WCE CURATED COLON DISEASE CLASSIFICATION USING DEEP LEARNING

A MAJOR PROJECT REPORT

Submitted to

JAWAHARLAL NEHRU TECNOLOGICAL UNIVERSITY, HYDERABAD

In partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

Submitted By

SRI CHAITHANYA SALLA (21UK1A05F7)

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Under the guidance of

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BOLLIKUNTA, WARANGAL (T.S) – 506005

2021-2025

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BOLLIKUNTA, WARANGAL(T.S)-506005

CERTIFICATE OF COMPLETION

UG PROJECT PHASE -I

This is to certify that the **UG PROJECT PHASE -I** entitled "**WCE CURATED COLON DISEASE CLASSIFICATION USING DEEP LEARNING**" is being submitted by **SRI CHAITHANYA SALLA (21UK1A05F7), GEETHA PABBOJU (21UK1A05H7), HARSHITH DIDDI (21UK1A05J5)** in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Computer Science & Engineering to Jawaharlal Nehru Technological University Hyderabad during the academic year 2024-2025, is a record of work carried out by them under the guidance and supervision.

Project Guide	**Head of the Department**
MR. M HEMANTH	**DR. K. SHARMILA REDDY**
(Assistant Professor**)**	**(**Professor**)**

EXTERNAL

DECLARATION

We declare that the work reported in the project entitled **" WCE CURATED COLON DISEASE CLASSIFICATION USING DEEP LEARNING"** is a record of work done by us in the partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science And Engineering, **VAAGDEVI ENGINEERING COLLEGE** (An Autonomous Institution & Affiliated to JNTU Hyderabad) Accredited by NAAC with 'A+' Grade, Certified by ISO 9001:2015 Approved by AICTE, New Delhi, Bollikunta, Warangal-506 005, Telangana, India under the guidance of **MR. M. HEMANTH**, Assistant Professor, CSE Department.

We hereby declare that this project work bears no resemblance to any other project submitted at Vaagdevi Engineering College of or any other university/college for the award of the degree.

SRI CHAITHANYA SALLA	**(21UK1A05F7)**
GEETHA PABBOJU	**(21UK1A05H7)**
HARSHITH DIDDI	**(21UK1A05J5)**

ACKNOWLEDGEMENT

We wish to take this opportunity to express our sincere gratitude and deep sense of respect to our beloved **Dr. SYED MUSTHAK AHAMED,** Principal, Vaagdevi Engineering College for making us available all the required assistance and for his support and inspiration to carry out this **UG PROJECT PHASE -I** in the institute.

We extend our heartfelt thanks to **Dr. K. SHARMILA REDDY**, Head of the Department of CSE, Vaagdevi Engineering College for providing us necessary infrastructure and thereby giving us freedom to carry out the **UG PROJECT PHASE -I.**

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ABSTRACT

The "WCE Curated Colon Disease Classification Using Deep Learning" project focuses on developing a robust deep learning model designed to classify colon diseases accurately based on medical imaging data, such as colonoscopy images and patient records. By leveraging advanced deep learning techniques, this project aims to significantly enhance early disease detection, treatment planning, and overall patient outcomes.

Colon diseases, including inflammatory conditions and neoplasms, present diagnostic challenges due to their overlapping symptoms and variable progression. Misdiagnosis or delayed diagnosis can lead to ineffective treatments and increased healthcare costs. This project addresses these challenges by creating a curated dataset and training a deep learning model to identify distinct disease features from high-resolution colonoscopy images. The model incorporates transfer learning, convolutional neural networks (CNNs), and other state-of-the-art AI methodologies to achieve high diagnostic accuracy.

The project emphasizes the importance of curated, high-quality datasets and interpretable AI models to ensure clinical relevance and regulatory compliance. With a focus on scalability and integration, this deep learning framework aims to revolutionize colon disease management across diagnostics, healthcare, and research domains. Ultimately, this project contributes to the broader vision of leveraging AI for advancing medical science and improving global health outcomes.

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1. INTRODUCTION

1.1. OVERVIEW

The "WCE Curated Colon Disease Classification Using Deep Learning" project is a pioneering initiative designed to address critical challenges in the diagnosis and management of colon diseases. Colon diseases, ranging from inflammatory conditions like Crohn's disease to malignant neoplasms, are often difficult to diagnose due to their subtle and overlapping presentations. This project focuses on developing a stateoftheart deep learning model trained on a curated dataset of colonoscopy images and patient records to enable accurate and timely disease classification.

The model leverages advanced techniques such as convolutional neural networks (CNNs) and transfer learning to extract meaningful features from medical images, ensuring high precision and reliability in disease identification. By incorporating this AI-powered solution, the project aims to transform healthcare across three primary domains. First, in **medical diagnostics**, the model enhances diagnostic accuracy, reduces human errors, and assists healthcare professionals in making informed treatment decisions. Second, for **healthcare providers**, it integrates seamlessly into electronic health record (EHR) systems to automate disease identification, improve workflow efficiency, and enable proactive patient management.

Finally, in **medical research**, the model facilitates large-scale analysis of colon disease patterns, aiding in understanding disease progression, supporting clinical trials, and driving personalized treatment approaches. This project emphasizes the importance of data quality, model interpretability, and clinical applicability to ensure trustworthiness and effectiveness. With its focus on innovation and impact, this initiative sets the foundation for advancing colon disease diagnosis and management, ultimately improving patient outcomes and contributing to global healthcare advancements.

1.2. PURPOSE

The primary purpose of the "WCE Curated Colon Disease Classification Using Deep Learning" project is to develop a reliable, AI-driven deep learning model that accurately classifies colon diseases using medical imaging data. Below is a detailed breakdown of the purpose:

1. Enhancing Diagnostic Accuracy

Traditional diagnostic methods are often prone to human error, especially in detecting subtle or early-stage conditions. By analyzing high-resolution colonoscopy images, the model identifies disease-specific features with high precision, aiding healthcare professionals in making more accurate and timely diagnoses.

2. Streamlining Treatment Decisions

The primary purpose of the "WCE Curated Colon Disease Classification Using Deep Learning" project is to develop a reliable, AI-driven deep learning model that accurately classifies colon diseases using medical imaging data. By leveraging advanced machine learning techniques, the project aims to enhance early disease detection, streamline diagnostic workflows.

3. Improve Healthcare Workflow Efficiency

By integrating the deep learning model into electronic health record (EHR) systems, the project seeks to automate the disease identification process. This reduces the burden on healthcare providers, shortens diagnostic timelines, and enhances overall workflow efficiency. Automation minimizes human errors and allows clinicians to focus more on patient management and less on repetitive diagnostic tasks.

4. Advancing Medical Research and Personalized Medicine

The project supports researchers in analyzing large datasets to uncover patterns in disease prevalence, progression, and treatment outcomes. By identifying patient specific disease characteristics, the model contributes to the development of personalized treatment strategies.

2. PROBLEM STATEMENT

Colon diseases, such as inflammatory bowel diseases (Crohn's disease and ulcerative colitis) and colorectal cancer, are challenging to diagnose due to their overlapping clinical presentations. Diagnosis often relies on colonoscopy, which provides high-resolution images essential for identifying disease indicators. However, interpreting these images demands significant expertise, and even skilled clinicians can miss subtle abnormalities, leading to potential misdiagnoses or delays. The increasing demand for colonoscopybased diagnostics also strains healthcare systems, causing bottlenecks that delay care and treatment.

This project aims to tackle these challenges by developing an AI-driven deep learning model for automatically classifying colon diseases using colonoscopy images and patient data. Leveraging AI's ability to detect patterns beyond human perception, the model aims to enhance diagnostic accuracy, reduce errors, and streamline workflows. The system provides standardized, consistent results to address variability in diagnoses and ensure even subtle disease features are identified early.

A curated, high-quality dataset is critical for training the model, ensuring its robustness and clinical relevance. Additionally, integrating the system with existing healthcare platforms, such as electronic health records (EHRs), will enable seamless automation of disease identification within clinical workflows. Designed to be scalable and interpretable, the system will accommodate diverse patient populations while earning trust from healthcare providers.

By assisting clinicians in making more informed decisions, reducing manual workloads, and analyzing patterns in disease progression, this deep learning model has the potential to improve patient care, minimize diagnostic errors, and transform colon disease diagnosis and management in healthcare systems.

3. LITERATURE SURVEY

3.1. EXISTING PROBLEM

Colon disease diagnosis relies heavily on subjective interpretation, leading to variability and diagnostic errors, especially in detecting subtle abnormalities. Additionally, the manual, time-intensive process delays timely detection, impacting early treatment and patient outcomes.

1. Subjectivity and Variability in Diagnosis

Colon disease diagnosis, especially through colonoscopy, heavily relies on the expertise and experience of healthcare professionals. This subjective approach leads to variability in diagnoses, as different clinicians may result is inconsistent diagnosis outcomes, especially in early stages with complex presentations, which can lead to misdiagnosis, delayed treatment, and poor patient outcomes.

2. Time Consuming and Resource – Intensive Process

Colonoscopy procedures are not only time-consuming but also require significant resources, including trained personnel and specialized equipment. The manual interpretation of colonoscopy images is a labor-intensive process that adds to the diagnostic delay, especially in busy healthcare environments. The timely detection of diseases, which could otherwise lead to better prognosis if identified early.

3. Challenges in Early Detection of Subtle Abnormalities

Colon diseases, particularly in their early stages, may exhibit subtle or non-specific visual signs that are difficult to detect even by experienced clinicians. This challenge is especially evident in conditions like early-stage colorectal cancer or inflammatory bowel diseases, where minor abnormalities can go unnoticed. The lack of an automated tool that can reliably detect such early indicators means that many patients remain undiagnosed until their condition worsens, making treatment more complicated and less effective.

3.2. PROPOSED SOLUTION

To address the challenges of colon disease diagnosis and provide a scalable, efficient, and accurate system, the proposed solution leverages advanced deep learning techniques, including Convolutional Neural Networks (CNNs) and transfer learning architectures. Below is a detailed explanation of the proposed solution:

1. Leveraging Deep Learning for Disease Detection

Manual diagnosis of colon diseases through colonoscopy is time-consuming, subjective, and prone to human error, often leading to variability in outcomes. To overcome these limitations, this project employs deep learning models, particularly CNNs, which automatically extract complex features. The system is designed to classify colonoscopy images into categories such as healthy, inflammatory diseases, enabling early detection and precise diagnosis.

2. Improved Generalization with a Curated and Augmented Dataset

The project utilizes a curated dataset of colonoscopy images that includes a diverse range of conditions under varying lighting, angles, and resolutions. Data augmentation techniques (e.g., rotation, flipping, contrast adjustment) are applied to increase the dataset's variability. This approach enhances the model's ability to generalize across different real-world scenarios, reduces overfitting, and ensures high accuracy.

3. Multi-class Disease Classification Capability

The system supports multiple classification tasks tailored to clinical requirements:

Binary classification: Differentiating between healthy and diseased colon tissues.

Multi-class classification: Identifying specific disease categories such as inflammatory bowel diseases (e.g., Polyphs, ulcerative colitis).

4. Use of Convolutional Neural Networks (CNNs) with Transfer Learning

CNNs are well-suited for image classification tasks because they can: Automatically extract hierarchical features from medical images, such as textures, shapes, and spatial patterns, which is essential for accurate medical diagnosis.The project employs transfer learning with the VGG16 architecture, utilizing pre-trained weights from the ImageNet dataset to leverage advanced feature extraction capabilities.

4.THEORITICAL ANALYSIS

4.1. BLOCK DIAGRAM

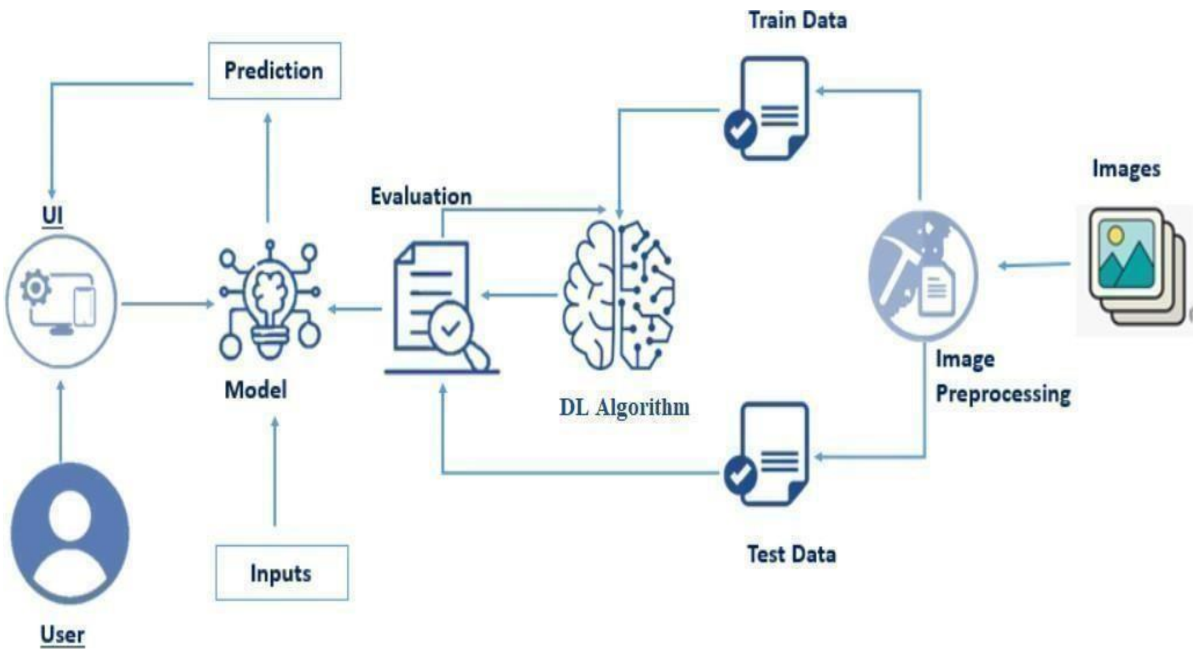

Figure 1: Block diagram

The block diagram represents a system for Colon Disease Detection Using Colonoscopy Images and deep learning.

1. User Interface: User uploads colonoscopy images for analysis.
2. Image Preprocessing: Images are enhanced for analysis.
3. Data Split: Dataset is divided into training and testing data.
4. Deep Learning Algorithm: Model (VGG16) learns features of both diseased and healthy colon tissues.
5. Evaluation: Model performance is tested for accuracy.
6. Prediction: Model predicts the type of colon disease.
7. Output: Results are displayed to the user.

This system aids in early and accurate detection of colon disease.

4.2. HARDWARE/SOFTWARE DESIGNING

Resource Type	Description	Specification/Allocation
Hardware		
Computing Resources	CPU/GPU specifications, number of cores	NVIDIA GPU, 16 GB VRAM
Memory	RAM specifications	8 GB
Storage	Disk space for data, models, and logs	1 TB SSD
Software		
Frameworks	Python frameworks	Flask
Libraries	Additional libraries	TensorFlow, PyTorch or Keras , scikit-learn, Matplotlib
Development Environment	IDE, version control	Jupyter Notebook, Git, Google Colab
Data		
Data	Source, size, format	Kaggle dataset, 11,000 images

Figure 2: Software requirement specification

The following software and tools were utilized to develop the Colon disease detection:

Development Environment :

Google Colab

Google Colab serves as the development and execution environment for the tomato disease detection system. It provides access to Python libraries and hardware acceleration (GPU/TPU), which is critical for: Data preprocessing and visualization, Training and fine-tuning deep learning models like VGG16.

Colon Disease Dataset

The dataset includes images of colonoscopy results, categorized into healthy and various colon disease classes (e.g., polyps, ulcerative-colitis, esophagitis etc.,.). The dataset is essential for training and testing model to classify different colon diseases and assist in the early detection and treatment planning.

Feature Selection and Preprocessing :

<u>Data Preprocessing:</u>
Preprocessing ensures high-quality input data for model training. The following steps were implemented:

1.Normalization:Colonoscopy Images were resized and normalized to a range of [0,1] to ensure consistent input format.

2.Data Augmentation: Applied random transformations (e.g., rotations, flipping, scaling) to artificially expand the dataset and improve model generalization.

<u>Feature Selection:</u>
Since image data does not require manual feature selection, deep learning automatically extracts relevant features during model training

Model Training Tools:

<u>Deep Learning Frameworks:</u>

1.TensorFlow/Keras: Used to build, train, and fine-tune the Convolutional Neural Network (CNN) and VGG16 architecture for image classification.

2.Pre-trained Model (VGG16): Transfer learning was used by fine-tuning the VGG16 model.

<u>Training Process:</u>
Optimized hyperparameters (learning rate, batch size, and number of epochs) to achieve maximum accuracy.

Model Accuracy Evolution :

The model's accuracy and performance were evaluated.

<u>Outcome:</u>
The model achieved 97% classification accuracy on the test dataset, demonstrating high reliability and robustness.

User Interface (UI) Based on Flask Environment :

<u>Flask Web Application</u>:
Flask, a Python-based lightweight web framework, was used to create the user interface.

5. EXPERIMENTAL INVESTIGATIONS

In this Project , we have used Colonoscopy Images Dataset .The dataset comprises high-resolution images categorized into different classes. All images were divided into 4 different classes, where one class is healthy and the other three classes represent different colon diseases: Ulcerative Colitis, Polyps, and Esophagitis. Some sample images, from the dataset for healthy and diseased classes are shown. A total of 4 classes are considered: Healthy, Ulcerative Colitis, Polyps, and Esophagitis.

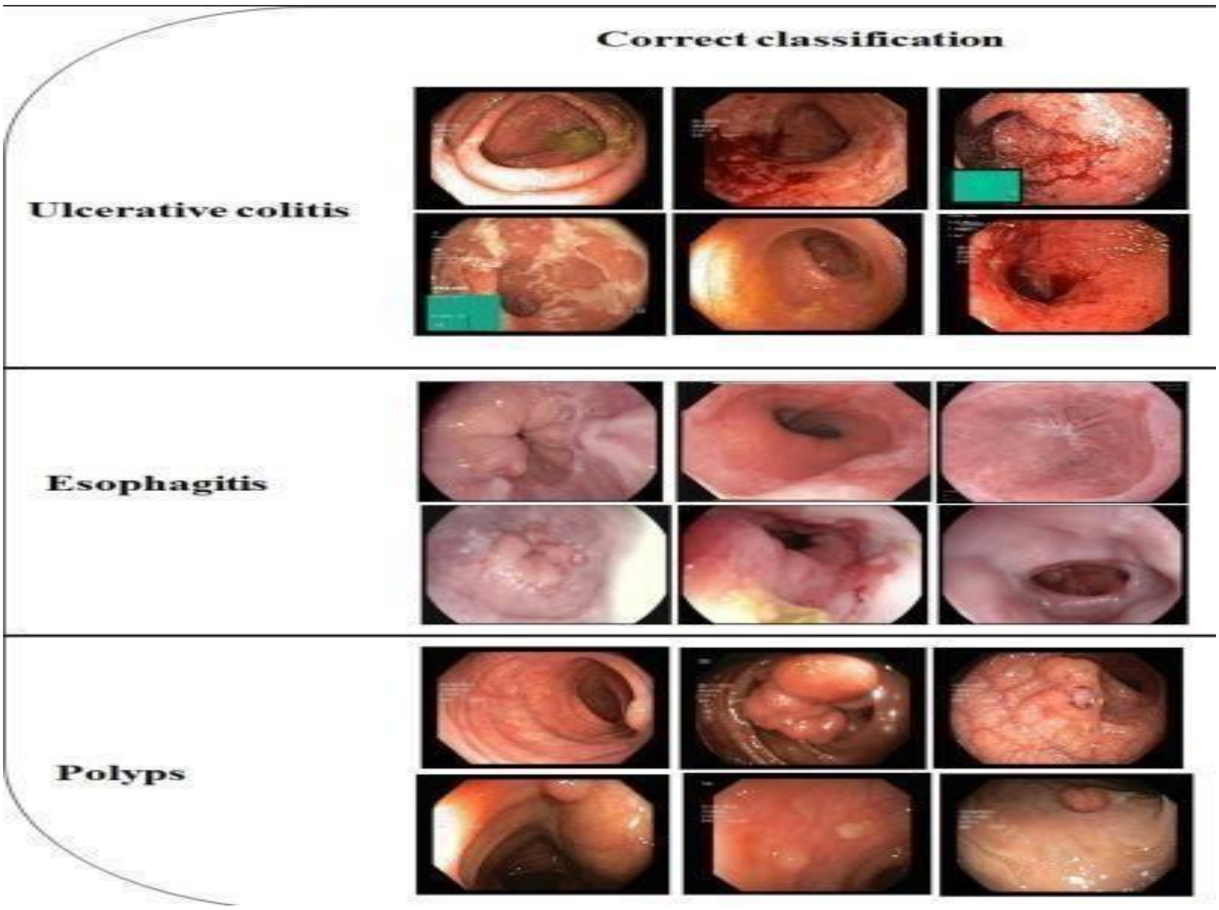

Figure 3: Colonoscopy Images of the project

6. FLOWCHART

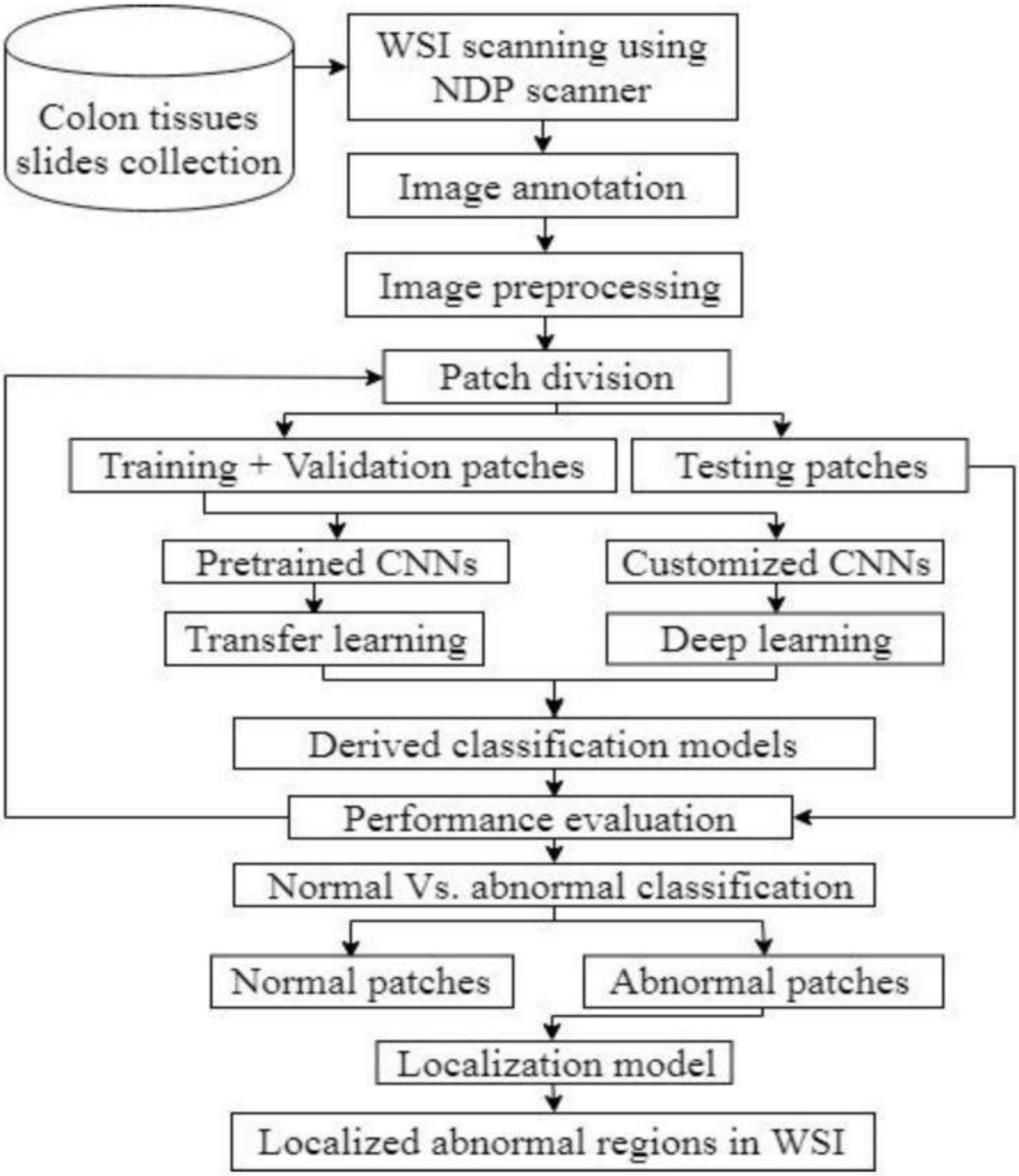

Figure 4: Flow chart for colon disease classification

7. FUTURE SCOPE

The block diagram and flowchart developed in Phase-1 will guide the system's development and ensure a structured implementation in Phase-2. The literature survey will continue to inform enhancements to the system by integrating the latest advancements in deep learning and medical imaging technology. The software and hardware design will be optimized further to ensure compatibility with real-world healthcare settings and user requirements. In Phase-2 of the project, the focus will shift to the practical implementation and comprehensive evaluation of the colon disease detection system. Building upon the strong foundation laid in Phase-1, the next phase will delve into several critical aspects to ensure the system's accuracy, reliability, and usability.

Code Snippets and Full Implementation

Phase-2 will involve the creation, testing, and optimization of the deep learning model. Key functionalities such as preprocessing, model architecture, and inference will be showcased through code snippets, culminating in the full implementation of the colon disease detection system. The system will be integrated with a Flask-based user interface, enabling users to upload colonoscopy images and receive predictions regarding the presence and type of colon disease.

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2021 – 2025

CERTIFICATE OF COMPLETION

UG PROJECT PHASE -II

This is to certify that UG PROJECT PHASE -I entitled "**WCE Curated Colon Disease Classification Using Deep Learning**" is being Submitted by **SRI CHAITHANYA SALLA (21UK1A05F7) , GEETHA PABBOJU (21UK1A05H7) , DIDDI HARSHITH (21UK1A05J5)** in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in computer science and Engineering to Jawaharlal Nehru Technological University Hyderabad during the academic year 2024 – 2025**,** is a record of work carries out by them under the guidance and supervision.

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(Assistant Professor)	(Professor**)**

EXTERNAL

ACKNOWLEDEMENT

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We express heartful thanks to the coordinator **Ms. T. SUSHMA**, Assistant professor, Department of CSE for her constant support and giving necessary guidance for completion of this **UG PROJECT PHASE -II**.

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1. INTRODUCTION

Colon disease classification using Wireless Capsule Endoscopy (WCE) images is a vital step in the early diagnosis and treatment of gastrointestinal disorders. The project focuses on automating the identification of colon-related diseases through deep learning techniques applied to curated WCE image datasets. Manual analysis of WCE footage is time-consuming and prone to human error, which can delay diagnosis and reduce accuracy. Hence, the use of computer-aided diagnosis systems helps in improving the efficiency, reliability, and accuracy of medical interpretations.

The dataset used in this project is collected from publicly available sources such as Kaggle, containing annotated images representing various types of colon diseases. Preprocessing techniques like resizing, normalization, and data augmentation are applied to prepare the images for training. Deep learning models, primarily Convolutional Neural Networks (CNNs), are employed to learn discriminative features from these medical images and classify them into respective disease categories.

UG Project Phase-2 comprises the complete implementation and coding based on the design established in UG Project Phase-1. During this phase, the deep learning model is trained, validated, and tested. Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate the effectiveness of the model. The outcomes, along with the project's applications, advantages, limitations, and future scope, are thoroughly discussed and documented in this phase.

2. CODE SNIPPETS

2.1 PYTHON CODE

Here we will train the dataset in Google colab such that it classifies the colon disease.

Create a file project.ipynb in Google colab.

Follow the sequence given below to execute the project practically.

- Collection of Data.
- Importing necessary libraries.
- Create test, train, valid sets.
- Train and Test the model .
- Save the model.
- Build the Application.
- Create HTML webpages.
- Create app.py file.
- Detects colon diseases through colonoscopy images.

IMPORTING THE LIBRARIES

To build and train the colon disease classification model, essential libraries are imported. This includes TensorFlow and Keras modules for deep learning, along with specific components like ImageDataGenerator, Dense, Flatten, Model, and softmax activation. The VGG16 model is imported from tensorflow.keras.applications, and utilities like preprocess_input, load_img, andimg_to_array are used for image handling.

```
import kagglehub
import os
from tensorflow.keras.preprocessing.image import ImageDataGenerator

#Importing the Model Building Libraries
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dense
from tensorflow.keras.activations import softmax
from tensorflow.keras.models import Model
#from keras.api._v2.keras import activations
#Importing the VGG16 model
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.layers import Flatten

#testing the data
from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input
from tensorflow.keras.preprocessing.image import load_img,img_to_array
import numpy as np

# Download the dataset
dataset_path = kagglehub.dataset_download("francismon/curated-colon-dataset-for-deep-learning")
```

Figure 1: Importing the necessary Libraries

CREATING TRAIN AND TEST DATASET

In colon disease classification, the training dataset consists of endoscopic image data captured through Wireless Capsule Endoscopy (WCE) such as:

- Ulcerative Colitis
- Polyphs
- Esophagitis

It includes labelled images representing various colon conditions to train a deep learning model for disease classification. The testing dataset includes a separate set of the images from the same or similar source, ensuring that the model is evaluated on unseen cases. Typically, 70–80% of the data is used for training and the remaining 20–30% for testing.

```
train_data_path = os.path.join(dataset_path, 'train')
test_data_path = os.path.join(dataset_path, 'test') # Path to the test data
print("Path to dataset files:", dataset_path)
# Configure ImageDataGenerator
train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2, horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255) # Only rescaling for test data

# Apply ImageDataGenerator
train_data = train_datagen.flow_from_directory(train_data_path,  # Updated path
                                               target_size=(224, 224),
                                               batch_size=15,
                                               class_mode='categorical')

test_data=test_datagen.flow_from_directory(test_data_path, # Using test_data_path for test data
                                           target_size=(224,224),
                                           batch_size=15,
                                           class_mode='categorical')
```

```
Downloading from https://www.kaggle.com/api/v1/datasets/download/francismon/curated-colon-dataset-for-deep-learning?c
100%|██████████| 1.41G/1.41G [00:10<00:00, 141MB/s]Extracting files...

Path to dataset files: /root/.cache/kagglehub/datasets/francismon/curated-colon-dataset-for-deep-learning/versions/1
Found 3200 images belonging to 4 classes.
Found 800 images belonging to 4 classes.
```

Figure 2: Creating training and testing datasets

TRAINING AND TESTING THE MODEL

VGG16 MODEL

The , VGG16 model pre-trained on ImageNet is used for classifying colon diseases from WCE images. The model input size is set to 224×224×3, and the top classification layer is removed using include_top=False. All base layers are frozen to retain learned features. A flatten layer and a dense softmax layer with 4 output classes are added for classification.

```
#Initializing the model
Image_size=[224,224]
sol=VGG16(input_shape=Image_size+[3],weights='imagenet',include_top=False)
for i in sol.layers:
    i.trainable=False
y=Flatten()(sol.output)
final=Dense(4,activation='softmax')(y)
# Create the final model
vgg16_model = Model(inputs=sol.input, outputs=final)
```

```
vgg16_model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0

Figure 3: Initializing the model

```
#compiling the model
vgg16_model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['Accuracy'])

#train the model
vgg16_model.fit(train_data,epochs=9,validation_data=test_data)

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset`
  self._warn_if_super_not_called()
Epoch 1/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 75s 314ms/step - Accuracy: 0.7735 - loss: 0.6124 - val_Accuracy: 0.8675 - val_loss: 0.3533
Epoch 2/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 67s 312ms/step - Accuracy: 0.9668 - loss: 0.1102 - val_Accuracy: 0.8975 - val_loss: 0.2410
Epoch 3/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 62s 290ms/step - Accuracy: 0.9640 - loss: 0.0846 - val_Accuracy: 0.8863 - val_loss: 0.2637
Epoch 4/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 62s 291ms/step - Accuracy: 0.9835 - loss: 0.0532 - val_Accuracy: 0.7950 - val_loss: 0.6908
Epoch 5/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 63s 294ms/step - Accuracy: 0.9778 - loss: 0.0640 - val_Accuracy: 0.8863 - val_loss: 0.3372
Epoch 6/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 63s 294ms/step - Accuracy: 0.9898 - loss: 0.0405 - val_Accuracy: 0.8275 - val_loss: 0.5569
Epoch 7/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 62s 292ms/step - Accuracy: 0.9785 - loss: 0.0560 - val_Accuracy: 0.7900 - val_loss: 0.9305
Epoch 8/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 84s 303ms/step - Accuracy: 0.9819 - loss: 0.0440 - val_Accuracy: 0.8763 - val_loss: 0.3427
Epoch 9/9
214/214 ━━━━━━━━━━━━━━━━━━━━ 66s 307ms/step - Accuracy: 0.9752 - loss: 0.0770 - val_Accuracy: 0.8562 - val_loss: 0.4955
<keras.src.callbacks.history.History at 0x7b0184622b10>
```

Figure 4: Training the model

SAVE THE MODEL

The trained VGG16-based model is saved using the HDF5 format with the command vgg16_model.save('cnn.h5').

```
#saving the model
vgg16_model.save('cnn.h5')

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`.
```

Figure 5: Saving the model

Testing the model:

The image is passed to the trained VGG16-based model for prediction. The output is a probability vector, and the class with the highest probability is identified using np.argmax().

```
img =load_img(img_path, target_size=(224, 224))
x =img_to_array(img)
x = preprocess_input(x)
preds= vgg16_model.predict(np.array([x]))
preds

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
array([[0., 0., 1., 0.]], dtype=float32)

labels[np.argmax(preds)]

'2_polyps'
```

Figure 6: Testing the model

APP.PY

```python
import os
import numpy as np
from flask import Flask, render_template, request, redirect, url_for,session
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import load_img, img_to_array

app = Flask(__name__, static_folder='static')
app.secret_key = 'your_secret_key'
# Load the pre-trained model
model = load_model('cnn.h5')

# Configuration for uploads folder
UPLOAD_FOLDER = 'uploads/'
if not os.path.exists(UPLOAD_FOLDER):
    os.makedirs(UPLOAD_FOLDER)
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
app.config['ALLOWED_EXTENSIONS'] = {'png', 'jpg', 'jpeg', 'gif'}

# Function to check allowed file types
def allowed_file(filename):
    return '.' in filename and filename.rsplit('.', 1)[1].lower() in app.config['ALLOWED_EXTENSIONS']

# Routes
@app.route('/')
def index():
    """Render the home page."""
    prediction = session.get('prediction', None)  # Retrieve and clear the prediction from the session
    session.pop('prediction', None)
    return render_template('index.html',prediction=prediction)
    if 'prediction' in session:
        prediction = session['prediction']
    return render_template('index.html', prediction=prediction)

@app.route('/about')
def about():
```

```python
def about():
    return render_template('about.html')
@app.route('/contact')
def contact():
    """Render the Contact page."""
    return render_template('contact.html')
@app.route('/inspect', methods=['GET', 'POST'])
def predict():
    """Handle file upload and predictions."""
    prediction = None
    image_path = None
    if request.method == 'POST':
        if 'file' not in request.files:
            return redirect(request.url)
        file = request.files['file']
        if file.filename == '':
            return redirect(request.url)
        if file and allowed_file(file.filename):
            # Save the file
            filepath = os.path.join(app.config['UPLOAD_FOLDER'], file.filename)
            file.save(filepath)
            # Preprocess the image
            img = load_img(filepath, target_size=(224, 224))
            img_array = img_to_array(img)
            img_array = np.expand_dims(img_array, axis=0)
            # Make prediction
            pred = np.argmax(model.predict(img_array), axis=1)
            classes = ['Normal', 'Ulcerative Colitis', 'Polyps', 'Esophagitis']
            prediction = classes[int(pred)]
            image_path = f"/{filepath}"  # To serve image in templates
            session['prediction'] = prediction
            return redirect(url_for('index'))
    return render_template('inspect.html', prediction=prediction, image_path=image_path)
if __name__ == '__main__':
    app.run(debug=True)
```

Figure 7: App.py (flask code)

2.2 HTML CODE:

This HTML code is designed. It serves as the front-end interface for users (e.g medical professionals, researchers, or diagnostic technicians) to interact with image-based predictions related to colon health conditions.

Home.html:

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Colon Disease</title>
    <link rel="stylesheet" href="./static/styles.css"> <!-- Add a linked CSS file if needed -->
    <style>···
    </style>
</head>
<body>
    <div class="navbar">
        <h1>COLON DISEASE</h1>
        <nav>
            <a href="/">Home</a>
            <a href="/about">About</a>
            <a href="/contact">Contact</a>
        </nav>
        <button class="inspect-button" onclick="location.href='/inspect'">Inspect</button>
    </div>
    <div class="hero">
        <h1>Colon Disease Prediction</h1>
        <p>Detection of Intestinal Diseases</p>
    </div>
    <div class="container">
        {% if prediction %}
        <p class="disease-name">The Disease is {{ prediction }}</p>
        {% endif %}
    </div>
</body>
</html>
```

Figure 8: Home page HTML code

About.HTML :

```html
<head>
</head>
<body>
    <div class="navbar">
        <h1>COLON DISEASE.</h1>
        <nav>
            <a href="/">Home</a>
            <a href="/about">About</a>
            <a href="/contact">Contact</a>
        </nav>
        <button class="inspect-button" onclick="location.href='/inspect'">Inspect</button>
    </div>
    <div class="content">
        <div class="details">
            <br>
            <br>
            <h2  style="border: 2px solid black; padding: 15px; color: darkred; display: inline-block; border-radius: 10px;">Why Co
            Important ?</h2><br>
            <p>Colon disease classification plays a crucial role in the early detection and diagnosis of gastrointestinal disorders
            inflammation, and tumors. Accurate identification of these conditions through Wireless Capsule Endoscopy (WCE) helps re
            and supports timely medical intervention. This classification is helpful to analyze WCE images and automatically classi
            doctors with faster, more reliable diagnostic support and improve patient outcomes. bridging the gap between technology
            <h2 style="border: 2px solid black; padding: 15px; color: darkred; display: inline-block; border-radius: 10px;">Why Ear
            <p>Early detection of colon diseases is crucial because it significantly improves treatment outcomes and survival rates
            such as polyps, ulcers, and early-stage tumors, may not show symptoms initially. Detecting them early allows for less i
            of progression into serious or life-threatening stages (like colorectal cancer), and supports timely medical interventi
            costs, minimize patient discomfort, and increase the chances of a full recovery. In short, early detection saves lives
           </p>

        </div>
    </div>
</body>
</html>
```

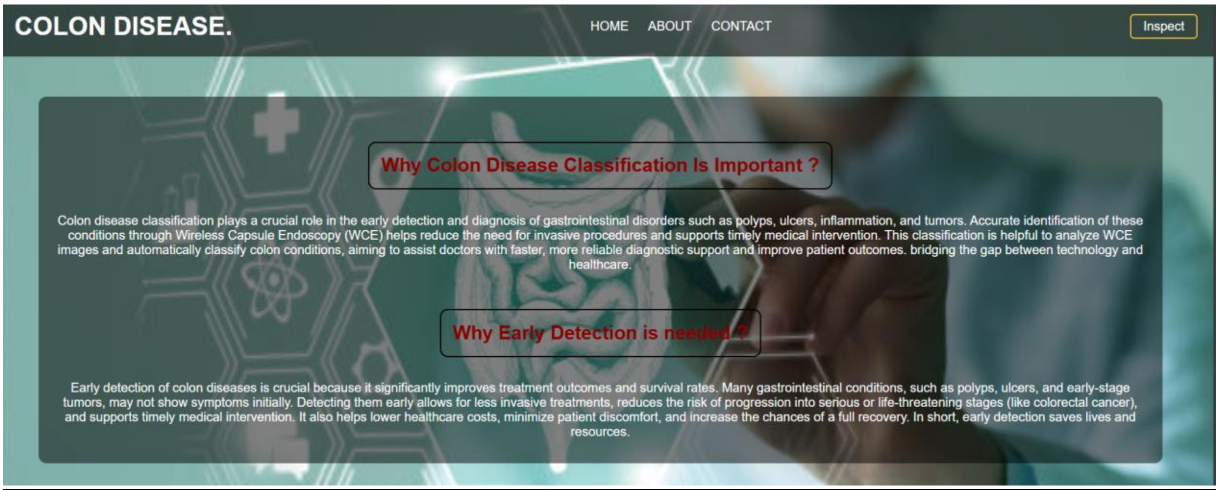

Figure 9: About page HTML code

Inspect.HTML:

```html
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Colon Disease Prediction</title>
    <link rel="stylesheet" href="./static/styles.css">
    <style>···
    </style>
</head>
<body>
    <div class="navbar">
        <h1>COLON DISEASE</h1>
        <nav>
            <a href="/">Home</a>
            <a href="/about">About</a>
            <a href="/contact">Contact</a>
        </nav>
    </div>
    <div class="container">
        <h1>Colon Disease Prediction</h1>
        <p class="instructions">Upload an image to predict the type of colon disease. After uploading, click the "Predict" button.</p>

        <form action="/inspect" method="POST" enctype="multipart/form-data">
            <input type="file" name="file" id="imageInput" accept="image/*" required>

            <!-- Image preview -->
            <div class="image-preview" id="imagePreview">
                <img id="previewImg" src="" alt="Image Preview">
            </div>
            <button type="submit" class="button">Predict</button>
        </form>
    </div>
    <script>···
    </script>
</body>
</html>
```

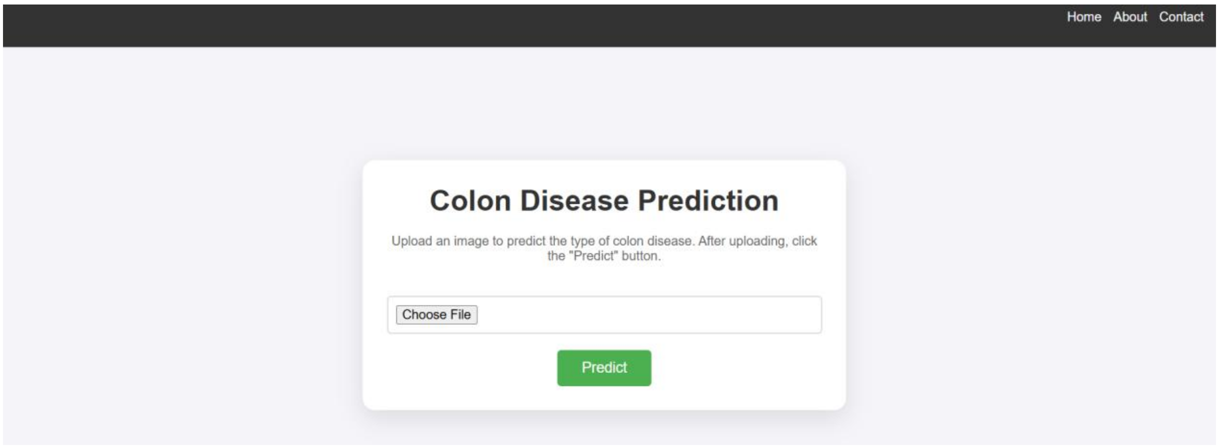

Figure 10: Inspect page HTML code

Predict.HTML:

```html
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <link rel="stylesheet" href="styles.css">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Image Classification</title>
    <style>···
    </style>
</head>
<body>
    <div class="container">
        <h1>Image Classification</h1>
        <form action="/predict" method="POST" enctype="multipart/form-data">
            <label for="imageUpload">Upload Your Image:</label>
            <input type="file" id="imageUpload" name="pc_image" accept="image/*" required>
            <br>
            <button type="submit">Predict</button>
        </form>
        {% if predict %}
        <div class="result">
            <h2>Prediction Result:</h2>
            <p>{{ predict }}</p>
        </div>
        {% endif %}
    </div>
</body>
</html>
```

Figure 11: Predict page HTML code

Contact.HTML:

```html
<body>    <!-- Navbar Section -->
    <div class="navbar">
        <div>
            <a href="/">Home</a>
            <a href="/about">About</a>
            <a href="/contact">Contact</a>
        </div>
        <button onclick="location.href='/inspect'">Inspect</button>
    </div>          <!-- Contact Section -->
    <div class="contact-container">        <!-- Left Section: Contact Details -->
        <div class="contact-left contact-details">
            <h2>Contact Information</h2>
            <div>
                <span>📍</span>
                <p><strong>Location:</strong> Survey no. 91, Sundarayya Vignana Kendram, Technical Block, 6th floor,
            </div>
            <div>
                <span>📧</span>
                <p><strong>Email:</strong> info@thesmartbridge.com</p>
            </div>
            <div>
                <span>📞</span>
                <p><strong>Call:</strong> +91 6304320044</p>
            </div>
        </div>
        <!-- Right Section: Contact Form -->
        <div class="contact-right">
            <h2>Get in Touch</h2>
            <form class="contact-form">
                <input type="text" name="name" placeholder="Your Name" required>
                <input type="email" name="email" placeholder="Your Email" required>
                <input type="text" name="subject" placeholder="Subject" required>
                <textarea name="message" rows="5" placeholder="Message" required></textarea>
                <button type="submit">Send Message</button>
            </form>
        </div>
    </div>
```

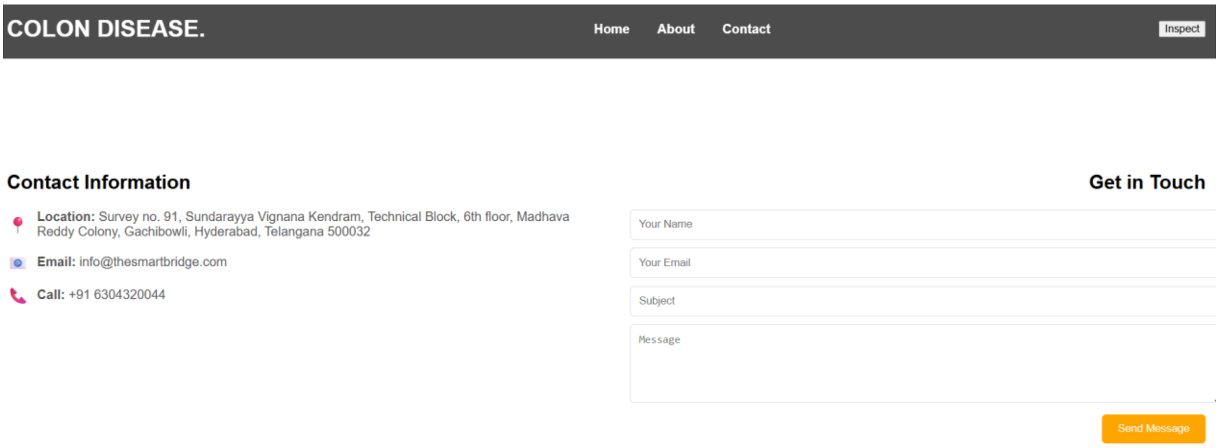

Figure 12: Contact page HTML code

3. RESULT

This user-friendly web interface enables the detection and classification of colon diseases using deep learning. Designed for clarity and ease of use, it allows users to upload intestinal images and receive instant predictions such as "Ulcerative Colitis" or "Polyp." The homepage features a visually informative background, highlighting the colon anatomy, and clearly presents the disease classification result. With dedicated navigation links (Home, About, Contact), it ensures smooth interaction for doctors, researchers, or general users seeking medical insight.

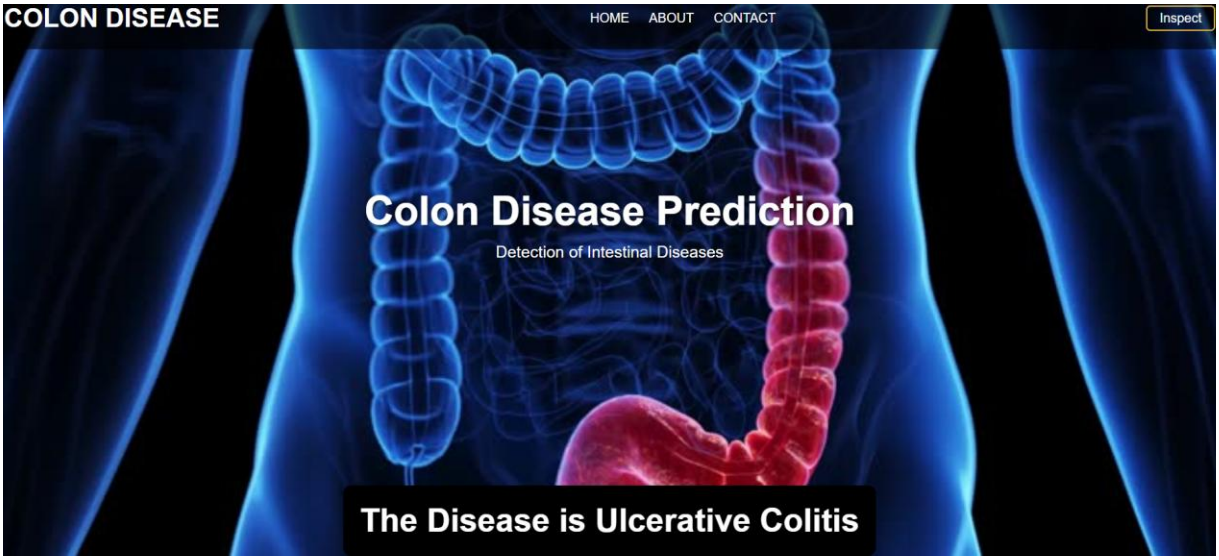

Figure 13: The output of the project

4. APPLICATIONS

1. **Automated Colon Disease Detection:**
   - **Objective:** Automatically detect and classify various colon diseases, such as colorectal cancer, polyps, Crohn’s disease, and colitis, from WCE images.
   - **Outcome:** Faster and more accurate diagnosis, reducing the dependence on human interpretation and increasing the efficiency of healthcare delivery.

2. **Early Diagnosis of Colorectal Cancer:**
   - **Objective:** Detect early-stage signs of colorectal cancer in WCE images, which may be missed by the human eye.
   - **Outcome:** Increased survival rates through early intervention and timely treatment.

3. **Inflammatory Bowel Disease (IBD) Detection:**
   - **Objective:** Classify images based on the presence of inflammation, ulceration, or other abnormalities associated with conditions like Crohn's disease or ulcerative colitis.
   - **Outcome:** Improved management of chronic conditions with timely flare-up detection and treatment adjustments.

4. **Polyps and Lesion Detection:**
   - **Objective:** Automatically detect and classify polyps, which are precursors to colon cancer, and other lesions such as diverticulosis.
   - **Outcome:** Early removal or monitoring of polyps reduces the risk of progression to cancer.

5. **Infection and Bleeding Detection:**
   - **Objective:** Detect signs of infection, internal bleeding, or abnormal vascularization in the colon using deep learning techniques.
   - **Outcome:** Early intervention to prevent severe complications or bleeding.

6. **Monitoring Disease Progression and Treatment Efficacy:**
   - **Objective:** Use WCE images to track disease progression in patients with chronic conditions and assess the effectiveness of treatments or medications.
   - **Outcome:** Provide doctors with data to make informed decisions on treatment plans, reducing unnecessary procedures and improving patient care.

7. **Personalized Treatment Plans:**
   - **Objective:** Based on the disease type and severity detected through WCE images, generate personalized treatment recommendations.
   - **Outcome:** Tailored treatment plans that optimize patient outcomes while minimizing unnecessary treatments.

5. ADVANTAGES

1. **Improved Diagnostic Accuracy:**

    - Deep learning models, particularly Convolutional Neural Networks (CNNs), excel in identifying subtle patterns in medical images. This reduces the likelihood of human error and increases the accuracy of diagnosing colon diseases, ensuring earlier and more reliable detection.

2. **Time Efficiency:**

    - WCE image analysis is traditionally time-consuming and labor-intensive when done manually. Automated systems can analyze large volumes of data quickly, allowing for faster diagnoses and reducing the workload on healthcare professionals.

3. **Consistency and Reproducibility:**

    - Unlike human interpretation, which can vary based on experience or fatigue, deep learning models provide consistent results across all images. This ensures reproducibility and standardization in diagnosis.

4. **Early Detection and Prevention:**

    - Early and accurate identification of colon diseases such as colorectal cancer, polyps, and inflammation can significantly improve treatment outcomes. Thus increasing patient survival rates.

5. **Reduced Human Error:**

    - Manual analysis of WCE footage is prone to oversight, especially given the complexity of human anatomy and the need for precise diagnosis. AI systems minimize this risk by focusing on fine details in images that might be missed by human eyes.

6. **Cost-Effective:**

    - While the initial setup for a deep learning-based diagnostic system can be costly, the long-term benefits of automating diagnosis (e.g., reduced reliance on expert practitioners, faster throughput, and fewer misdiagnoses) can make the system cost-effective for healthcare institutions.

6. DISADVANTAGES

1**. Data Dependency:**

- Deep learning models require large, high-quality annotated datasets to train effectively. In medical applications, such datasets can be scarce, expensive to acquire, and sometimes incomplete.

2. **High Computational Requirements:**

- Training deep learning models requires significant computational power, often requiring specialized hardware like GPUs. This can make the development and deployment of these systems expensive.

3. **Limited Generalization Across Different Populations:**

- Models trained on specific datasets may not generalize well across diverse patient populations, geographical regions, or different equipment types.

4. **Lack of Explainability (Black-box Nature):**

- Deep learning models, particularly CNNs, are often considered "black-box" models, meaning it's difficult to understand how the model arrived at a specific decision or diagnosis.

5. **Difficulty in Handling Rare Diseases:**

- Deep learning models may struggle with rare or atypical diseases due to the limited amount of training data available for these conditions.

6. **Over-reliance on Automation:**

- Over-reliance on AI for diagnosis can reduce human engagement with the decision-making process, potentially leading to a loss of critical thinking and clinical judgment.

7 . CONCLUSION

The Colon Disease Classification System, powered by deep learning and medical imaging, has demonstrated substantial promise in the early detection and categorization of gastrointestinal conditions. In Phase-1, the project laid a comprehensive theoretical foundation by exploring the importance of timely diagnosis in gastrointestinal health, particularly for conditions like polyps, ulcers, and esophagitis. Through detailed study and system design, this phase established the significance of Wireless Capsule Endoscopy (WCE) as a non-invasive imaging method, outlining how deep learning models can enhance the diagnostic process by identifying critical features in WCE images with greater consistency and accuracy than manual observation.

In Phase-2, the project transitioned from theoretical design to practical implementation by developing and testing a colon disease classification web application. The system utilizes the VGG16 convolutional neural network model to analyze WCE images uploaded through a user-friendly web interface. This real-time system enables healthcare practitioners and researchers to upload colonoscopy images and receive accurate predictions, such as ulcerative colitis, polyps, or healthy tissue, thereby accelerating diagnosis and treatment planning.

The application incorporates an image preprocessing pipeline that includes resizing, normalization, and application of preprocess_input, ensuring compatibility with the pretrained model. The backend uses Flask for request handling, while the frontend is designed with HTML and CSS to provide an intuitive user experience. The integration of real-time inference and model prediction into the web interface makes the solution accessible and actionable for end users.

Furthermore, the model has been tested using curated datasets from Kaggle, and the predictions have shown encouraging accuracy, indicating the potential of this tool in aiding clinical decision-making. By successfully bridging theory and implementation, the project validates the use of deep learning in medical diagnostics and paves the way for future enhancements, such as multi-class disease detection, and mobile deployment for field diagnostics.

In conclusion, the Colon Disease Classification System developed through this UG project exemplifies how deep learning and image analysis can be leveraged to support early detection, improve healthcare accessibility, and assist doctors in making faster, data-driven decisions. The combined efforts of Phase-1's system design and Phase-2's practical implementation offer a robust platform for advancing diagnostic precision in gastroenterology.

8. FUTURE WORK

Expanding The Dataset:

To improve the model's robustness, future work will focus on collecting a more diverse dataset, including rare diseases, different patient demographics, and images from various WCE capsule brands. This will help enhance the model's generalization and performance across a broader range of cases.

Real-Time Monitoring Integration:

Integrating the model with real-time WCE image analysis during procedures will allow for immediate feedback. This would support faster decision-making and enable quicker intervention during endoscopic procedures, improving patient outcomes.

Multi-Model Data Integration:

Combining WCE images with additional patient data (e.g., medical history, lab results) could lead to more accurate and personalized disease classification. This holistic approach could better inform treatment plans and diagnosis.

Continuous Learning and Model Updates:

Implementing continuous learning frameworks will allow the model to stay current with new data, emerging diseases, and clinical feedback, ensuring long-term relevance and improved performance over time.

Performance in Low-Resource Settings:

Developing lightweight, efficient models that can be deployed in low-resource settings, where infrastructure and connectivity may be limited, is a priority. This will make AI-powered diagnostics more accessible to underserved regions.

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10.HELPFILE

PROJECT EXECUTION:

STEP-1: Go to **start,** search and launch **VISUAL STUDIO .**

STEP-2: After launching of **VISUAL STUDIO,** OPEN FOLDER.

STEP-3: Run **“APP.PY”** code**.**

STEP-4: Open another file**.**

STEP-5: Create the **home.html, about.html, inspect.html, predict.hml and contact.html** files to create webpages.

STEP-8: Also run **app.py** code.

STEP-9: After running, the URL is created **“localhost:5000”**.

STEP-10: Copy the URL and paste it in the Web Browser.

STEP-11: Then **colon disease classification** webpage is opened.

STEP-12: In the opened webpage, give **colon image** as input.

STEP-13: Then the output is displayed on webpage **predicting colon disease name**.