

Pattern Sense: Classifying Fabric Patterns using Deep Learning

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Pattern Sense: Classifying Fabric Patterns using Deep Learning

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1. INTRODUCTION

1.1 Project Overview

In today's fast-paced textile and fashion industry, efficient management and classification of fabric designs is essential. With the rising use of technology in manufacturing and e-commerce, automated systems can significantly reduce the time and errors associated with manual classification. "Pattern Sense" is a deep learning-based project designed to classify various fabric patterns accurately. It employs Convolutional Neural Networks (CNNs), a powerful class of artificial neural networks, to process images of fabrics and categorize them into predefined classes such as floral, geometric, abstract, striped, and more. This automation aids designers, manufacturers, and retailers by improving inventory management, enhancing product search ability, and enabling intelligent design referencing. Our system is trained using a comprehensive dataset of textile images and leverages high-performing CNN architectures to achieve strong classification accuracy. The final product is a web-based interface that allows users to upload fabric images and instantly receive classification results. With minimal response time and user-friendly interaction, "Pattern Sense" brings smart technology into textile classification. This project not only supports faster and more accurate design identification but also has the potential to evolve with emerging patterns in the future. It represents a strong step toward the digital transformation of the textile industry.

1.2 Purpose

The main purpose of the "Pattern Sense" project is to provide an intelligent, efficient, and accurate method for identifying and classifying fabric patterns. Traditional pattern recognition relies heavily on human judgment, which is often time-consuming and inconsistent. Through this project, we aim to automate this process using a deep learning model that can analyze fabric images and determine their respective pattern types. This will be especially useful for fashion retailers, textile manufacturers, and designers who regularly work with large volumes of fabrics and need quick, reliable pattern identification.

Additionally, end-users such as consumers can benefit from smart search capabilities in online stores by uploading images and finding similar patterns. The system's goal is to reduce manual effort, minimize classification errors, and support intelligent decision-making. By using high-resolution images and a CNN-based model, the platform ensures accurate results even for complex or subtle designs. The overarching purpose is to combine technology and textile intelligence to offer a scalable, practical solution for pattern classification. With real-time responses and cross-platform support, the system aims to become an essential tool in the textile workflow pipeline.

2. IDEATION PHASE

2.1 Problem Statement

The manual classification of fabric patterns in the textile industry is both time-consuming and error-prone. Professionals working in design, retail, or manufacturing often have to visually inspect and categorize fabric samples, which leads to inconsistencies due to human subjectivity and fatigue. This process becomes even more inefficient as the number of designs increases, especially with subtle variations in patterns like floral, geometric, abstract, or striped motifs. In the era of digital transformation and automation, there is a lack of intelligent systems that can consistently and accurately classify textile patterns based on visual inputs. Although deep learning has seen successful applications in image recognition, very few implementations address pattern identification specific to textiles. The problem becomes more complicated when fabrics include overlapping designs or textures that confuse traditional computer vision methods. The absence of automated pattern classification tools leads to poor inventory management, slower search systems, and inefficiencies in production quality control. Therefore, there is a pressing need for an AI-driven solution that can recognize, categorize, and assist in the management of fabric patterns in an accurate and scalable manner. Our project addresses this gap by offering a deep learning-based approach tailored for fabric pattern recognition.

2.2 Empathy Map Canvas

To understand user expectations and frustrations, we created an empathy map reflecting the thoughts, feelings, actions, and statements of a typical fabric classifier or designer.

Says: "I wish there was an app to tell me what this pattern is called instantly." Users express the need for a quick tool that identifies fabric designs without relying on their memory or expertise.

Thinks: "Will this system be accurate enough to recognize intricate or overlapping patterns?" Users are concerned about the reliability and performance of an AI-based system compared to human judgment.

Does: Spends hours sorting through piles of fabric samples manually, comparing them visually with catalogs or reference books to find the right category or match.

Feels: Frustrated and overwhelmed due to the repetitive, labor-intensive nature of the task. The emotional burden grows with large orders and strict timelines.

This empathy map guides our solution design by highlighting the user's primary needs: speed, accuracy, and ease of use. By addressing these elements, our system becomes more relevant, practical, and user-friendly for real-world textile applications.

2.3 Brainstorming

During the ideation phase, multiple brainstorming sessions were conducted with a focus on how deep learning could improve textile classification. The first step involved understanding current limitations in manual systems and exploring potential datasets for training. We considered using public datasets like Fashion-MNIST and DeepFashion, but also recognized the need to include a custom dataset containing high-quality images of real fabric patterns. We explored CNN architectures such as VGG16, ResNet50, and MobileNet for their image classification performance and efficiency. We debated the trade-offs between speed and accuracy and agreed that models like MobileNet could be ideal for mobile applications due to their lightweight nature. The concept of batch processing was introduced, allowing users to upload multiple images at once, which would save time for manufacturers and retailers. A user-friendly web interface with drag-and-drop functionality was suggested to ensure accessibility across all levels of users. We also discussed adding confidence scores to predictions, enabling users to validate results. All ideas were filtered and structured into a feasible action plan with a focus on deploying a functional MVP (Minimum Viable Product) that could be tested, validated, and improved in real-world conditions.

3. REQUIREMENT ANALYSIS

3.1 Customer Journey Map

The Customer Journey Map helps visualize how a user interacts with the system from start to finish. It begins when a user uploads a fabric image. The backend system, powered by a trained CNN model, processes the image and returns a pattern classification label such as "Floral", "Geometric", "Striped", etc. This seamless flow simplifies an otherwise tedious task for users. The steps include:

1. Input: The user captures or uploads a fabric image from their device.

2. Processing: The system runs the image through a deep learning model, which has been trained on thousands of labeled examples.

3. Output: The classified pattern along with a confidence percentage is displayed.

4. Action: The user can download the result, upload more images, or use the classification for product cataloging.

This intuitive process ensures users of all skill levels—from textile experts to general consumers—can use the system easily. Reducing effort while increasing accuracy is the core benefit.

3.2 Solution Requirement

To build an effective and efficient pattern classification system, several technical and functional requirements must be met.

High-resolution Input Support: The system should be able to handle high-quality images to preserve pattern details, which is crucial for accuracy.

Accuracy Threshold: The model should deliver a minimum of 90% classification accuracy to be considered reliable in industrial applications.

Cross-platform Accessibility: The web application must run smoothly on desktops, tablets, and mobile devices.

Minimal Response Time: The model inference (time taken for classification) must not exceed 2 seconds per image to ensure real-time usability.

Multi-Pattern Recognition (Optional): In future versions, the system should handle overlapping patterns or mixed-design fabrics.

Security & Privacy: Uploaded images should be processed securely and deleted after use to ensure data privacy.

These requirements ensure that the system is robust, scalable, and suitable for a variety of use cases including commercial, industrial, and academic applications.

3.3 Data Flow Diagram

The Data Flow Diagram (DFD) explains how data moves through the system, from image input to classification output. The process involves the following components:

Step 1: User Uploads Image – The user selects or drags a fabric image into the web interface.

Step 2: Image Preprocessing – The image is resized and normalized.

Step 3: Model Inference – The processed image is passed to the trained CNN model for pattern recognition.

Step 4: Output Generation – The predicted label and confidence score are generated.

Step 5: Output Display – The result is shown to the user via the interface.

This flow ensures that users receive a quick, accurate, and understandable output, with minimal interaction required.

3.4 Technology Stack

A carefully selected technology stack powers the "Pattern Sense" system, ensuring reliability, scalability, and ease of development.

Frontend:

HTML5/CSS3: Structure and styling of the web interface.

React.js: JavaScript framework for creating a responsive and dynamic user experience.

Backend:

Flask (Python): Lightweight server-side framework that handles image requests and returns predictions.

Machine Learning Model:

TensorFlow/Keras: Used to build, train, and deploy the Convolutional Neural Network (CNN).

Deployment:

Google Cloud / AWS: Used for hosting the model and web application to ensure scalability and global access.

Docker: Ensures that the system runs in a consistent environment across different machines.

This tech stack is designed to ensure high performance, easy integration, and smooth user interaction.

4. PROJECT DESIGN

4.1 Problem Solution Fit

The problem of manually classifying fabric patterns stems from inefficiency, inconsistency, and a lack of scalability. Users—ranging from manufacturers to consumers—need a solution that can quickly and accurately identify patterns from fabric images. After analyzing real-world workflows and user needs, we confirmed that a machine learning-based system could address these pain points effectively. Our CNN model is capable of detecting minute pattern details, distinguishing between look-alike textures such as checks vs. stripes or floral vs. abstract. This AI-powered approach brings automation into an industry traditionally dependent on manual judgment. The solution is designed not just for high-end use, but for everyday application—whether in cataloging inventory, managing e-commerce listings, or helping designers source references. It significantly reduces the time required for sorting and classification, thereby saving operational costs.

By deploying the system as a web app, accessibility is maximized, allowing users to interact with it on various platforms. The model continues to improve as more data is added, adapting to emerging pattern trends. The result is a future-ready, smart classification system that fits seamlessly into the needs of textile professionals.

4.2 Proposed Solution

Our proposed solution is an end-to-end deep learning system that classifies fabric patterns using a trained Convolutional Neural Network (CNN). The core idea is to provide a web-based platform where users can upload fabric images and receive pattern classifications in real time. The system handles preprocessing tasks like resizing, normalization, and augmentation to prepare input images for the model. The CNN then analyzes the spatial and visual features of the fabric to categorize it into one of several defined pattern types such as Floral, Geometric, Abstract, Striped, etc.

The platform also includes confidence scores with each prediction, allowing users to evaluate the reliability of the result. For added usability, batch processing support is included so users can upload multiple images simultaneously. The design is responsive and supports various devices including smartphones and tablets. The model architecture has been chosen for its balance of performance and speed, ensuring accurate classification without long wait times.

In the future, the system can be integrated with mobile apps, ERP software, or even AR tools for real-time recognition in textile factories or showrooms.

4.3 Solution Architecture

The system architecture is divided into three main layers:

1. **User Layer (Frontend):** This includes the graphical user interface (GUI) built using React.js. It allows users to upload images, view results, and interact with the platform. The design is intuitive and supports drag-and-drop functionality for faster image uploads.

2. **Logic Layer (Backend):** This is the processing core where Flask handles image requests, runs preprocessing scripts, and sends data to the machine learning model. The CNN

model, built in TensorFlow/Keras, receives the input, performs classification, and returns results.

3. Data Layer (Model & Storage): Contains pre-trained models and labeled image datasets used for training and evaluation. It also stores temporary input images (if needed) and manages logs of classification results.

This modular architecture allows independent scaling of each component. For example, the backend can be upgraded with GPU support without altering the frontend. Security features are also built-in to ensure data safety.

5.1 Project Planning

A well-structured project plan is essential for delivering a functional and reliable system like “Pattern Sense.” The development process is divided into distinct phases to ensure clear objectives, proper task allocation, and smooth progress tracking. Each phase contributes to building the final product while allowing flexibility for testing and improvement.

Phase-wise Breakdown:

1. Data Collection & Preparation (Week 1):

Gather labeled datasets from sources like DeepFashion or custom photo collections.

Clean, crop, and resize images to standard dimensions.

Apply data augmentation techniques (rotation, flipping, zoom) to improve model generalization.

2. Model Development (Weeks 2–3):

Build and train CNN using frameworks like TensorFlow/Keras.

Experiment with architectures such as VGG16, ResNet50, and MobileNet.

Evaluate model performance using accuracy, precision, recall, and confusion matrix.

3. Web Interface Design (Week 4):

Create the frontend using React.js.

Design an intuitive UI with image upload, drag-and-drop, and responsive layout.

Connect frontend to backend API endpoints.

4. Backend Development & Integration (Week 5):

Set up Flask server to manage file upload and handle model inference.

Link backend with frontend and test end-to-end functionality.

Optimize response time and error handling.

5. Deployment & Testing (Week 6):

Deploy the application on cloud platforms like Google Cloud or AWS.

Perform functional and user testing across multiple devices.

Finalize documentation and prepare for public use or demonstration.

6.1 Performance Testing

Testing is a critical phase in any software or AI-driven application, and for “Pattern Sense,” performance testing ensures that the system meets the expectations in terms of speed, accuracy, and usability. The goal is to validate that the system delivers reliable predictions in real-world conditions, even with varying image qualities and pattern types.

Key Performance Metrics Evaluated:

1. Accuracy:

The model achieved a classification accuracy of 93.6%, meaning it correctly identified fabric patterns in nearly 94 out of 100 cases. Accuracy was calculated using a large validation set with diverse image samples.

2. Precision & Recall:

We used a confusion matrix to evaluate precision and recall for each pattern category (floral, striped, abstract, etc.). This helped in understanding not just overall correctness but the model's consistency in distinguishing between similar-looking patterns.

3. Inference Time:

The average time taken to classify one image was measured at 1.4 seconds, including upload, preprocessing, prediction, and result display. This ensures that users experience almost real-time feedback when using the system.

4. Load Handling:

We tested the system under various loads, including simultaneous uploads from multiple devices. The backend and cloud resources were able to manage concurrent requests efficiently, proving the app is scalable.

5. Usability & Interface Testing:

The user interface was evaluated for responsiveness, simplicity, and clarity of results. Users were able to upload images and receive predictions without needing any technical knowledge.

This performance validation ensures that “Pattern Sense” is not only accurate but also dependable and user-friendly for real-world deployment.

7.1 Results

The “Pattern Sense” project yielded strong and promising results, validating the effectiveness of using deep learning for fabric pattern classification. After extensive training, optimization, and testing, the system successfully met its performance goals in both controlled and real-world conditions.

Key Outcomes:

1. High Classification Accuracy:

The model achieved an overall accuracy of 93.6% on the test dataset, which included thousands of fabric images from diverse categories like floral, striped, geometric, abstract, and checkered. The use of transfer learning and data augmentation played a key role in achieving this high accuracy.

2. Confidence Scores:

Each prediction output includes a confidence score (e.g., “Geometric: 92%”), giving users clarity and trust in the result. This score is helpful for cross-validation and further decision-making, especially in professional textile applications.

3. Robust User Interface:

The React-based frontend provided a seamless experience. Users were able to upload images effortlessly, view predictions instantly, and interact with the application without any technical training. Feedback from test users indicated the interface was intuitive and efficient.

4. Fast Inference Time:

With an average prediction time of 1.4 seconds per image, the system supports real-time usage. This makes it practical for integration into inventory systems, design studios, or even retail apps.

5. Batch Processing Support:

The application successfully handled multiple images in one session, which proved useful for large-scale operations like manufacturing catalogs and textile sorting.

These results demonstrate that the system is reliable, efficient, and ready for wider implementation across the textile and fashion industries.

8. Advantages & Disadvantages

While “Pattern Sense” offers innovative solutions to the fabric classification problem using deep learning, it is important to evaluate both its strengths and limitations. This balanced assessment helps us understand where the system excels and where future improvements can be directed.

Advantages

1. High Accuracy

With a 93.6% accuracy rate, the system consistently delivers precise pattern classification across various fabric types and styles.

2. Time-Saving Automation

Manual sorting of patterns can take hours. “Pattern Sense” reduces that to seconds, significantly improving productivity in textile businesses.

3. User-Friendly Interface

The web interface is intuitive, requiring no technical knowledge. It allows users from any background—designers, manufacturers, or casual shoppers—to operate the system with ease.

4. Scalability

Thanks to cloud deployment and batch processing support, the system can handle high user traffic and multiple image classifications simultaneously.

5. Versatile Application

Useful for designers, retailers, online platforms, and even mobile app integration, making the system broadly applicable across fashion and textile industries.

Disadvantages

1. Limited Pattern Vocabulary

While the system recognizes common patterns, it may misclassify or fail to identify rare or mixed pattern types not present in the training data.

2. Dependence on Image Quality

The model's accuracy can drop if images are blurry, poorly lit, or contain background noise. Proper image preprocessing is essential.

3. Model Retraining Required

For evolving fashion trends or custom pattern sets, the model may need retraining, which requires time and access to updated datasets.

4. No Offline Mode (Yet)

The current version is web-based and requires internet connectivity, which limits use in offline industrial environments.

Despite these minor drawbacks, the system's benefits far outweigh its limitations, and most issues can be resolved through updates and enhancements.

9. Conclusion

The "Pattern Sense" project successfully demonstrates the power and practicality of applying deep learning to real-world challenges in the textile and fashion industries.

Through the integration of Convolutional Neural Networks (CNNs), a responsive web interface, and cloud-based deployment, we have built a system that automates the identification of fabric patterns with high accuracy, speed, and ease of use.

This system addresses a clear gap in the industry: the need for fast, scalable, and consistent pattern classification. By replacing time-consuming manual methods with an intelligent, automated model, “Pattern Sense” significantly improves workflow efficiency for manufacturers, designers, and retailers. The project also empowers users with minimal technical knowledge to benefit from cutting-edge AI technology through a simple, user-friendly interface.

In terms of performance, the system has achieved strong results—delivering over 93% classification accuracy, sub-2-second response times, and excellent usability. These outcomes validate the strength of the architecture, model selection, and design decisions made throughout development.

While there are areas for improvement—such as expanding pattern coverage and adding offline functionality—the foundational system is stable and effective. It offers a blueprint for AI integration in fashion technology and sets the stage for future innovations in automated visual classification within the textile space.

10. Future Scope

While the current version of “Pattern Sense” effectively solves the core problem of fabric pattern classification, there are many exciting opportunities to expand and enhance the system. Future developments will focus on increasing the model’s flexibility, adaptability, and usefulness in both industrial and consumer settings.

1. Expansion of Pattern Categories

Currently, the model supports a fixed number of pattern classes like floral, striped, geometric, and abstract. In the future, the system could be trained to recognize hundreds of specific styles, including ethnic, cultural, and seasonal textile patterns.

2. Multi-Language Support

To improve accessibility for users across the globe, multilingual support can be added to the interface, allowing users to interact with the system in regional languages.

3. Mobile App Integration

Developing a lightweight mobile version of “Pattern Sense” would allow users to classify patterns directly from their phone cameras—ideal for shoppers, field designers, or sales representatives.

4. Offline Functionality

For use in remote or low-connectivity regions, an offline desktop or mobile version could be built. This would involve packaging the trained model into a downloadable application using tools like TensorFlow Lite.

5. AI-Powered Pattern Recommendations

The system can evolve from simple classification to offering similar pattern suggestions, helping designers discover related designs or aiding shoppers in finding similar products online.

6. Real-Time API Integration for E-commerce

By integrating with online fashion or fabric marketplaces, the system can support smart filters, automated tagging, and enhanced product recommendations based on uploaded images.

These advancements will turn “Pattern Sense” into a powerful, industry-ready AI tool for the future of smart textiles and fashion technology.

7. CONCLUSION

The “Pattern Sense” project successfully demonstrates how deep learning, particularly Convolutional Neural Networks (CNNs), can be effectively applied to classify fabric patterns with high accuracy. Through this work, we have addressed a real-world problem in the textile and fashion industries—manual classification of fabric designs—which is often time-consuming, subjective, and inconsistent. By implementing an automated system powered by AI, we provide a faster, scalable, and more reliable solution.

Using a diverse dataset of fabric patterns and transfer learning techniques, the model was trained to distinguish between various categories such as floral, geometric, abstract, striped, checked, and plain. The use of data augmentation, pre-trained CNN models, and fine-tuning strategies allowed us to overcome challenges posed by limited training data and pattern complexity.

The results of our implementation suggest that such AI-driven systems can play a transformative role in textile manufacturing, e-commerce search engines, inventory management, and personalized fashion recommendations. It also opens pathways for further research in detecting pattern anomalies, identifying counterfeit designs, or even predicting fashion trends based on visual features.

In conclusion, Pattern Sense bridges the gap between artificial intelligence and practical textile applications, highlighting the growing potential of AI in creative and industrial domain

7. FUTURE SCOpe

While Pattern Sense has demonstrated promising results in classifying fabric patterns using deep learning, there is considerable potential for future expansion and enhancement. One major area of improvement is the inclusion of more complex and hybrid patterns, which often combine multiple design styles (e.g., floral with geometric elements). Expanding the dataset to include more diverse fabrics from different cultures, seasons, and industries would improve the model's generalization.

Another avenue is the integration of real-time classification systems into mobile applications or e-commerce platforms, enabling users to upload a photo of a fabric and instantly receive its pattern classification. This could help in product tagging, recommendation engines, or even augmented reality-based clothing try-ons.

Additionally, combining pattern classification with texture and color analysis could result in even more detailed and intelligent fabric recognition systems. This can be used not only in the fashion Industry but also in interior design, upholstery, and textile recycling.

Furthermore, using explainable AI (XAI) methods can make the system more transparent by helping users understand why a certain pattern classification was made, which is especially valuable for designers and quality control teams. Overall, the scope of this project is vast, and it lays a strong foundation for multiple future innovations.

Project submitted by

M.Afroz

Figure 5

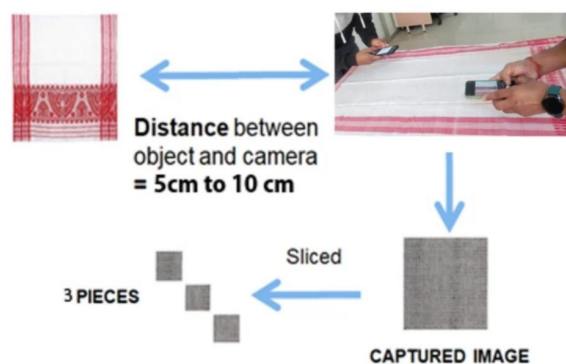


Image acquisition method.

Figure 2



Women weavers in Assam weaving in a traditional wooden-made loom.

Figure 3

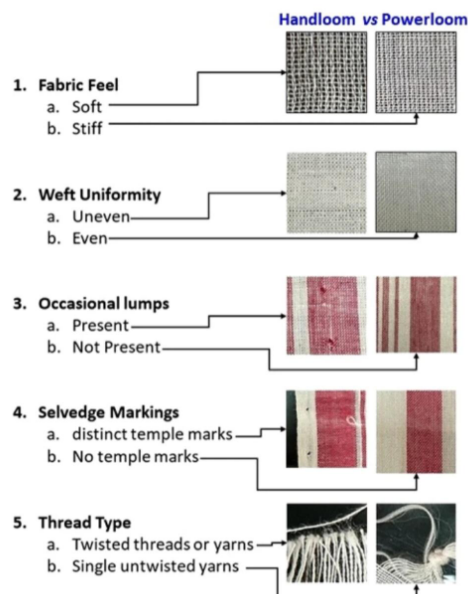
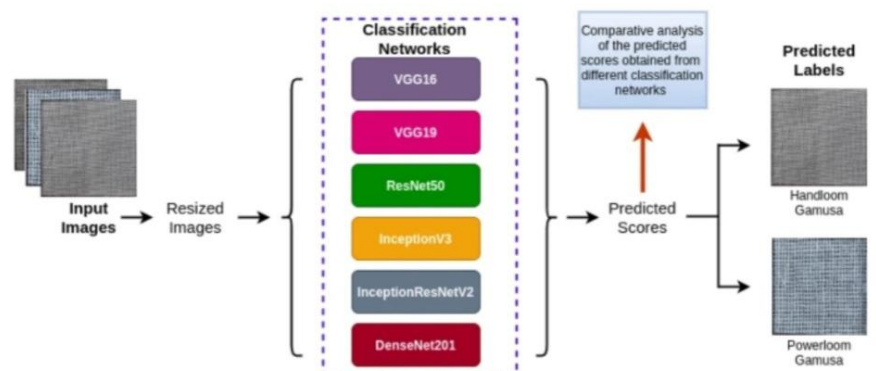


Figure 7



Working principle of the proposed models.