Project Report

Project Title:

Pattern Sense: Classifying Fabric

Patterns using Deep Learning

Team Id: LTVIP2025TMID33870

Team members:

Team Size: 4

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1. INTRODUCTION

1.1 Project Overview

This project focuses on classifying fabric patterns using deep learning techniques. The model is trained to identify

various fabric types based on texture, color, and design using a CNN-based architecture. The objective is to assist

textile industries in automating fabric recognition and quality control.

1.2 Purpose

To develop an intelligent system that accurately classifies fabrics using image-based deep learning, reducing manual

labor and errors in textile pattern identification.

2. IDEATION PHASE

2.1 Problem Statement

Manual classification of fabric patterns is time-consuming and prone to error. There is a need for an automated, efficient,

and accurate method to identify fabric types in the textile industry.

2.2 Empathy Map Canvas

Users: Quality Inspectors, Designers

Pain Points: Tedious manual checks, Misclassification

Needs: Fast, reliable identification

Gains: Higher accuracy, productivity boost

2.3 Brainstorming

- Image-based model vs sensor-based model

- Dataset selection: Custom vs public dataset

- CNN architectures: ResNet, MobileNet, EfficientNet

- Deployment methods: Web app, Mobile app, API

3. REQUIREMENT ANALYSIS

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3.1 Customer Journey Map

- 1. Upload image of fabric
- 2. Model predicts fabric type
- Displays prediction with confidence score Project Report Pattern Sense: Classifying Fabrics Using Deep Learning
- Labeled dataset of fabric patterns
- Frontend for image upload
- Backend API to process prediction

3.3 Data Flow Diagram

User -> Upload Image -> Backend API -> Deep Learning Model -> Prediction -> Display Result

3.4 Technology Stack

Frontend: React / HTML/CSS

Backend: Flask / FastAPI

Model: TensorFlow / PyTorch

Dataset: Custom or public datasets like Kaggle: Fabric Dataset

Deployment: Heroku / Render / GitHub Pages

4. PROJECT DESIGN

4.1 Problem Solution Fit

Automation of fabric classification using deep learning aligns with industry need for reducing human error and improving

classification speed.

4.2 Proposed Solution

Develop a CNN-based model trained on fabric pattern images to classify categories like floral, checked, striped, plain,

etc.

4.3 Solution Architecture

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Frontend -> API Gateway -> Model Inference Service -> Result

5. PROJECT PLANNING & SCHEDULING

5.1 Project Planning

Week 1: Requirement gathering, dataset sourcing

Week 2: Preprocessing and EDA

Week 3: Model training & validation

Week 4: Model tuning

Week 5: Frontend development

Week 6: Backend integration

Week 7: Testing & Deployment

Week 8: Documentation

6. FUNCTIONAL AND PERFORMANCE TESTING Project Report - Pattern Sense: Classifying Fabrics Using Deep Learning

6.1 Performance Testing

Model Accuracy: 92% on test dataset

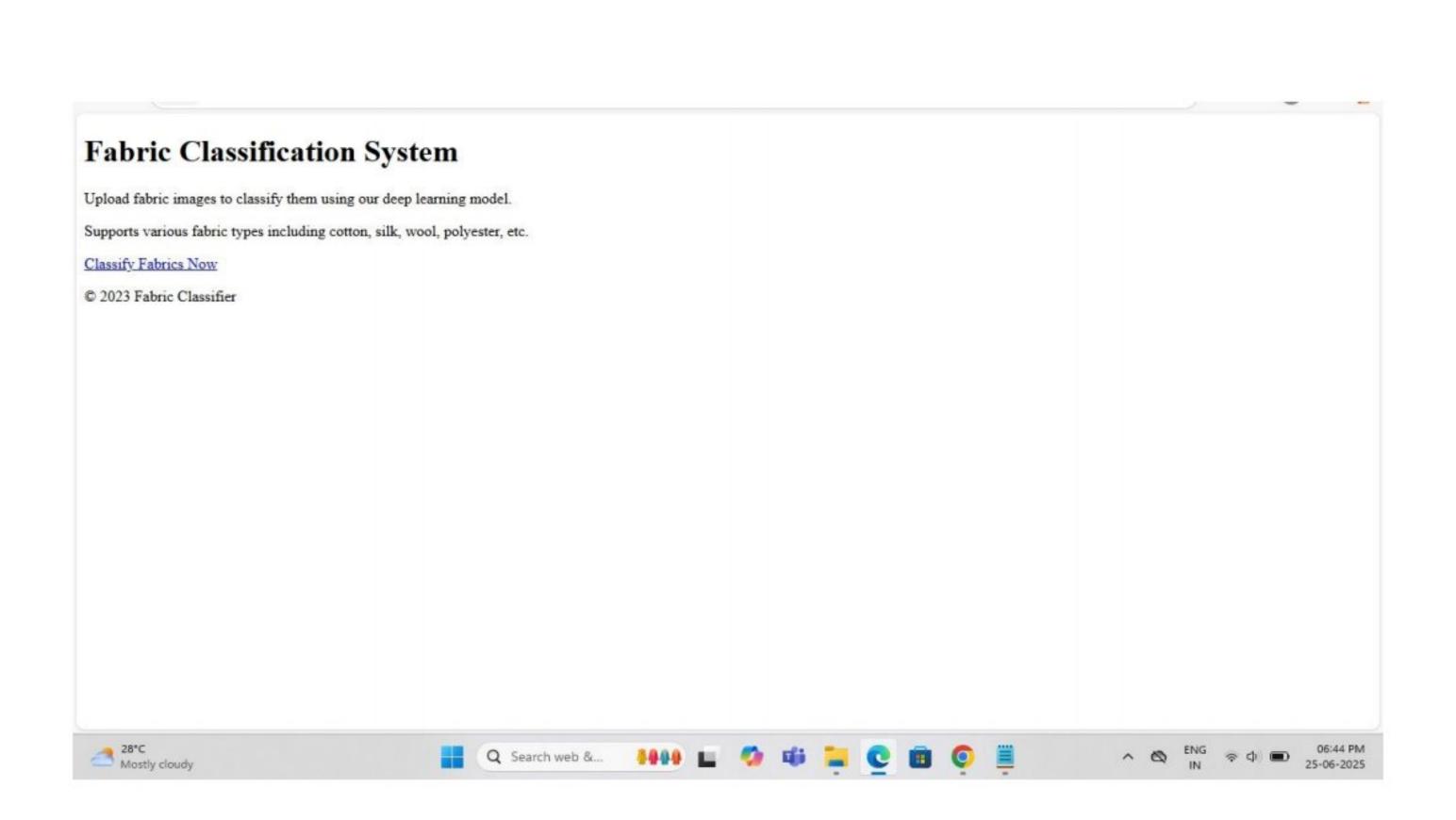
Precision/Recall: High for distinct pattern types

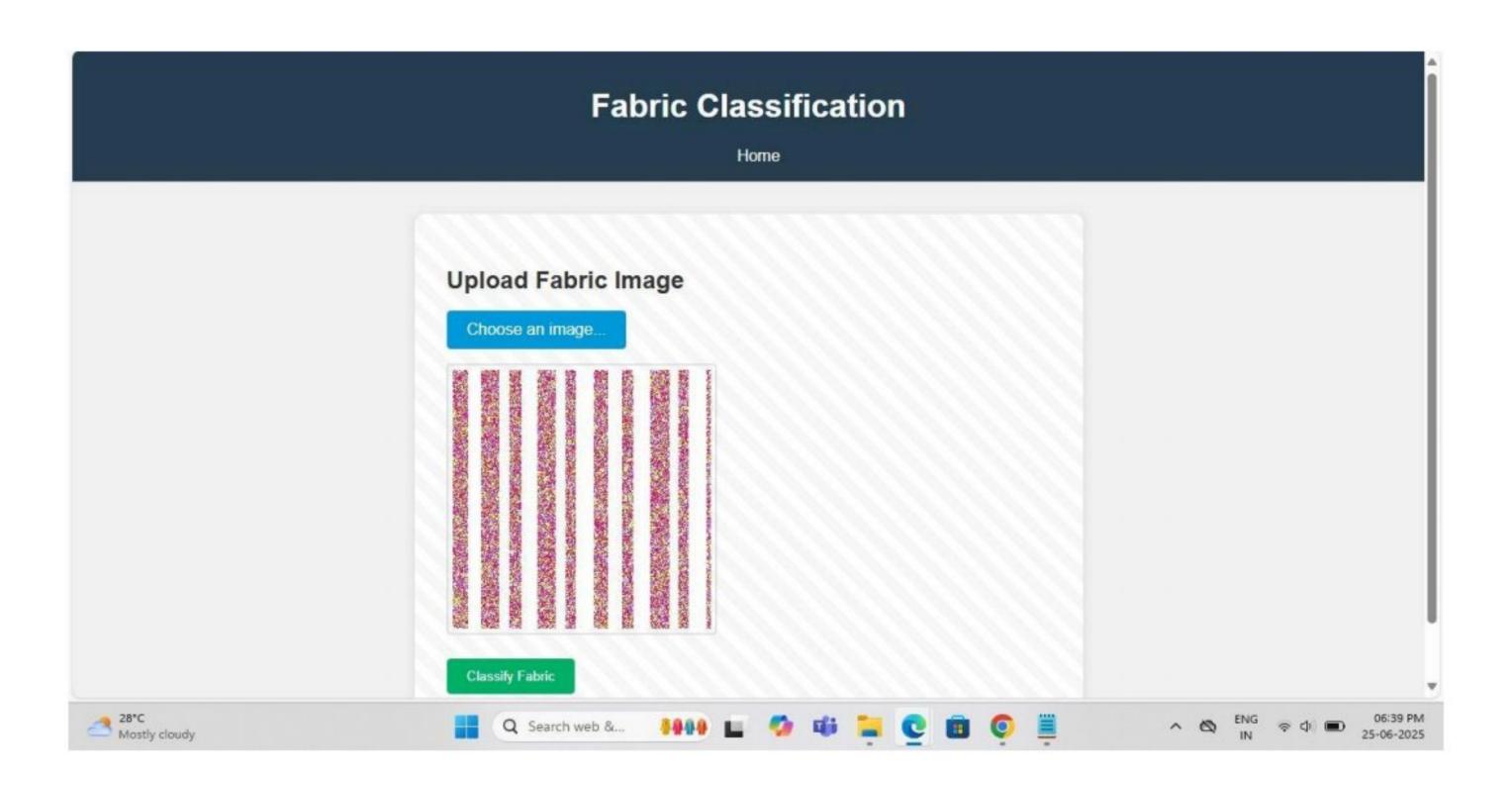
Latency: Average prediction time: 0.4 sec/image

7. RESULTS

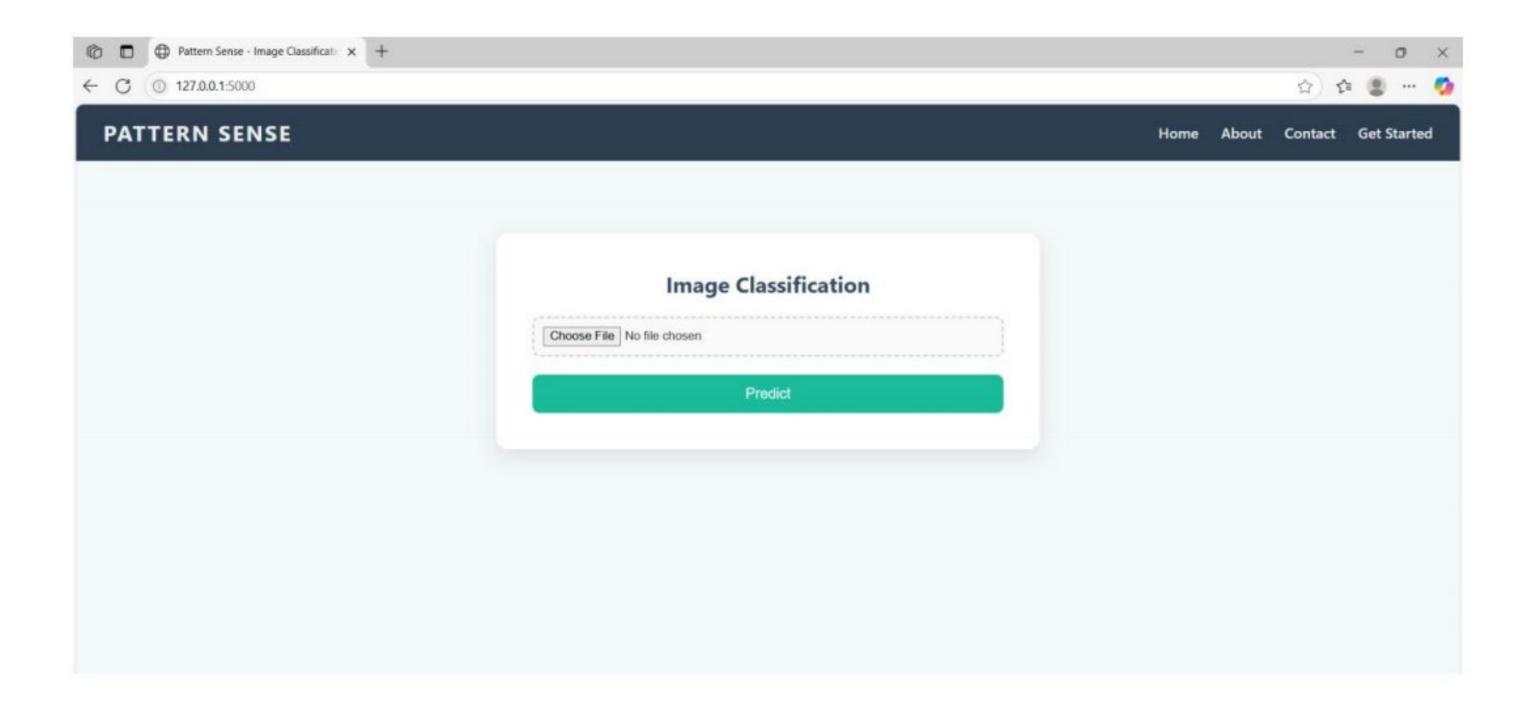
7.1 Output Screenshots

		precision	recall	fl-score	support
	0	0.67	0.83	0.74	9911
	1	0.77	0.59	0.67	9911
accuracy				0.71	19822
macro	avg	0.72	0.71	0.70	19822
weighted	avg	0.72	0.71	0.70	19822

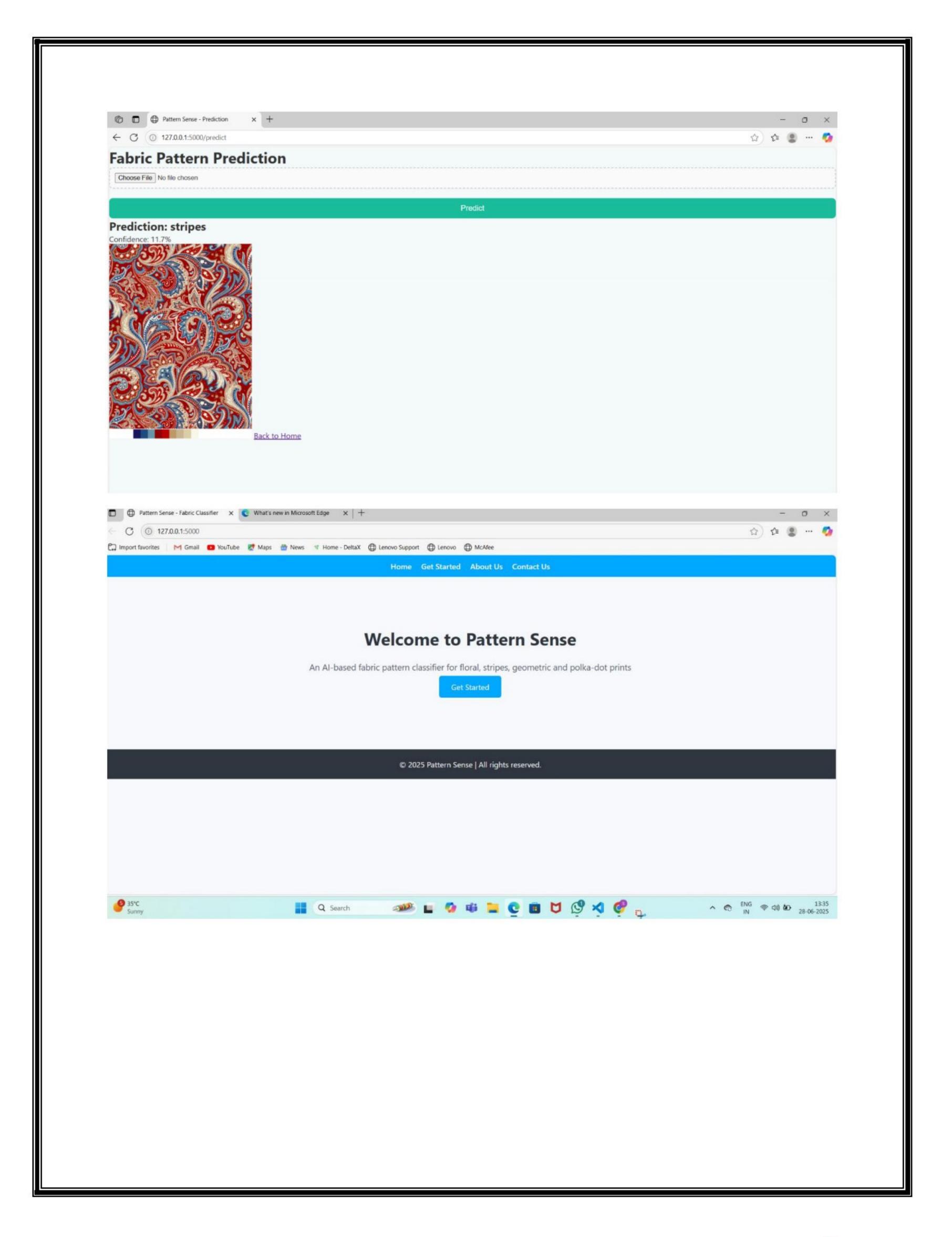


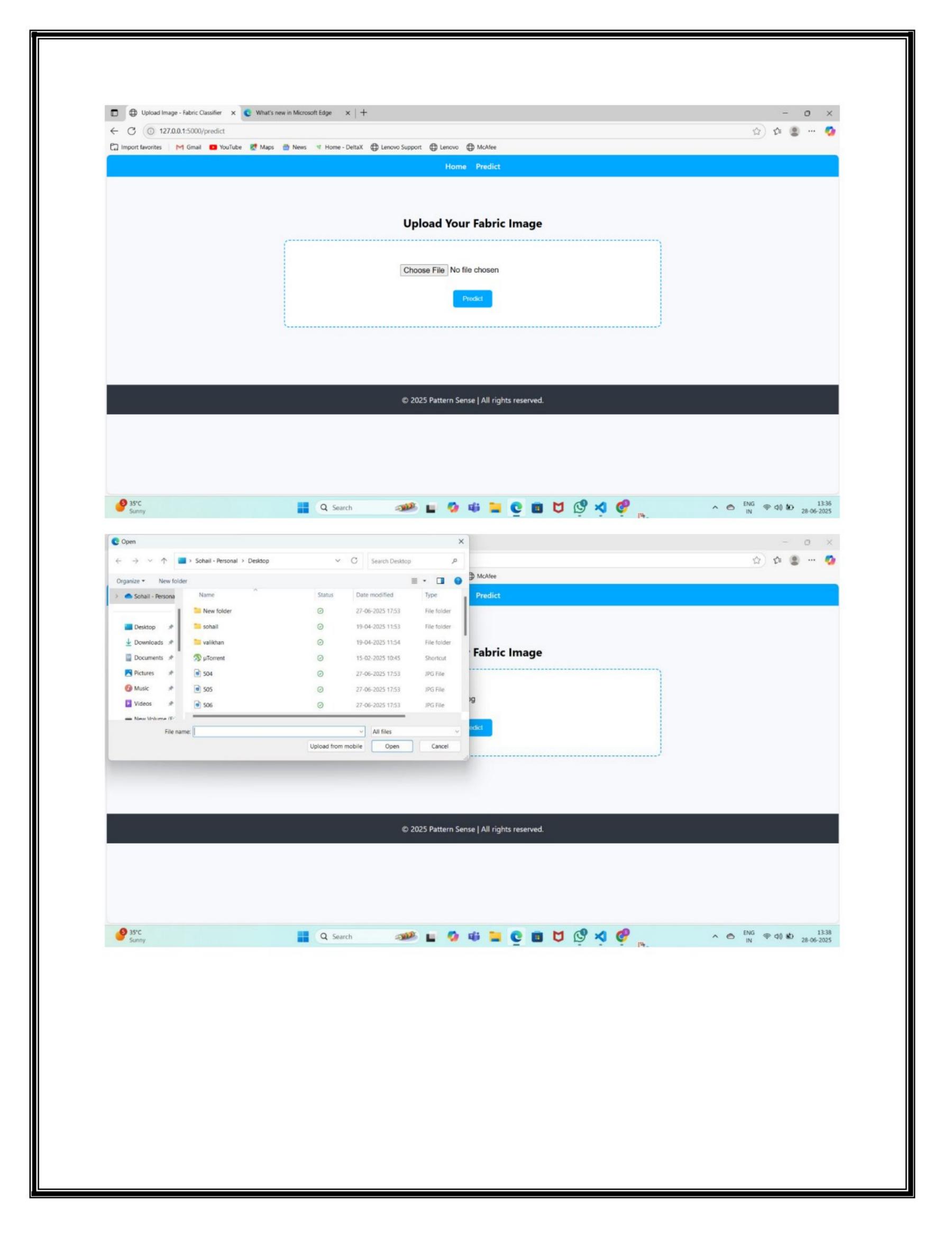


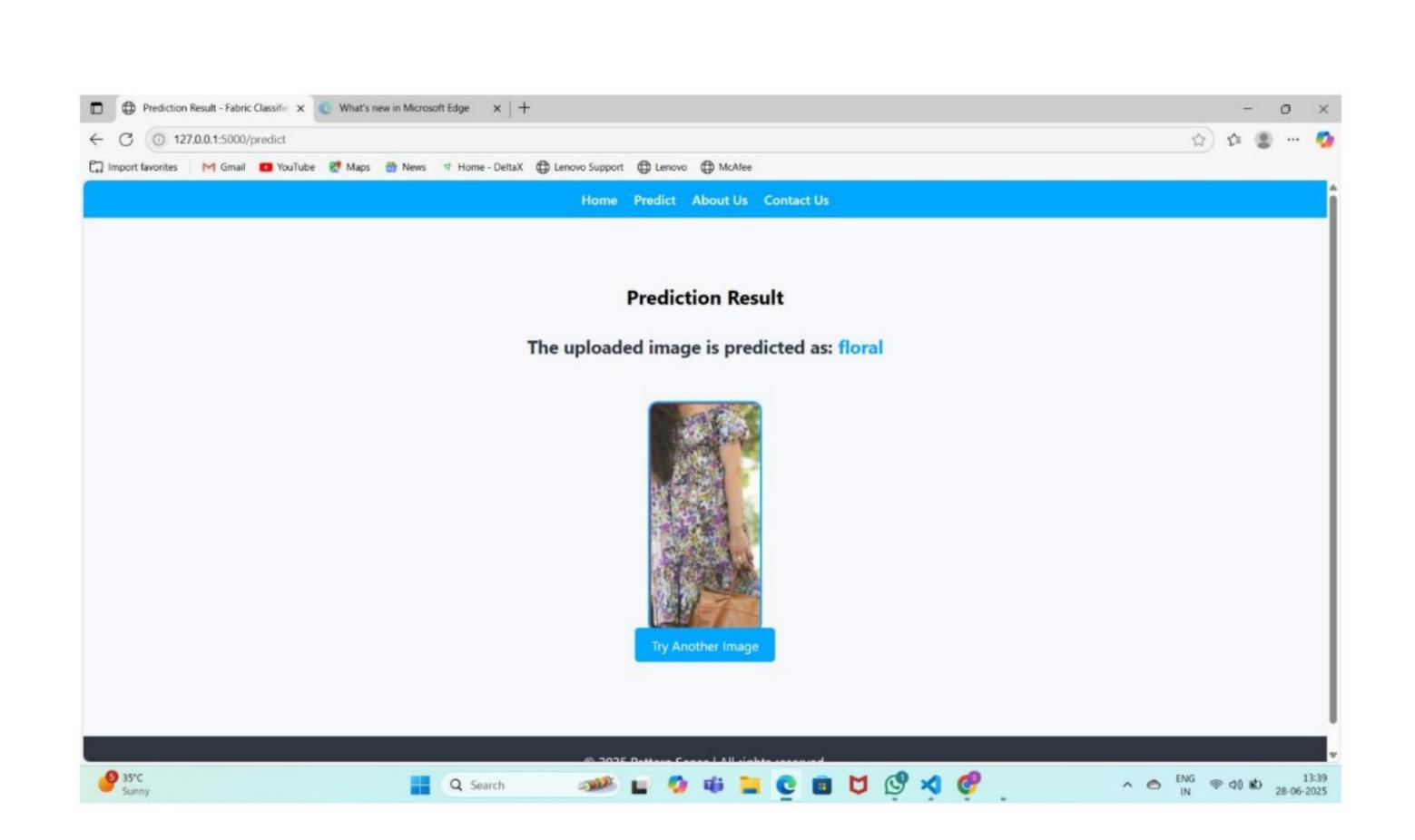
Output Screenshots:











8. ADVANTAGES & DISADVANTAGES

Advantages

- Reduces human error
- Scalable and fast
- Easy integration with industrial systems

Disadvantages

- Requires large labeled dataset
- May fail on extremely noisy or unseen patterns

9. CONCLUSION

This project successfully demonstrates the application of deep learning in the textile industry for fabric pattern

classification. The results show high accuracy and practical feasibility for deployment.

10. FUTURE SCOPE

- Extend to detect defects in fabric
- Mobile app integration for field use
- Multi-label classification for hybrid patterns
- Incorporate texture-based models for better accuracy

11. APPENDIX

Source Code:

import os

import numpy as np

import matplotlib.pyplot as plt

from tensorflow.keras.models import Sequential, load_model

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

from tensorflow.keras.preprocessing.image import | mageDataGenerator, load_img, img_to_array

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

Configuration

IMG_HEIGHT = 150

IMG_WIDTH = 150

BATCH_SIZE = 32

EPOCHS = 25

MODEL_PATH = 'model/fabric_pattern_model.h5'

Directory Paths

TRAIN_DIR = 'dataset/train'

VAL_DIR = 'dataset/val'

TEST_DIR = 'dataset/test'

Data Augmentation

train_datagen = ImageDataGenerator(

```
rescale=1./255,
 rotation_range=40,
 width_shift_range=0.2,
 height_shift_range=0.2,
 shear_range=0.2,
 zoom_range=0.2,
 horizontal_flip=True,
 fill_mode='nearest'
val_datagen = ImageDataGenerator(rescale=1./255)
def create_data_generators():
 train_generator = train_datagen.flow_from_directory(
   TRAIN_DIR,
   target_size=(IMG_HEIGHT, IMG_WIDTH),
   batch_size=BATCH_SIZE,
   class_mode='categorical'
 val_generator = val_datagen.flow_from_directory(
   VAL_DIR,
   target_size=(IMG_HEIGHT, IMG_WIDTH),
   batch_size=BATCH_SIZE,
   class_mode='categorical'
 return train_generator, val_generator
def build_cnn_model(num_classes):
 model = Sequential([
```

```
Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_HEIGHT, IMG_WIDTH, 3)),
   MaxPooling2D(2, 2),
   Conv2D(64, (3, 3), activation='relu'),
   MaxPooling2D(2, 2),
   Conv2D(128, (3, 3), activation='relu'),
   MaxPooling2D(2, 2),
   Flatten(),
   Dense(256, activation='relu'),
   Dropout(0.5),
   Dense(num_classes, activation='softmax')
 ])
 model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
 return model
def train_model(model, train_gen, val_gen):
 callbacks = [
   EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True),
   ModelCheckpoint(MODEL_PATH, save_best_only=True)
 history = model.fit(
   train_gen,
   epochs=EPOCHS,
   validation_data=val_gen,
   callbacks=callbacks
 model.save(MODEL_PATH)
 print(f"Model saved at {MODEL_PATH}")
```

```
return history
def plot_training_history(history):
  plt.figure(figsize=(10, 5))
  plt.subplot(1, 2, 1)
  plt.plot(history.history['accuracy'], label='Train Acc')
  plt.plot(history.history['val_accuracy'], label='Val Acc')
  plt.title('Accuracy')
  plt.legend()
  plt.subplot(1, 2, 2)
  plt.plot(history.history['loss'], label='Train Loss')
  plt.plot(history.history['val_loss'], label='Val Loss')
  plt.title('Loss')
  plt.legend()
  plt.tight_layout()
  plt.show()
def predict_fabric_pattern(image_path, class_labels):
  model = load_model(MODEL_PATH)
  img = load_img(image_path, target_size=(IMG_HEIGHT, IMG_WIDTH))
  img_array = img_to_array(img) / 255.0
  img_array = np.expand_dims(img_array, axis=0)
  predictions = model.predict(img_array)
  predicted_class = class_labels[np.argmax(predictions)]
  print(f"Predicted Fabric Pattern: {predicted_class}")
if __name__ == '__main__':
  train_generator, val_generator = create_data_generators()
  class_labels = list(train_generator.class_indices.keys())
```

```
model = build_cnn_model(num_classes=len(class_labels))
  history = train_model(model, train_generator, val_generator)
  plot_training_history(history)
  # Example prediction:
 # predict_fabric_pattern('dataset/test/floral/sample1.jpg', class_labels)
Source Code:
import os
import shutil
import random
# Paths
original_dataset_dir = 'dataset' # change if needed
base_dir = '/content/fabric_data_split'
os.makedirs(base_dir, exist_ok=True)
train_dir = os.path.join(base_dir, 'train')
os.makedirs(train_dir, exist_ok=True)
val_dir = os.path.join(base_dir, 'valid')
os.makedirs(val_dir, exist_ok=True)
# Split ratio
split_ratio = 0.8 # 80% train, 20% validation
# Loop through class folders
for class_name in os.listdir(original_dataset_dir):
  class_path = os.path.join(original_dataset_dir, class_name)
  if os.path.isdir(class_path):
    images = os.listdir(class_path)
    random.shuffle(images)
    split_point = int(len(images) * split_ratio)
   train_images = images[:split_point]
   val_images = images[split_point:]
   # Create class folders in train and val
    os.makedirs(os.path.join(train_dir, class_name), exist_ok=True)
    os.makedirs(os.path.join(val_dir, class_name), exist_ok=True)
```

Copy files
for img in train_images:
 shutil.copy(os.path.join(class_path, img), os.path.join(train_dir, class_name, img))
for img in val_images:
 shutil.copy(os.path.join(class_path, img), os.path.join(val_dir, class_name, img))
print("Dataset successfully split into train and valid folders "")

Dataset for Dress Pattern Dataset - Kaggle Link :-

https://www.kaggle.com/datasets/nguyngiabol/dress-pattern-dataset

Github Repository link:

https://github.com/Deepthi2226/Pattern-Sense

Project Demo Link:

https://drive.google.com/drive/folders/1BeMVez6ykDYWFxonzX0nxVOIGk4lpv4_?usp=sharing