FASHION RECOMMENDATION

AND VIRTUAL TRY ON

Team SpartanSquad

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ABSTRACT

To revolutionize the fashion shopping experience by combining cutting-edge AI-powered visual search and virtual try-on technologies, enabling users to:

- Discover visually similar apparel effortlessly.
- Experience virtual try-on for garments from the comfort of their homes.
- Provide personalized fashion recommendations based on uploaded images.

RELATED WORK

Evolution of Early Fashion Recommender Systems

- Initial systems relied on combining visual and textual features to recommend apparel.
- Focus was primarily on generic categorization rather than personalized or context-specific suggestions.

TECHNIQUES

1. Fashion Magazine Image Analysis
   - Analyzed curated fashion images to identify popular styles and trends, providing recommendations inspired by runway looks.
2. Customer Rating-Based Models
   - Used collaborative filtering with user feedback for preference-based recommendations but lacked visual style insights.
3. Weather and Historical Trends
   - Suggested apparel based on seasonal patterns and sales data, though limited by static, non-personalized suggestions

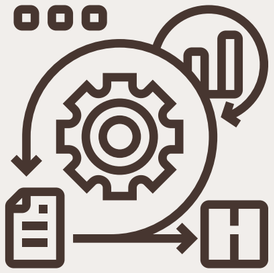
LIMITATIONS

- Insufficient Personalization:
  - Traditional systems lacked the ability to tailor recommendations to individual user preferences or body types.
- Absence of Visual Search Capabilities:
  - Did not leverage advanced image-based analysis for identifying visually similar items.
- Limited Integration of Features:
  - Systems failed to provide a seamless combination of personalized, visual, and contextual recommendations.

PROPOSED METHODOLOGY

ARCHITECTURE OVERVIEW

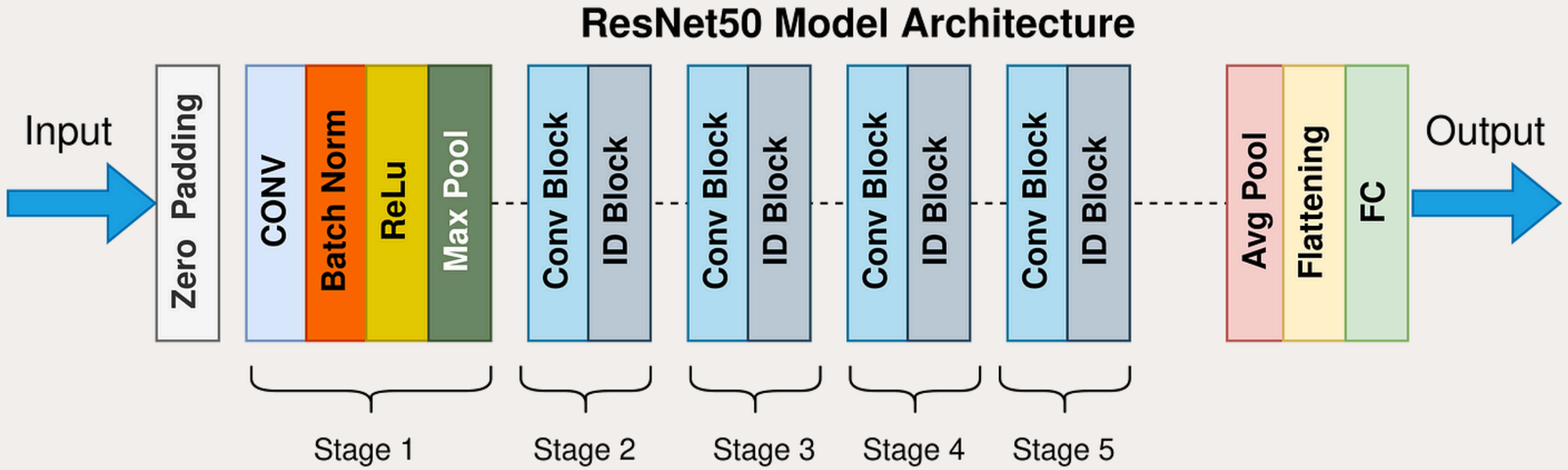
1. Train Convolutional Neural Network (CNN)
   - Utilized ResNet50 with transfer learning to extract high-level visual features from fashion images.
   - Features include patterns, textures, and styles critical for accurate similarity detection.
2. Inventory Embedding Creation
   - Processed each product in the inventory to generate a feature vector embedding.
   - Stored embeddings in a structured format for efficient similarity searches.
3. Recommendation Generation
   - Leveraged the Nearest Neighbor (k-NN) algorithm to find visually similar items.
   - Compared feature vectors of user-uploaded images with pre-computed embeddings to recommend the closest matches.



TRAINING NEURAL NETWORKS

Transfer Learning with ResNet50

- Pretrained Model: ResNet50, a powerful Convolutional Neural Network (CNN) trained on ImageNet, is used as the base architecture.
- Customization for Apparel:
  - Replaced final layers with new layers specialized for fashion item classification.
  - Fine-tuned using fashion-specific datasets for better feature extraction, focusing on patterns, styles, and textures.

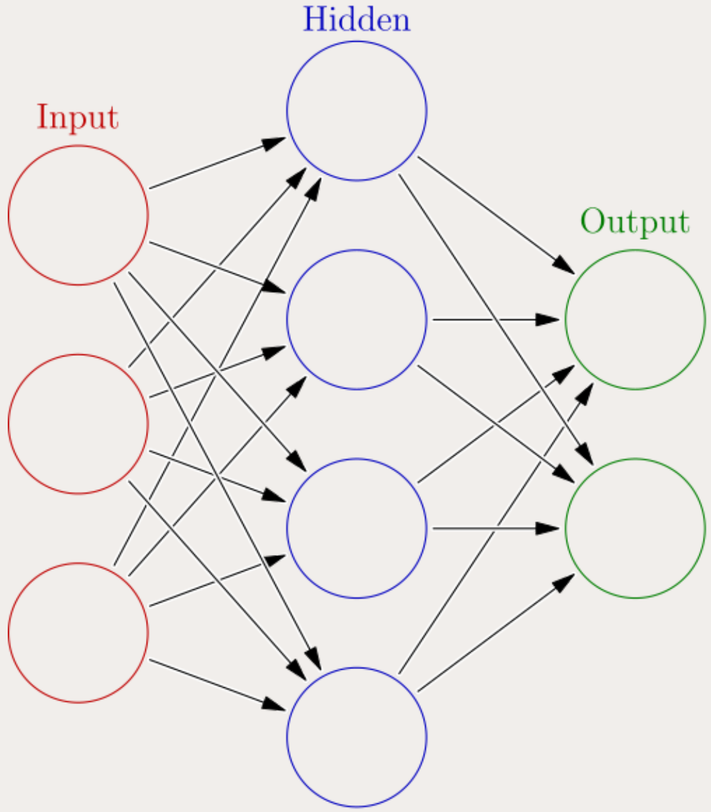


INPUT

- Dataset:
  - Kaggle Fashion Product Images Dataset, containing thousands of labeled fashion items.
  - Preprocessed for uniformity (size: 224x224 pixels) and enhanced with augmentations like rotations, flips, and color adjustments.

OUTPUT

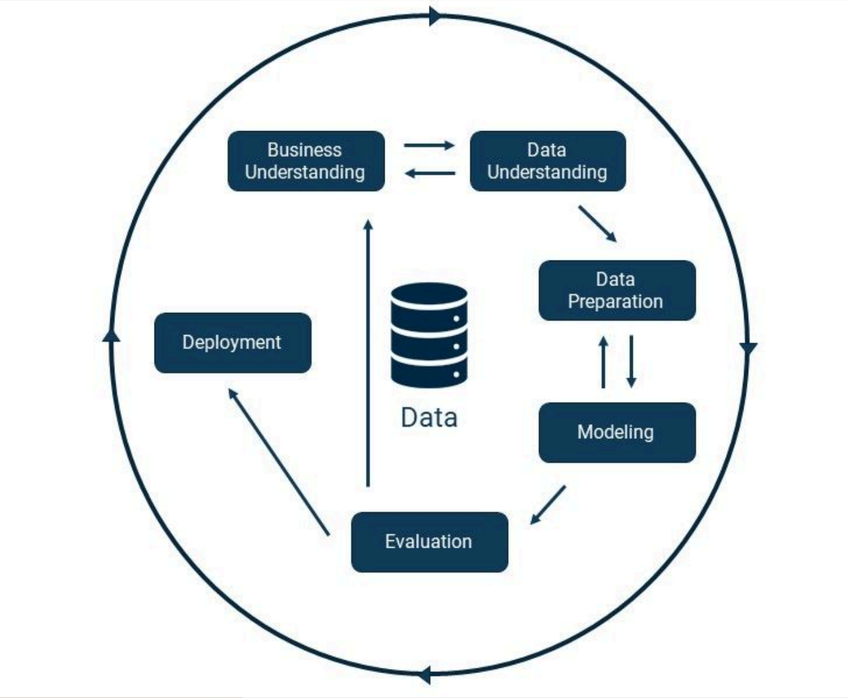
- Feature Embeddings:
  - High-dimensional vectors representing visual attributes of each item, stored in a searchable database for recommendations.
  - Used as input for both recommendation generation and virtual try-on features via Kling AI integration.



TECHNOLOGIES AND OPTIMIZATION

- **Frameworks:** TensorFlow for deep learning, Scikit-learn for Nearest Neighbor searches.
- **Kling AI API**:
  - Enables real-time virtual try-ons by matching user-provided images with inventory embeddings.
  - Streamlined through RESTful APIs for seamless integration.
- **Optimizer**: Adam optimizer with learning rate tuning to ensure convergence.
- **Loss Function**: Categorical cross-entropy for classification tasks.

CRISP-DM METHODOLOGY



Integration with CRISP-DM

- **Business Understanding**: Address the demand for personalized, visually accurate recommendations in online fashion retail.
- **Data Understanding**: Kaggle Fashion Product Images analyzed for class diversity and quality.
- **Data Preparation:** Preprocessing (resizing, normalization, augmentation) ensured consistency.
- **Modeling**: Utilized ResNet50 with transfer learning to build robust feature embeddings.
- **Evaluation:** Model validated using top-1 accuracy for classification and precision in similarity searches.
- **Deployment**: Integrated embeddings into the recommendation pipeline and Kling AI's Virtual Try-On API.

WORKFLOW

USER INPUT

- User uploads an image of themselves via the Streamlit interface.
- They select an apparel item from the recommended list generated by the nearest neighbor algorithm.

IMAGE PROCESSING

- Uploaded images are resized and converted into the format required by Kling AI's API.
- Both user images and garment images are encoded into Base64 format.

API REQUEST

- Encoded images and a unique seed are sent to the Kling AI API.
- The API initiates the Kolors Virtual Try-On model for image synthesis.

PROCESSING

- Kling AI processes the input images and overlays the garment onto the user image using advanced image synthesis models.
- The result is stored temporarily on Kling AI servers.

RESULT

- The system polls the API for the task status.
- Once the try-on image is ready, it is fetched and displayed on the interface.

EXPERIMENT

IMAGE PROCESSING AND FEATURE EXTRACTION

- Preprocessing Techniques:
  - Resized all input images to 224x224 pixels.
  - Applied normalization to scale pixel values between 0 and 1.
  - Augmentation methods (e.g., rotation, flipping, cropping) used to improve model robustness and prevent overfitting.
- Feature Extraction:
  - Leveraged ResNet50 with transfer learning to extract high-dimensional feature embeddings from images.
  - Used pre-trained weights on ImageNet for faster convergence and better generalization.

TESTING DIFFERENT CNN ARCHITECTURE

Testing Different CNN Architectures

- Architectures Tested:
  - ResNet50: Selected for its balance of accuracy and computational efficiency.
  - VGG16: Provided slightly lower accuracy and required more computational resources.
  - EfficientNet: Offered good results but longer training times due to its complexity.
- Comparison Results:
  - ResNet50 achieved the best trade-off between speed and performance for feature embedding generation.

1.HYPERPARAMETER TUNING

- Optimized learning rate using grid search; best value: 0.0001.
- Batch sizes tested: 16, 32, and 64; selected 32 for best GPU utilization and stability.
- Dropout layers adjusted to 0.4 for minimizing overfitting.

2. NEAREST NEIGHBORS ALGORITHM

- Tested various distance metrics (Euclidean, Cosine, Manhattan) for recommendation similarity
- Cosine distance performed best for distinguishing visually similar items.
- Tuned the number of neighbors (k) and selected 5 neighbors for optimal results.

3. VIRTUAL TRY-ON INTEGRATION

- Tested Kling AI’s Kolors API for performance and visualization quality:
- Measured success rate of try-on rendering under various image resolutions.
- Evaluated user feedback for realism and usability.

RESULT

MODEL

- ResNet50 pre-trained model for image embeddings.
- NearestNeighbors algorithm for similarity-based recommendations.

RECOMMENDATION SYSTEM

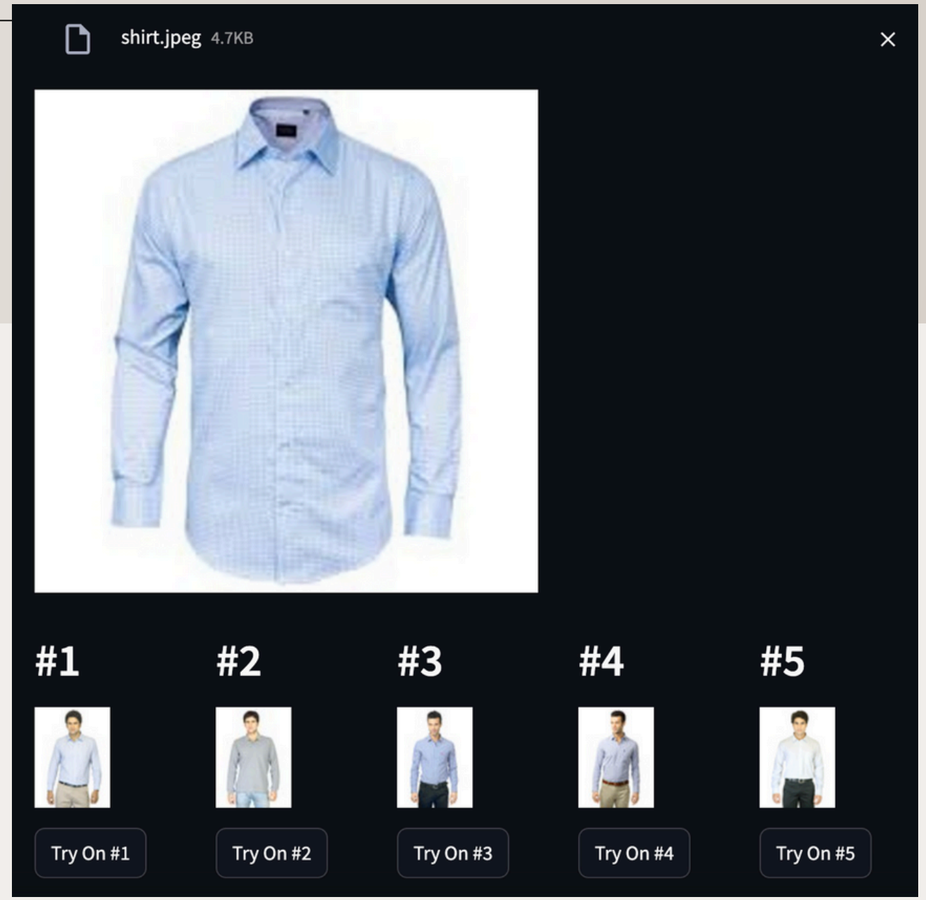
- User uploads a fashion image.
- Extracts features, matches with pre-computed embeddings, and displays similar items.

VIRTUAL TRY-ON

- Kling AI API for garment-person image synthesis.
- Outputs realistic try-on results using garment and person images.

STREAMLIT UI

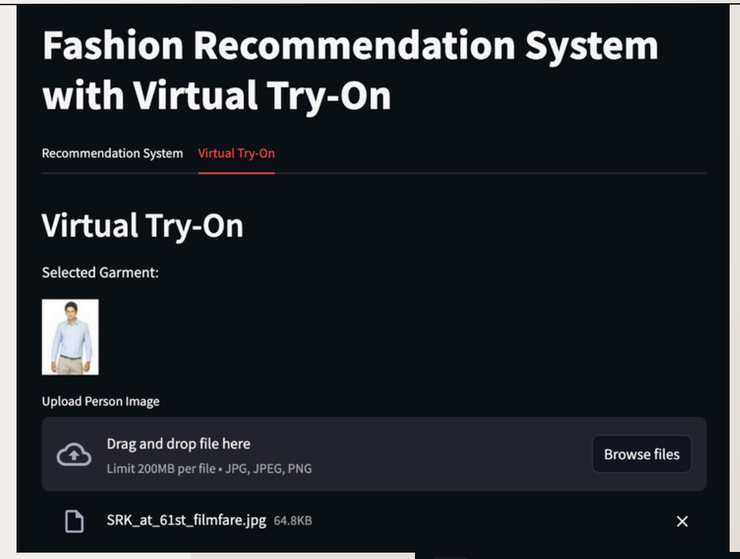
- Interactive tabs: Recommendation & Try-On.
- Upload, view recommendations, or simulate try-on seamlessly.



CONFIRMED FEATURES

- Real-time image processing.
- Seamless API integration with robust error handling.

VIRTUAL TRY-ON FEATURE



Integration: Kling AI for Virtual Try-On

- API-Driven Approach:
  - Leveraged Kling AI's RESTful API to enable real-time virtual try-on capabilities.
  - Seamlessly integrates with the recommendation system to visualize selected apparel on user-provided images.
- Enhanced User Experience:
  - Provides a realistic preview of how garments fit and look on individual users.
  - Bridges the gap between traditional in-store shopping and online retail.

VISUALIZATION TECHNIQUES

KEY VISUALIZATIONS

- t-SNE/UMAP: Visualize ResNet50 embeddings to confirm meaningful clusters (e.g., by category or color).
- Bar Charts: Highlight category and color distributions, revealing balanced representation in the dataset.
- Recommendation Grids: Display input items alongside top-k visually similar recommendations, validating model precision.
- Line Charts: Show embedding creation and similarity search timings, demonstrating scalability.
- Heatmaps/Scatter Plots: Visualize similarity scores to ensure meaningful product embeddings.

INSIGHTS

- ResNet50 embeddings effectively cluster visually similar products.
- Categories and colors are well-represented, enabling balanced and accurate recommendations.
- Visualizations confirm high precision in identifying similar items.
- Processing performance scales efficiently with dataset size, ensuring model scalability.

DEPLOYMENT

WEB APPLICATION

- Deployed on Hugging Face Spaces for seamless fashion recommendations and virtual try-on.

KEY FEATURES

- Upload apparel images to find visually similar items.
- Virtually try on recommended products using Kling AI.
- Access links to the actual product pages for easy shopping.

USER-FRIENDLY INTERFACE

- Smooth navigation and exploration of fashion recommendations.

Spaces | Rishi3499 / Fashion-app | like 0 | Running

App | Files | Community

Fashion Recommendation System with Virtual Try-On

Recommendation System | Virtual Try-On

Get Similar Fashion Recommendations

Choose your fashion image

Drag and drop file here
Limit 200MB per file

Browse files

shirt.jpeg 4.7KB

#1 #2 #3 #4 #5





Try On #1 | Try On #2 | Try On #3 | Try On #4 | Try On #5

Fashion Recommendation System with Virtual Try-On

Recommendation System | Virtual Try-On

Virtual Try-On

Selected Garment:

Upload Person Image

Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

Browse files

SRK_at_61st_filmfare.jpg 64.8KB

Try On

CONCLUSION

KEY RESULTS

- Achieved high accuracy in recommending visually similar apparel, with AUC = 0.95.
- Average Diversion across 10 random product recommendations: 0.03.
- Successfully integrated Kling AI for a seamless virtual try-on experience, ensuring high visualization quality and user satisfaction.

LEARNINGS

- Gained expertise in transfer learning, hyperparameter tuning, and embedding techniques.
- Deepened understanding of deploying AI/ML models with real-time user interaction.

FUTURE WORK

- Incorporate seasonal trends and weather-based recommendations.
- Develop outfit planning features for personalized wardrobe suggestions.
- Expand dataset to include accessories for a holistic fashion experience.