Pattern Sense: Classifying Fabric Patterns Using Deep Learning

Project Documentation format

1. Introduction

Project Title: [Pattern Sense: Classifying Fabric Patterns Using Deep Learning]

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2. Project Overview

- **Purpose:**
- The purpose of "PATTERN SENSE: CLASSIFYING FABRIC PATTERNS USING DEEP LEARNING" is to develop a system that automatically identifies and categorizes different fabric patterns using deep learning techniques. This aims to automate a task that is currently often done manually, improving efficiency and accuracy in the textile industry.
- To automatically recognize and classify different fabric patterns (e.g., plain, satin, twill, stripes, plaids, floral) using deep learning, replacing manual inspection and handcrafted feature extraction with an end-to-end, scalable image analysis approach
- **Goals:**
- The main goal of "Pattern Sense: Classifying Fabric Patterns Using Deep Learning" is to automate the process of classifying fabric patterns, specifically using deep learning techniques to improve accuracy and efficiency compared to traditional manual methods.
- This involves developing a system that can accurately identify and categorize different fabric patterns from images.
- The primary goal is to move away from manual, labor-intensive methods of classifying fabric patterns, which are prone to errors and time-consuming
- Automated classification can significantly speed up the process of identifying and categorizing fabric patterns, leading to increased efficiency in textile production and management.
- **Features:**
  Dataset & Preprocessing
    - High-quality fabric images captured under controlled illumination, using consistent focal length and ISO settings for clarity
    - Data augmentation to create robust variance: flips, rotations (e.g., every 30°), zoom, shear, brightness changes — boosting generalization and avoiding overfitting

CNN Architectures & Transfer Learning

- Pre-trained models like ResNet-50, VGG-16/19, Google Net/Inception are fine-tuned for fabric textures — combining strong feature abstraction with task adaptation
- Architecture improvements include identity shortcuts (ResNet) to combat vanishing gradients, small-kernel stacks (VGG), and inception modules for multi-scale feature capture

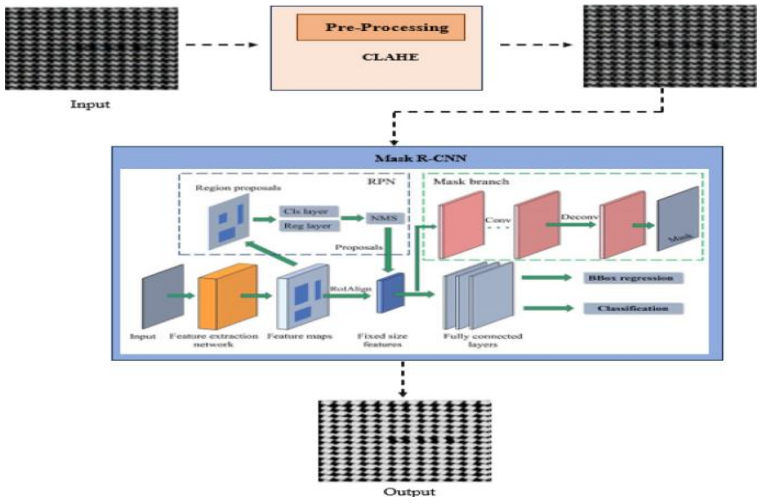
Texture-Specific Feature Enhancements

- Feature fusion: Combine CNN features with classical descriptors like HOG, HSV histograms, LBP, and GLCM to enrich shape and color cues
- Attention-enhanced networks such as DenseNet variants emphasize discriminative texture regions, boosting accuracy

Scalability & Efficiency

- Integration of depth wise-separable convolutions (e.g., Mobile Net-style) and channel pruning for lightweight and fast inference—vital for deployment on embedded devices
- Optional ensemble or segmentation heads for defect detection, allowing multi-task operation in production

3. Architecture



4. Setup Instructions

- **Prerequisites**:
  To complete this project, you must require the following software and packages.
- Software Requirements:
  - Visual Studio Code (VS Code) or any Python-supported IDE
  - Python 3.10 for better suitable to all packages
- Python packages:
  - Open VS code terminal prompt etc.,

- Type “pip install NumPy” and click enter.
- Type “pip install pandas” and click enter.
- Type “pip install scikit-learn” and click enter.
- Type “pip install matplotlib” and click enter.
- Type “pip install scipy” and click enter.
- Type “pip install seaborn” and click enter.
- Type “pip install tenser flow” and click enter.
- Type “pip install Flask” and click enter

Installation:

Create a Virtual Environment (Optional but Recommended):

python -m venv .venv

source .venv/Scripts/activate For Windows

source .venv/bin/activate For Mac/Linux

Install Required Packages:

Ensure you run:

pip install numpy

pip install pandas

pip install scikit-learn

pip install matplotlib

pip install scipy

pip install seaborn

pip install tensorflow

pip install Flask

pip install Pillow

Download Dataset:

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

Prepare the Dataset:

python data_preparation.py

Clean the Dataset (Optional for Transparency Issues):

python rgb_cleaner.py

Train the Model:

python model_training.py

Test the Model (Optional):

python model_testing.py

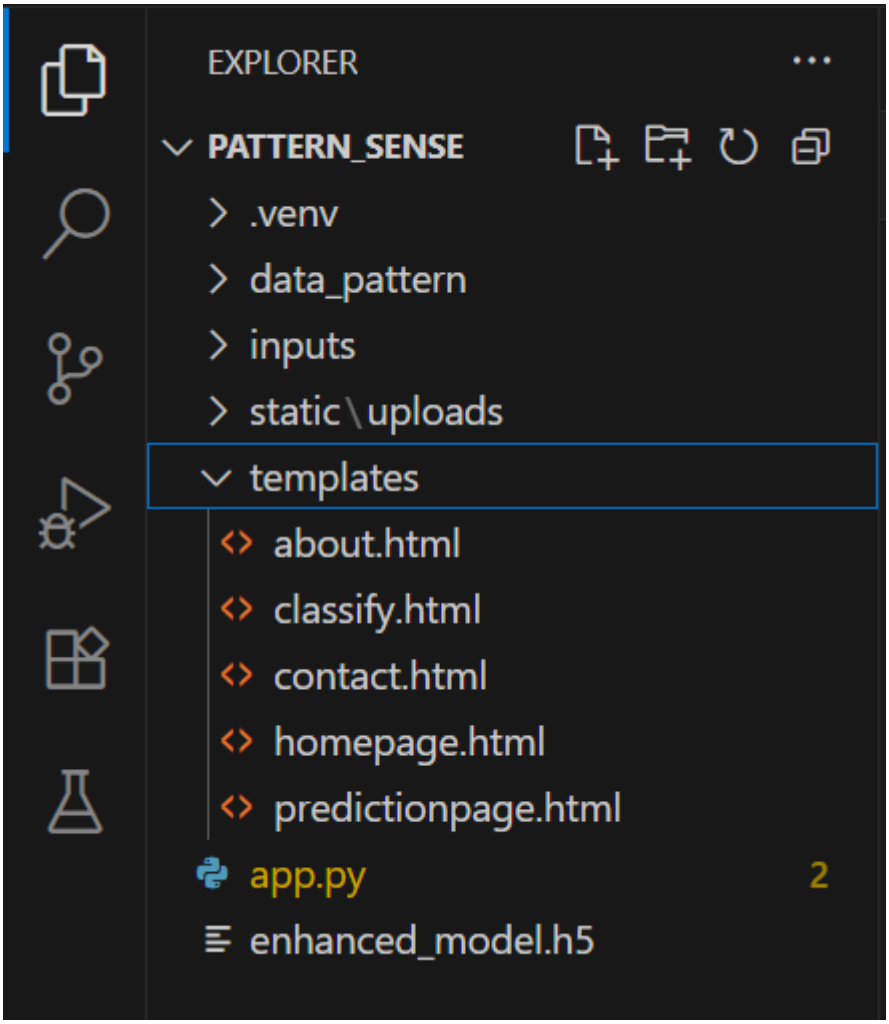
Run the Flask Web Application:

python app.py

Access the Application:

Open your browser and visit: [http://127.0.0.1:5050]

5. Folder Structure



6. Running the Application

A. Backend (Model & API):

1.Deep Learning Model

- Common architectures: ResNet-50, VGG16/VGG19, DenseNet, Inception, Xception—typically pretrained on ImageNet and fine-tuned on specialized fabric datasets.
- Training pipeline includes:
    - Image preprocessing (resizing, normalization)
    - Data augmentation (rotations, flips, brightness, zoom)

2. Model Serving API

- Typically deployed with a lightweight web server (e.g., Flask/FastAPI).
    - Accepts image uploads (or base64 streams), preprocesses, runs inference through the model, returns JSON results (class label + confidence).
    - Seen in fabric defect detection literature using TensorFlow/Keras and Inception-based systems

B. Frontend (UI/UX & Deployment)

Streamlit Dashboard

- Use Streamlit to create an interactive UI where users can upload fabric images and view classification results instantly
- Error handling, result display, basic charts, and batch submission are built-in features.

Full Stack Web (React/Next.js)

- **Frontend**: React or Next.js web UI for image upload, progress indicators, and result display (class + probability + sample textures).
- **API Gateway**: A lightweight Node.js/Express layer can sit between frontend and Python model server. This proxy handles data formatting, CORS, and routing.

7. API Documentation

a) Home Page

- **URL:** /
- **Method:** GET
- **Description:** Displays the landing page of the application.
- **Response:** Returns the index.html template.

b) About Page

- **URL:** /about
- **Method:** GET
- **Description:** Displays information about the project.
- **Response:** Returns the about.html template.

c) Inspect Page (Upload & Predict UI)

- **URL:** /inspect
- **Method:** GET

- **Description:** Displays the image upload form for prediction.
- **Response:** Returns the inspect.html template.

d) Image Prediction API

- **URL:** /predict
- **Method:** POST
- **Description:** Accepts an image file, performs classification using the trained model, and returns the prediction.

Request Parameters:

Name	Type	Description
image	File	The image file to be uploaded (JPG, PNG, etc.).

Example Request using HTML Form:

```
<form method="POST" action="/predict" ectype="multipart/form-data">
  <input type="file" name="image" required>
  <button type="submit">Predict</button>
</form>
```

Example Response (Rendered on Inspect Page):

Upon successful prediction, the following details are displayed:

- Uploaded image preview
- Predicted class label (e.g., "tribal")
- Confidence score (percentage)

Example Backend Response (if it were JSON API):

(Note: Your current implementation renders a template, but if converted to pure JSON API, it would look like this)

```
{“predicted_label": "cartoon",
 "confidence": 97.35,
 "Image_path": "static/uploads/cartoon.jpg"
}
```

8. Authentication

Current Status:

Many textile manufacturers and retailers are exploring AI solutions to automate fabric inspection and pattern recognition. The application is designed as a publicly accessible image classification tool intended for demonstration purposes, allowing any user to:

✓ Access the website

✓ Upload images for fabric classification

✓ View results without requiring login or registration

Future Scope for Authentication (Optional Enhancements):

Hybrid AI Models & Explainability

- Physics-informed and hybrid models: Combining CNNs with physics-based models (e.g., fabric drape, fibre structure) can improve authentication robustness and interpretability
- Explainable AI (XAI): Especially for high-value fabrics (e.g., silk, Pashmina), systems that clearly show "why" a pattern is flagged as fake—based on thread density, weave irregularities—will foster trust.

Enhanced Data & Real-Time Vision

- High-resolution imaging improvements: Adoption of line-scan cameras, multi-spectral/hyperspectral imaging, and 3D capture can uncover authenticity features invisible to the naked eye.
- Real-time authentication during production: Inline visual inspection can identify anomalies on the fly—enhancing QC and reducing waste

Generative AI & Pattern Design

- GAN-based counterfeit detection: As counterfeiters use generative AI to create near-perfect fake patterns, authentication systems will need GAN-based "tampering detectors" to spot synthetic sequences
- Adaptive, co-created patterns: Counterparts could include AI-based modules that generate unique, traceable pattern IDs for each production batch, simplifying downstream verification.

Sustainability & Circular Fashion

- Automated sorting for recycling: AI systems will classify fabric prints and materials for optimal recycling—for instance, segregating cotton vs polyester blends for better reuse streams
- Waste reduction & traceability: Authentication tied to lifecycle metadata (e.g., recycled content, eco-certifications) supports sustainable sourcing claims

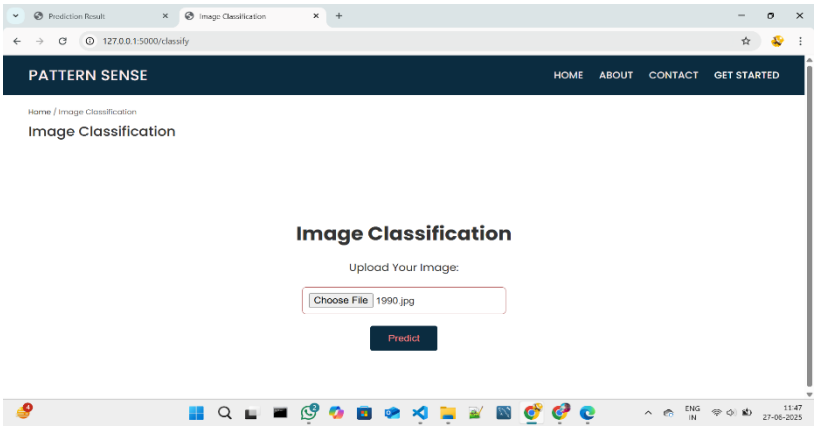
Recommended Future Features:

✓ Admin Login: Only authorized personnel can retrain or upload new datasets.

✓ User Dashboard: Registered users can track prediction history.

✓ API Access Tokens: Protect REST APIs for mobile or external application integration.

9. User Interface



10. Testing

Testing Strategy

Dataset Preparation & Splitting

- High-quality, balanced dataset: Collect diverse, high-res fabric images across all pattern classes. Remove duplicates, fill missing labels, and balance classes via augmentation or sampling
- Split into train/validation/test:
    - Common split: 60–70% train, 15–20% validation, 15–20% test.

- Use stratified sampling to preserve class distributions.

Cross-Validation for Robustness

- Stratified k-fold (e.g. k = 5 or 10) during training/validation. Ensures each fold well represents pattern categories
- Evaluate model consistently across folds—use mean performance and standard deviation to detect variability

Data Augmentation & Test-Time Augmentation

- Train-time augmentation: Apply flips, rotations, scale, crop, brightness, shearing, translation, noise—key for texture generalization
- Test-time augmentation (TTA): Average predictions over multiple augmented crops/scales to improve stability

Evaluation Metrics & Error Analysis

- Use multiple metrics: accuracy, precision, recall, F1-score, ROC–AUC to address class imbalance
- Employ confusion matrices to check misclassification patterns and identify confusing fabric classes.
- Conduct error-slice analysis: evaluate performance across image conditions like lighting, fabric type, camera resolution

Preventing Overfitting

- Use early stopping based on validation loss or accuracy
- Apply regularization: L2 weight decay, dropout layers.
- Monitor both train and validation performance to detect divergence or overfitting.

Robustness & Bias Testing

- Stress-test with perturbed inputs (e.g., noise, lighting variations) to gauge stability .
- Evaluate on different subgroups (e.g., handloom vs machine-made, varying capture devices) to identify biases
- Optional: adversarial attacks for edge-case analysis

Final Testing & Generalization

- After tuning, evaluate on the held-out test set one final time—this is the true measure of generalization
- Ensure test data is not used for hyperparameter tuning—it's only for final assessment

Continuous Monitoring Post-Deployment

- Use a monitoring pipeline (e.g., MLflow, Tensor Board) to track model drift: monitor changes in accuracy, input data distribution, class representation.
- Implement proactive retraining triggers when performance drops below thresholds (e.g., F1 < 90%).

Tools Used

Tool/Library	Purpose
TensorFlow, Keras, PyTorch, Caffe	Core deep learning frameworks.
ResNet, DenseNet, VGG, Inception	Pretrained models for feature extraction.
Matplotlib/Seaborn	Visualization of confusion matrix and performance metrics.
GLCM, LBP via scikit-image	Handcrafted texture descriptors
Deep-TEN, wavelet-CNN, Texel-Att	Specialized texture representation.

11. Screenshots or Demo

Screenshots

The complete execution of the Pattern sense application is shown in the images step by step as shown below.

Step 1: Run the app.py code and you will get a link in terminal as https://127.0.0.1.5000 to access web page and to do the other process

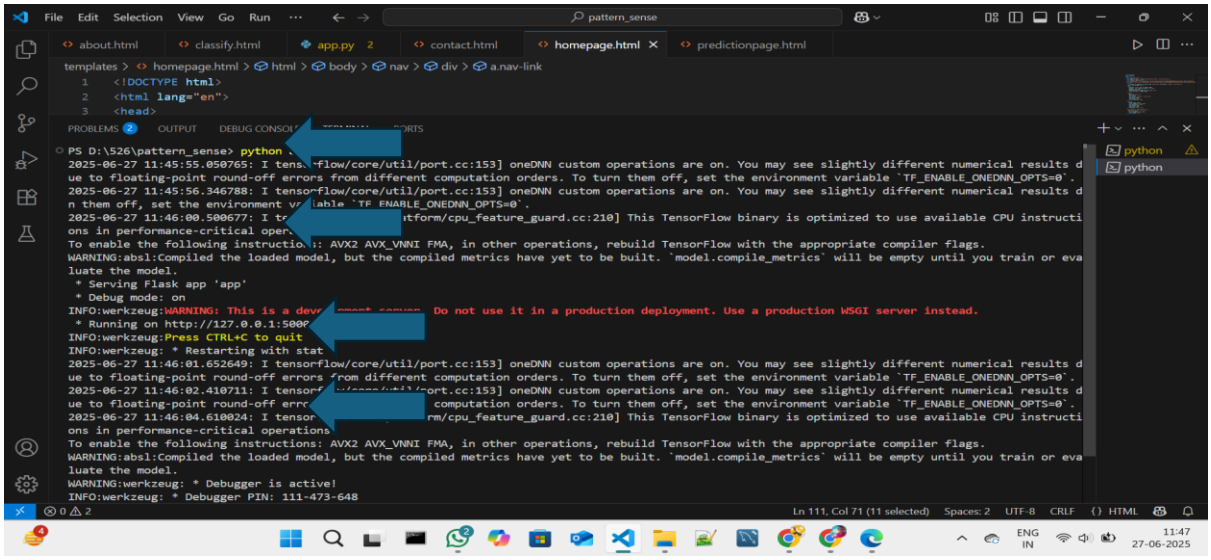


Fig 7.1.1: Code running in Terminal

Step 2: Click on that link a web page of fabric patterns will be open in the web browser.

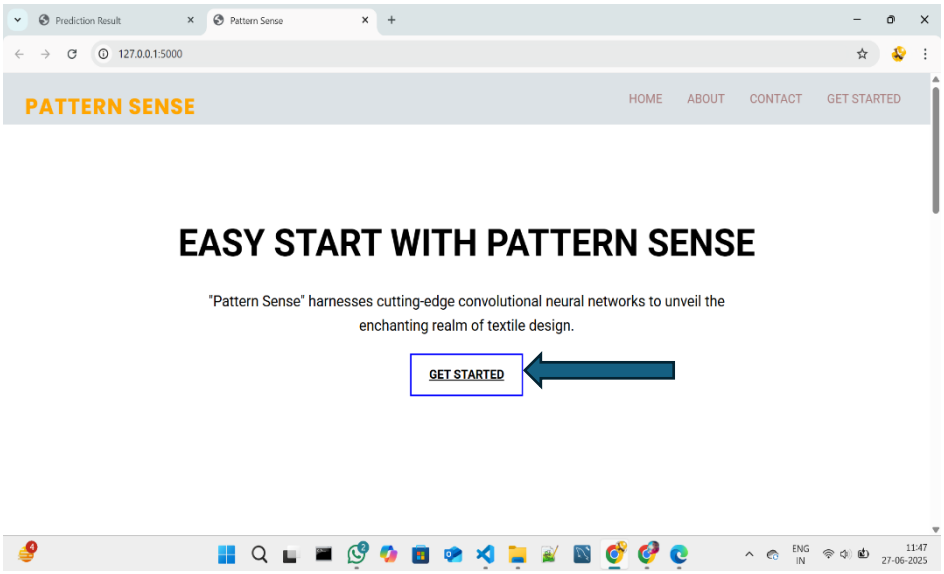


Fig 7.1.2: Fabric Pattern sense Home Page

Step 3: Click on GET STARTED or PREDICT option to open the prediction page.

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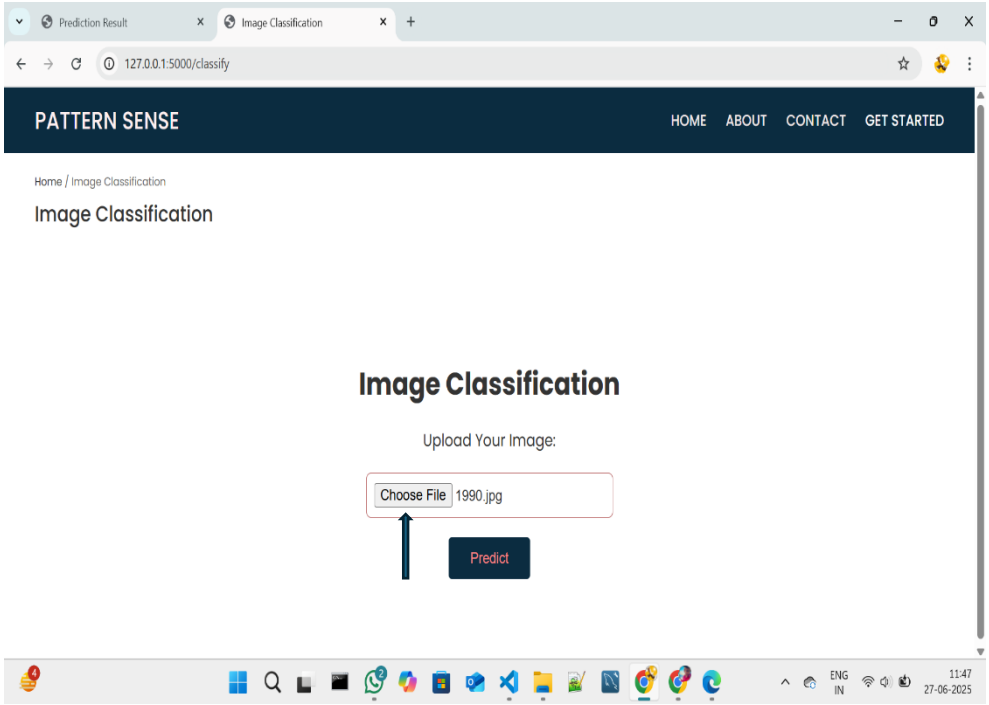


Fig 7.1.3: Prediction page in pattern sense

Step 4: Click on choose file option to choose the images that need to predict

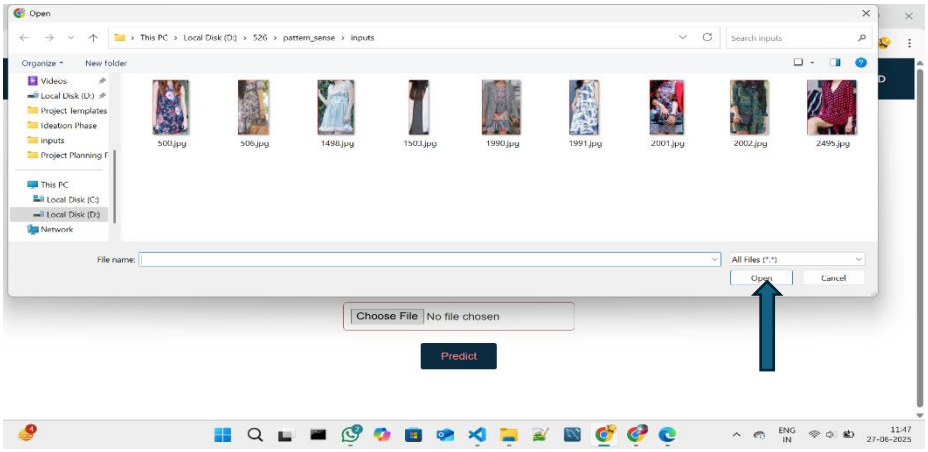


Fig 7.1.4: Window to choose image for prediction

Select any image for prediction and click on Open.

Step 5: Click on Predict to predict the quality of selected image.

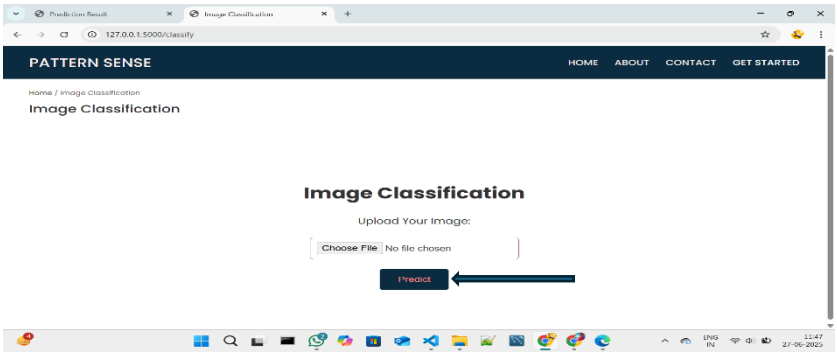
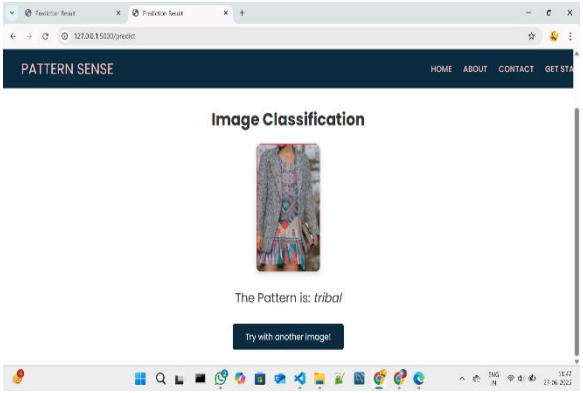


Fig 7.1.5: Image selected in prediction page

Step 6: After clicked on the predict button the model predicts the image quality and displays the quality of image.
The below images are the some of samples tested for prediction.



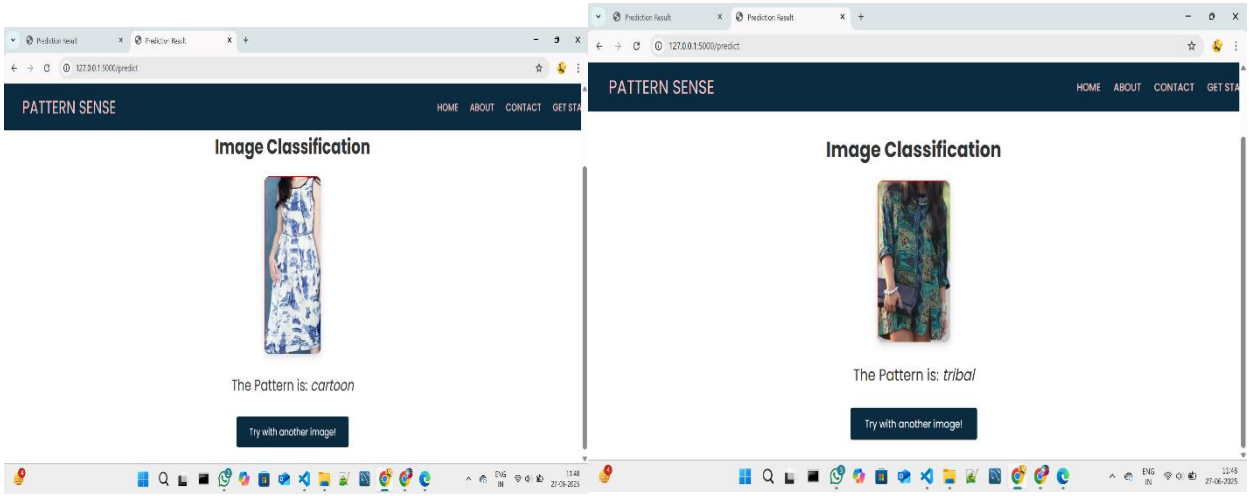
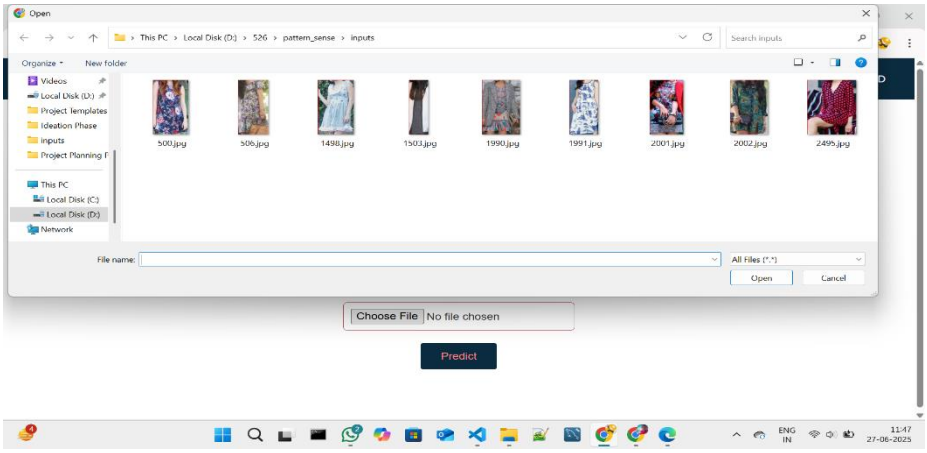
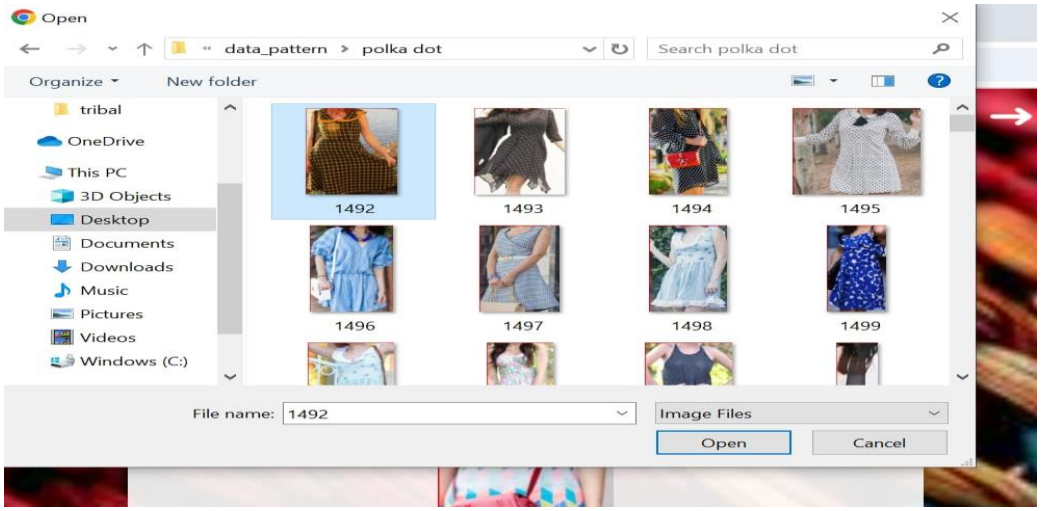


Fig 7.1.6: Prediction output for the several inputs with accuracy

After the Images Predicted the images will be stored in the uploads folder as fresh and rotten as shown in the figure given below.





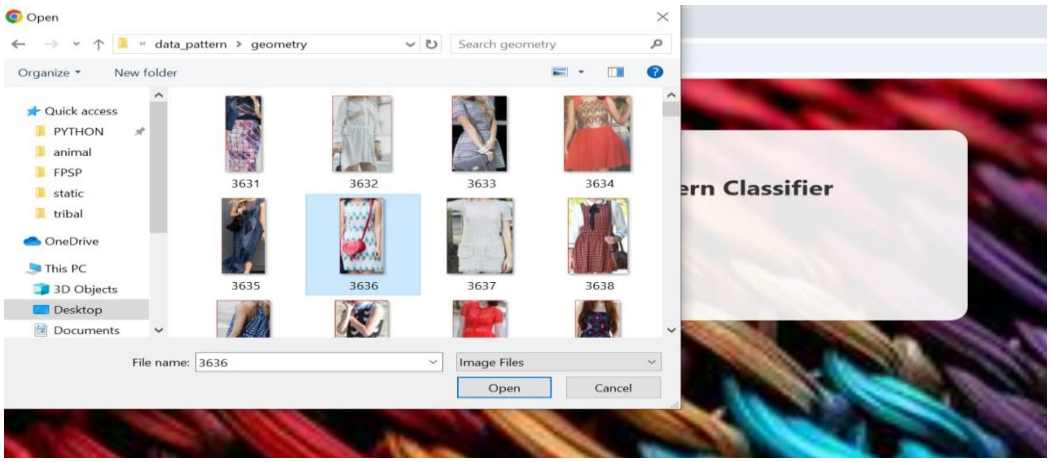


Fig 7.1.7: Folder Structure to store predicted images

Project Demo Link:

https://drive.google.com/file/d/1UrcIGw5ZFwvoOvn5i39NIdt2OKl8JVVk/view?usp=sharing

12. Known Issues

Limited & Biased Datasets

- Small dataset sizes restrict coverage of pattern diversity. Fabric image datasets are often limited (e.g., 3K–10K images), hurting generalization and risking overfitting
- Sampling bias: Majority class images dominate, underrepresenting rare patterns, so models generalize poorly to unseen types

CNN Bias Toward Texture Over Shape

- Pretrained CNNs (e.g., ResNet-50) tend to overly rely on texture, neglecting shape information. This bias can lead to misclassification under distortion or when fabrics vary substantially
- Mitigation: training with stylized-image augmentation or shape-texture debiasing methods can improve robustness

Sensitivity to Rotation, Scale, & Lighting

- Fabric textures change wildly with orientation, zoom, or lighting. Standard CNNs struggle without specific augmentation or encoding mechanisms.
- Wavelet CNNs or Deep-TEN encoding layers help gain invariance to scale and viewpoint

Insufficient Texture-Specific Feature Encoding

- Typical fine-tuning can't fully capture micro-structures in patterns. Advanced modules (e.g., Deep-TEN, bilinear pooling) improve representation but add complexity and training data requirements

Computational Bottlenecks

- High-capacity CNNs (e.g., DenseNet, ResNet) with encoding layers are expensive in memory/compute—problematic for edge devices
- Solutions include compact models, pruning, or knowledge distillation—but may reduce accuracy.

13. Future Enhancements

Topological Deep Learning for Structural Awareness

- Incorporate topological layers (e.g. persistence homology) to explicitly learn fabric's multi-scale structure and weave topology—offering robustness to distortions and enhancing texture understanding beyond pixel-level features

Multi-Modal & Depth-Enhanced Inputs

- Add RGB-D or multi-view inputs (e.g., depth maps, multi-angle captures) to capture 3D surface features like fabric drape, thickness, and texture shadows—ideal for distinguishing similar weaves

Advanced Texture Encoding Modules

- Integrate state-of-the-art modules such as Deep-TEN, wavelet-based CNNs, or mixture-enhancement + attribute clustering to learn richer, more invariant texture representations

Multi-Task Learning: Defect Detection + Classification

- Implement unified pipelines combining classification + segmentation/detection heads (e.g., MobileNetV2-SSD-FPN, YOLOv5, U-Net) to detect defects alongside pattern types in industrial contexts

Lightweight & Efficient Models

- Apply model compression, pruning, quantization, or distillation to tailor models for edge devices—enabling real-time deployment in resource-constrained manufacturing workflows

Unsupervised Anomaly Detection

- Incorporate unsupervised or self-supervised techniques (e.g., motif-based CNNs trained on defect-free fabric) to detect rare or unseen defects with minimal labelling effort

Domain Adaptation & Robustness Strategies

- Deploy advanced augmentations (adversarial, style, lighting, geometric), as well as self-training / domain adaptation approaches, to ensure stability across new fabrics, lighting conditions, and production lines

Explainability & Model Interpretability

- Use Grad-CAM, topological insights, or feature-importance mappings to highlight the fabric structures driving decisions—crucial for user trust and model validation in industrial settings.

Automated Robotic Feedback Integration

- Connect with robotic knitting/fabrication systems (e.g., reverse-engineering pipelines or CAM integrations) to adapt manufacturing based on detected pattern/defect insights.