_optimizer_name:
        best_optimizer_config = config
        break

if best_optimizer_config is None:
    print("Error: Best optimizer configuration not found.")
else:
    best_optimizer = best_optimizer_config['optimizer'](best_model.parameters(), **best_optimizer_config['params'])


    best_criterion = nn.BCELoss()


    best_epochs = best_hyperparameters['epochs']
    print(f"Training the best model with Optimizer: {best_optimizer_config['name']}, Parameters: {best_optimizer_config['params']}, Epochs: {best_epochs}")

    # Training loop for the best model
    for epoch in range(best_epochs):
        best_model.train()
        X_train_device = X_train.to(device)
        y_train_device = y_train.to(device)

        best_optimizer.zero_grad()
        outputs = best_model(X_train_device)
        loss = best_criterion(outputs, y_train_device)
        loss.backward()
        best_optimizer.step()

        if (epoch+1) % 10 == 0:
            print(f"Epoch [{epoch+1}/{best_epochs}], Loss: {loss.item():.4f}")

    # Evaluate the best model on the test set
    best_model.eval()
    with torch.no_grad():
        X_test_device = X_test.to(device)
        y_test_device = y_test.to(device)
        y_pred_best = best_model(X_test_device)
        y_pred_class_best = (y_pred_best >= 0.5).float()
        accuracy_best = (y_pred_class_best == y_test_device).float().mean()
        print(f"\nFinal Best Model Test Accuracy: {accuracy_best:.4f}")

best_model.eval()
with torch.no_grad():
    X_test_device = X_test.to(device)
    y_pred_prob = best_model(X_test_device)


y_pred_prob_cpu = y_pred_prob.cpu().numpy()

print("Predicted survival probabilities (first 10):")
print(y_pred_prob_cpu[:10])

from sklearn.metrics import precision_score, recall_score, f1_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt


y_test_cpu = y_test_device.cpu().numpy()
y_pred_class_cpu = y_pred_class_best.cpu().numpy()

precision = precision_score(y_test_cpu, y_pred_class_cpu)
recall = recall_score(y_test_cpu, y_pred_class_cpu)
f1 = f1_score(y_test_cpu, y_pred_class_cpu)

print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")

# Confusion Matrix
cm = confusion_matrix(y_test_cpu, y_pred_class_cpu)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Survived', 'Survived'], yticklabels=['Not Survived', 'Survived'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

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plt.title('Confusion Matrix')
plt.show()

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np



plt.figure(figsize=(8, 6))
sns.histplot(y_pred_prob_cpu, bins=50, kde=True)
plt.title('Distribution of Predicted Survival Probabilities')
plt.xlabel('Predicted Probability of Survival')
plt.ylabel('Frequency')
plt.show()

from sklearn.metrics import precision_score, recall_score, f1_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np


# Trying a lower classification threshold
threshold = 0.3
y_pred_class_lower_threshold = (y_pred_prob_cpu >= threshold).astype(int)

# Calculate metrics with the new threshold
precision_lower_threshold = precision_score(y_test_cpu, y_pred_class_lower_threshold)
recall_lower_threshold = recall_score(y_test_cpu, y_pred_class_lower_threshold)
f1_lower_threshold = f1_score(y_test_cpu, y_pred_class_lower_threshold)

print(f"Evaluation with threshold = {threshold}:")
print(f"Precision: {precision_lower_threshold:.4f}")
print(f"Recall: {recall_lower_threshold:.4f}")
print(f"F1-score: {f1_lower_threshold:.4f}")

# Confusion Matrix with the new threshold
cm_lower_threshold = confusion_matrix(y_test_cpu, y_pred_class_lower_threshold)

plt.figure(figsize=(8, 6))
sns.heatmap(cm_lower_threshold, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Survived', 'Survived'], yticklabels=['Not Survived', 'Survived'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix with Threshold = {threshold}')
plt.show()

survived_count = df['survived'].sum()
print(f"Number of people who survived in the dataset: {int(survived_count)}")

total_people = len(df)
not_survived_count = total_people - survived_count
print(f"Number of people who did not survive in the dataset: {int(not_survived_count)}")

import torch


model_save_path = '/content/drive/My Drive/best_lung_cancer_model.pth'


torch.save(best_model.state_dict(), model_save_path)

print(f"Best model saved to {model_save_path}")

"""## Summary of Fine-tuning Process and Model Performance

We have performed several steps to fine-tune the initial neural network model for predicting lung cancer survival and evaluated its performance.

1.  **Data Loading and Preprocessing**: We loaded the dataset, explored its features, and preprocessed the data by dropping irrelevant columns, encoding categorical va

2.  **Initial Model Training and Evaluation**: We built and trained a basic neural network model and obtained an initial test accuracy.

3.  **Fine-tuning**: We performed fine-tuning by:
    *   Experimenting with different hyperparameters (learning rate, epochs, dropout rate) to find a better configuration. The best hyperparameters found were `{'learn
    *   Comparing different optimizers (Adam, SGD, RMSprop) and found that RMSprop performed best with the chosen learning rate.
    *   Exploring L2 regularization, which did not significantly improve performance in this case.
    *   Using 5-fold cross-validation to obtain a more robust estimate of the model's performance, with an average cross-validation accuracy of 0.7797.

4.  **Final Model Training and Evaluation**: We trained the best performing model configuration on the training data and evaluated it on the test set.
    *   Initially, using a default classification threshold of 0.5, the model predicted 'Not Survived' for all instances, resulting in 0.0000 for Precision, Recall, ar
    *   We investigated the distribution of predicted survival probabilities, which showed a skew towards lower values.
    *   By lowering the classification threshold to 0.3, the model is now able to predict both survival outcomes. The evaluation metrics with this threshold are:
        *   Precision: 0.2212
        *   Recall: 0.8426
        *   F1-score: 0.3504
    *   The confusion matrix with the 0.3 threshold shows the breakdown of true positives, true negatives, false positives, and false negatives, indicating the model's

**Conclusion:**

The fine-tuning process helped identify a model configuration that achieves a test accuracy of approximately 77.89%. However, the initial evaluation metrics revealed a

This analysis provides a foundation for understanding the model's performance. Depending on the application, further work could involve exploring techniques to improve
"""
```