Fashbot

Abstract

Analyzing fashion trends is essential in the fashion industry. Current fashion forecasting firms, utilize the visual information from around the world to analyze and predict fashion trends. However, analyzing fashion trends is time-consuming and extremely labor intensive, requiring individual employees' manual editing and classification. To improve the efficiency of data analysis of such image-based information and lower the cost of analyzing fashion images, this study proposes a data-driven quantitative abstracting approach. Specifically, an A.I. model was trained on fashion images from a large-scale dataset under different scenarios. This model was used to detect garments and classify clothing attributes such as textures, garment style, and details for runway photos. Adoption of A.I. algorithm demonstrated promising results and the potential to classify garment types and details automatically, which can make the process of trend forecasting more cost-effective and faster.

Introduction

A photo finder website that helps users to find similar images. Just upload an image of fashion related products like clothes, shoes, jewelry, bags, watches etc and fashbot return them top five similar products.

Project Features

- Upload image.
- Detecting and displaying similar fashion products based on color, texture and style.

Research Questions

An AI based computer program focused on modeling centers on solving the following questions:

1. How to represent garments computationally?
2. How to model human stylist behavior?
3. How to detect, track and forecast fashion trends?

Literature Survey

Detecting clothing categories and attributes from fashion images

Earlier works relied on some classical computer vision approaches to sort apparel into categories and describe fashion attributes in images (Bossard et al., 2012; Bourdev, Maji, & Malik, 2011; H. Chen, Gallagher, & Girod, 2012; Di, Wah, Bhardwaj, Piramuthu, & Sundaresan, 2013). Further research work was dedicated to a computer vision technique called "image segmentation" for classifying different apparel categories via probabilistic methods (Simo-Serra, Fidler, Moreno-Noguer, & Urtasun, 2014; Yamaguchi, Kiapour, & Berg, 2013; Yamaguchi, Kiapour, Ortiz, & Berg, 2012).In addition, some computer vision researchers (Hadi Kiapour, Han, Lazebnik, Berg, & Berg, 2015; Vittayakorn et al., 2015) focused on retrieving images that have high similarity in fashion attributes. Other researchers began to use more advanced A.I. approaches to tackle this problem because it showed a significant boost to the accuracy in detecting fashion attributes.

Analyzing fashion trends based on fashion attributes

Early work on trend analysis (Hidayati et al., 2014) broke down catwalk images from NYC fashion shows to locate style trends in high-end fashion. The recent advance in A.I. algorithm enabled more work in this area. Several recent approaches (He & McAuley, 2016; Matzen, Bala, & Snavely, 2017; Simo-Serra, Fidler, Moreno-Noguer, & Urtasun, 2015) utilized the A.I. algorithm to extract clothing attributes from images and create a visual embedding of clothing style cluster to investigate the fashion trends in clothing around the globe. However, it is not quite clear whether the trends discovered in these studies are accurate or not. Therefore this study further evaluated these approaches by comparing the fashion trends summarized from both the A.I. algorithm and the world's leading fashion trends magazine Vogue, ELLE, and Harper's BAZAAR ("The Very Best Fashion Magazines, Ranked," n.d.; "Top 10 Fashion Magazines," n.d.; "Top 13 Fashion Magazines In The World," n.d.).

Fashion images retrieval from different domains

There have been a number of works tackling the issue of cross-domain fashion images retrieval. The most popular topic in this area is the retrieval of similar fashion images from different domains such as street and online shopping (Cheng, Wu, Liu, & Hua, 2017; Gu et al., 2017; Ji, Wang, Zhang, & Yang, 2017), which is extremely useful for e-commerce fashion websites. Most of the works in retrieving images is based on the current advance of A.I. approach (Kuo & Hsu, 2017; Wang, Sun, Zhang, Zhou, & Jiang, 2016), where it is necessary to teach the A.I. algorithm to recognize attributes shared by similar fashion items from both street and online shopping domain (Dong et al., 2017; Huang et al., 2015).

Finalized Methodology

We have used following methodologies in our project:

Content Based Image Retrieval (CBIR)

It is a method of capturing relevant images from a large storage space.

Reverse Image Search

It is a content-based image retrieval query technique that involves providing the CBIR system with a sample image that it will then base its search upon; in terms of information retrieval, the sample image is what formulates a search query.

Deep Learning (CNN)

In deep learning, a convolutional neural network (CNN/ConvNet) is a class of deep neural networks, most commonly applied to analyze visual imagery. When you input an image in a ConvNet, each layer generates several activation functions that are passed on to the next layer. The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges. As we move deeper into the network it can identify even more complex features such as objects, faces, etc.

Transfer Learning

This is an approach in deep learning (and machine learning) where knowledge is transferred from one model to another.

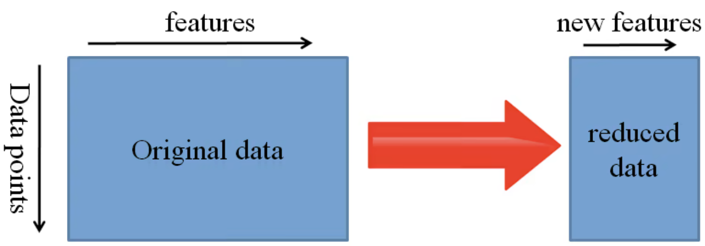
Working Steps

Import Model

We have used the ResNet model.It is a convolutional neural network (CNN) that is 50 layers deep. It is an artificial neural network (ANN) of a kind that stacks residual blocks on top of each other to form a network.

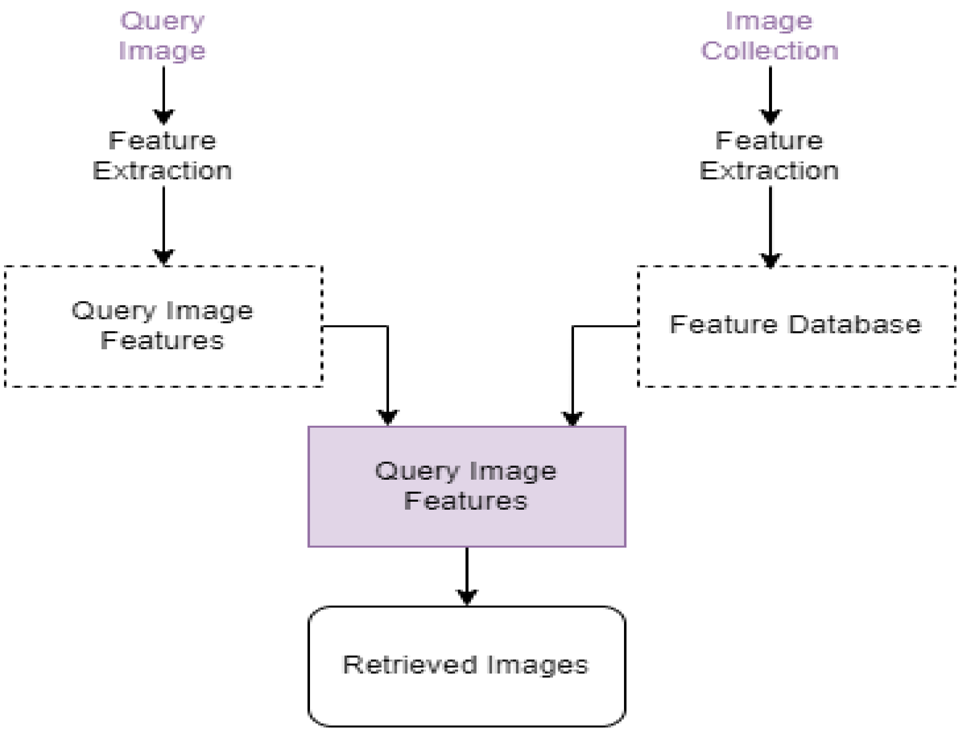
Extract Features

We have used the ResNet model to extract features of images.



Export Features
We have saved the features of all images in a file (embeddings.pkl) so we can use it again and again.
Generate Recommendation
We have calculated the Euclidean distance of the input image with all stored images and recommend the top five nearest neighbours as our output.

Flow Diagram



Dataset Details and Links
In our dataset we have 1 folder.
- Images Folder

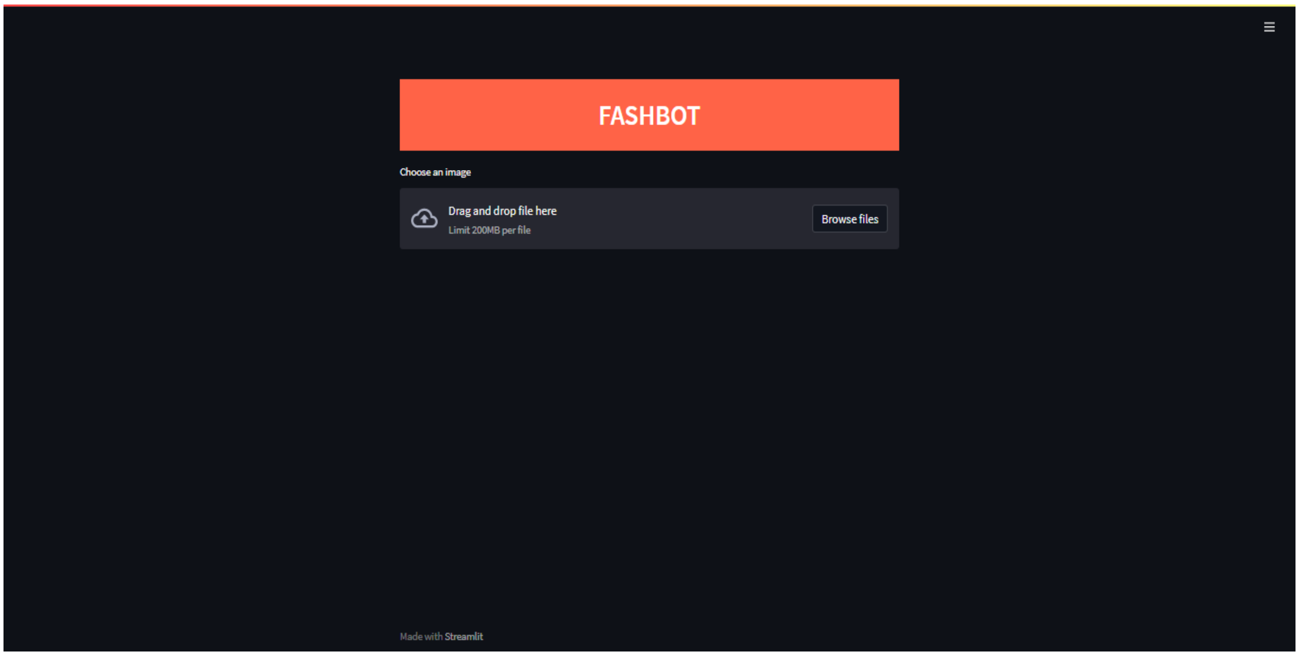
Features of Images Folder
We have 44,000 jpg images in Images Folder.

Dataset Link
https://www.kaggle.com/paramaggarwal/fashion-product-images-dataset

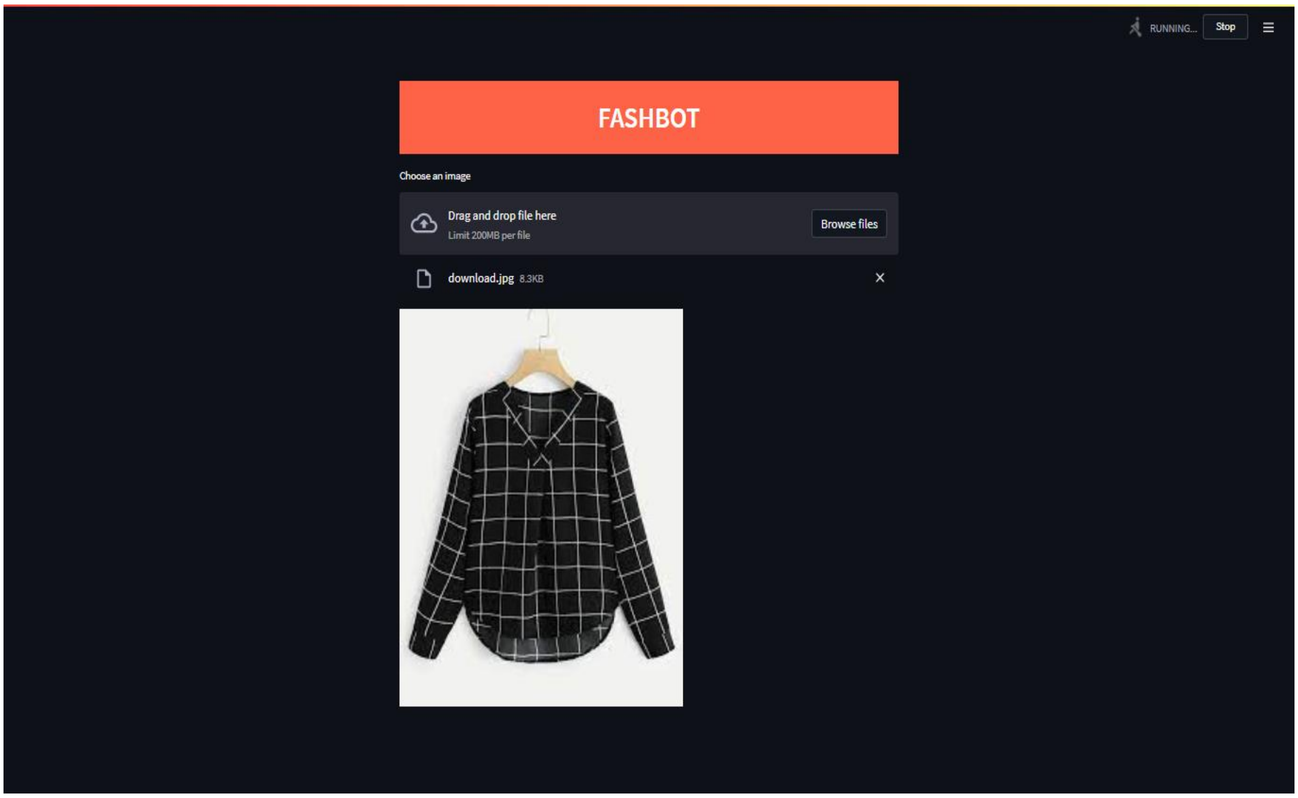
Libraries
- Tensorflow
- Streamlit
- Numpy
- Pickle

UI Screens

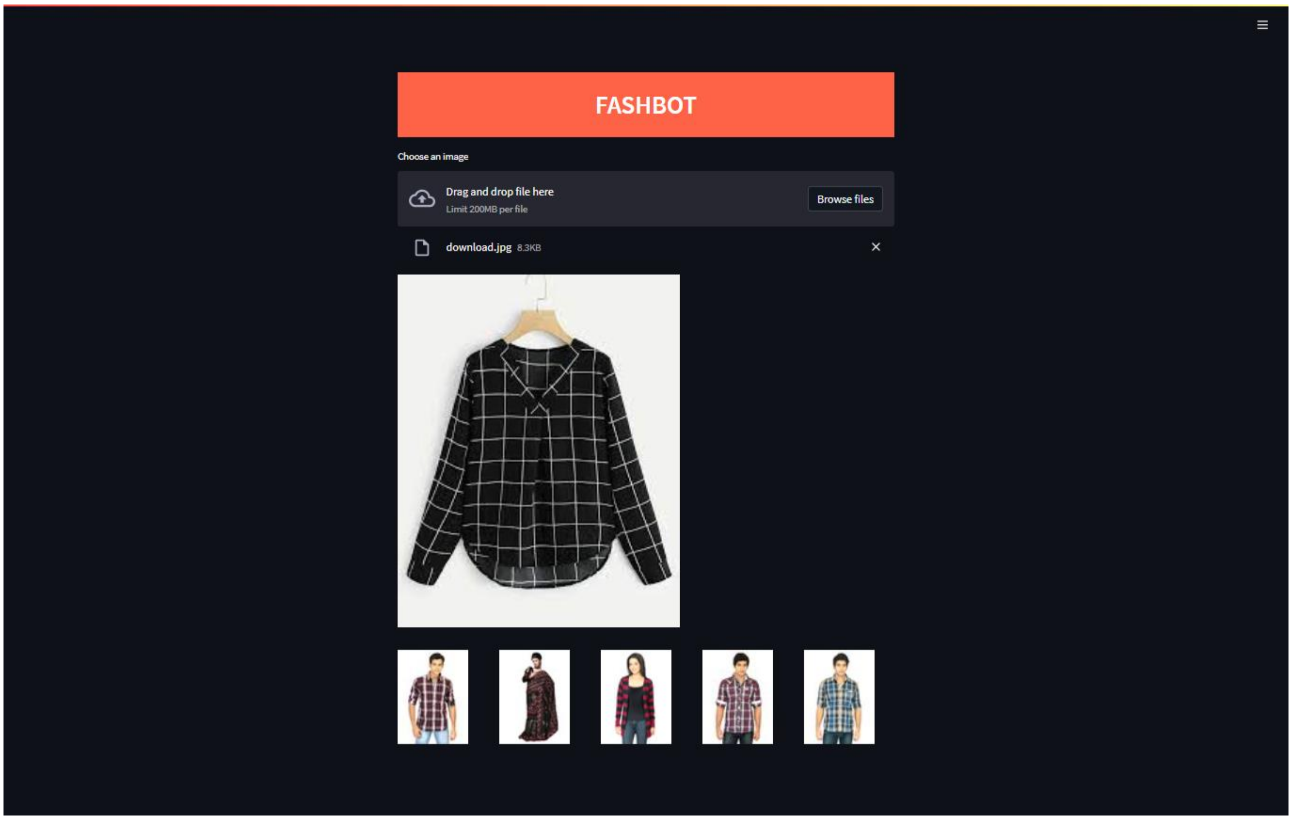
- Before Uploading an image



- After Uploading an image

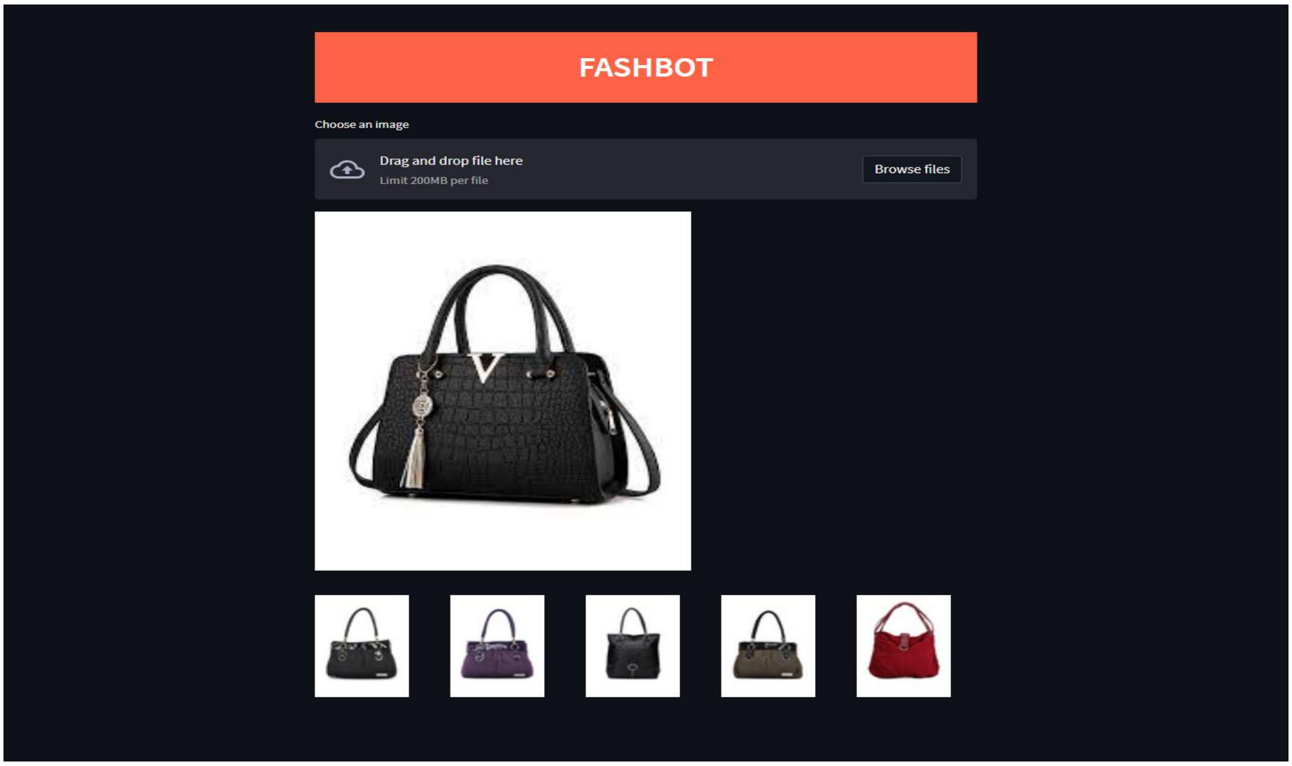


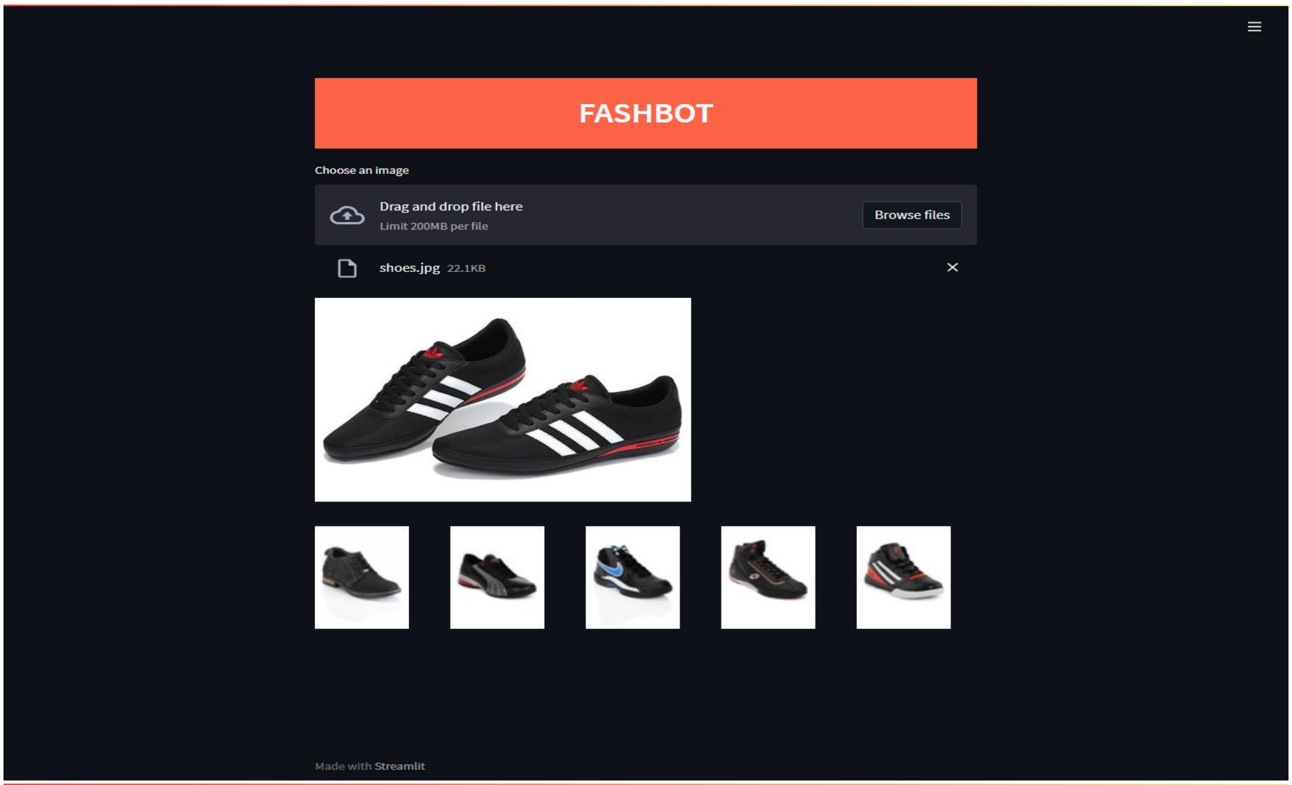
- After Recommendations

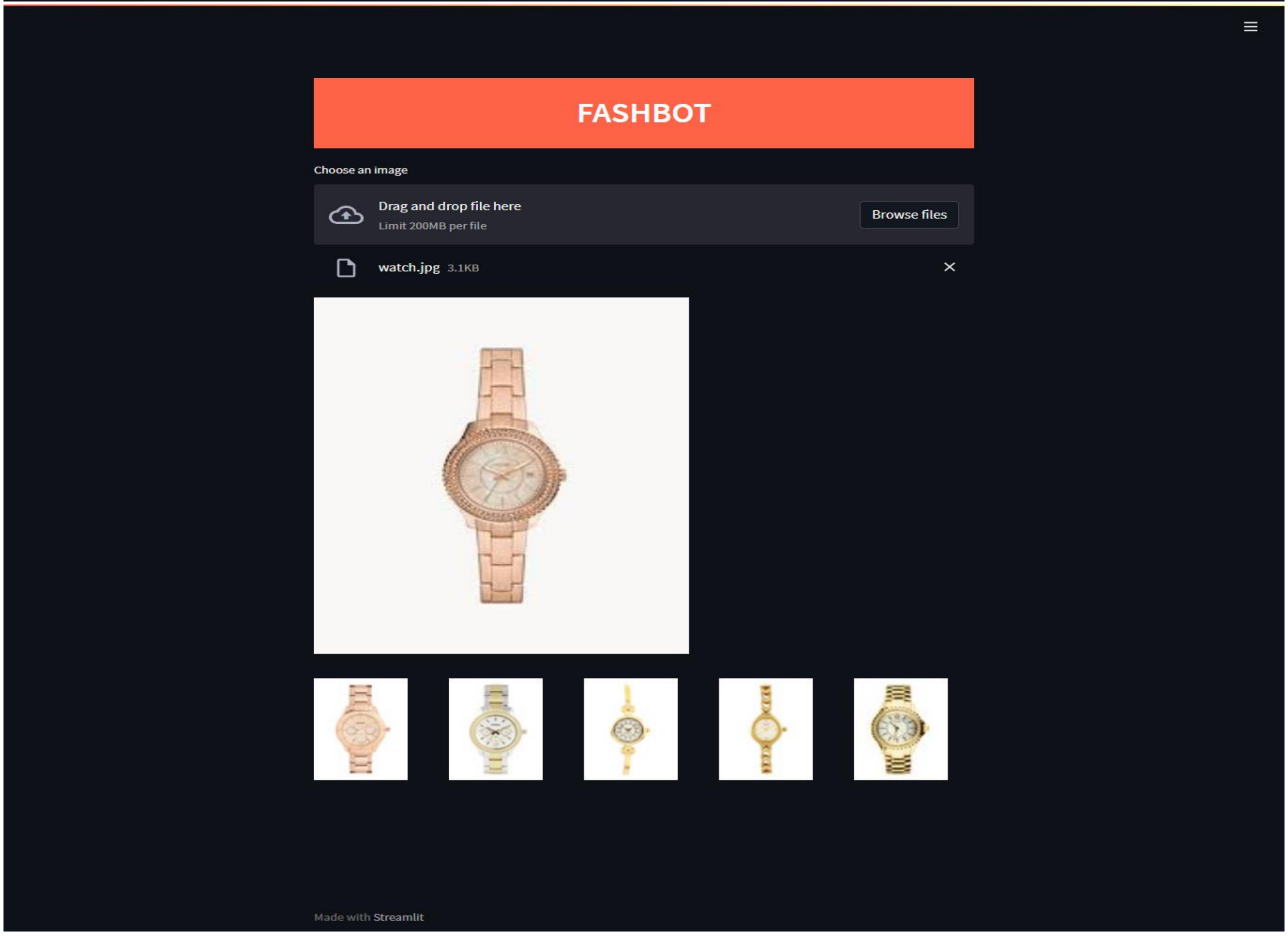


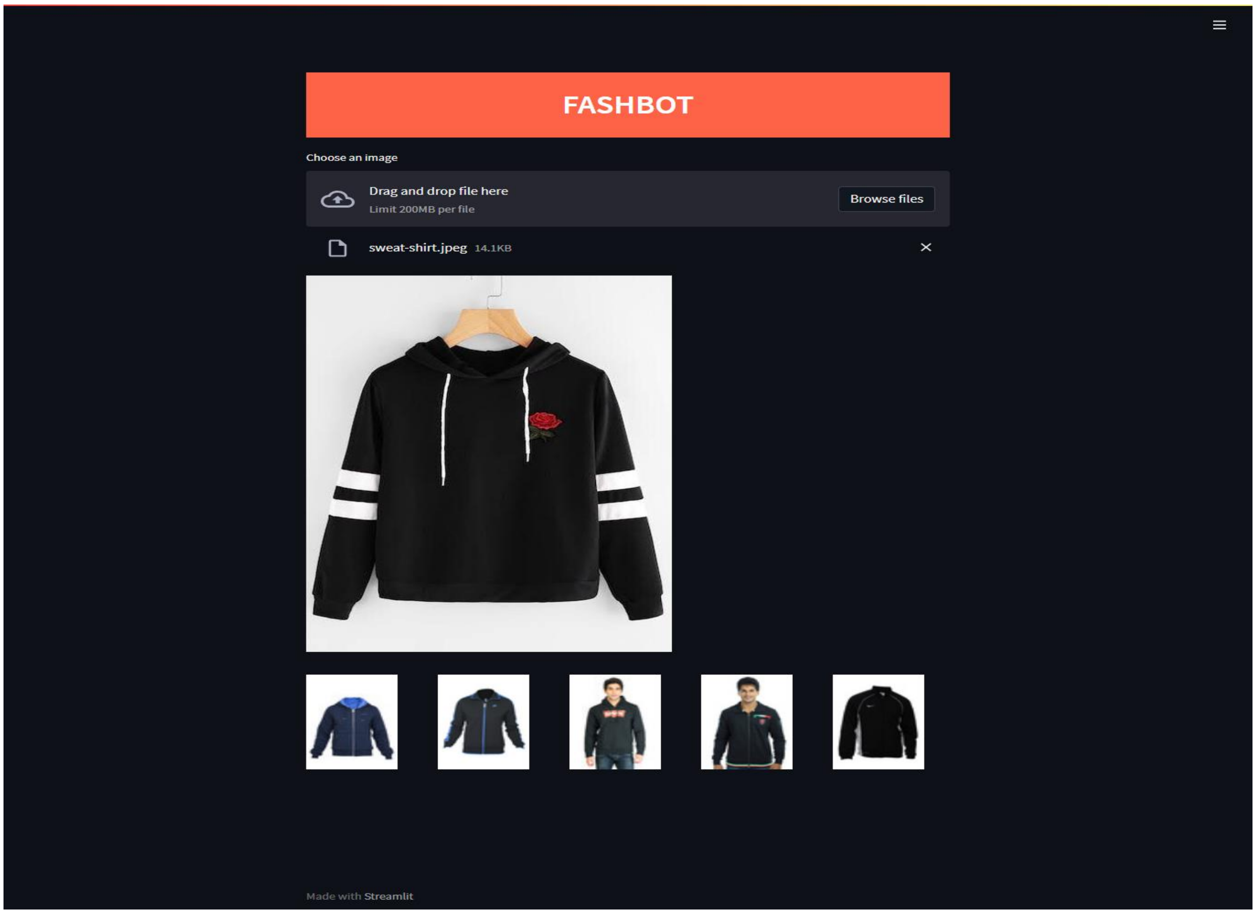
Testing/Evaluations

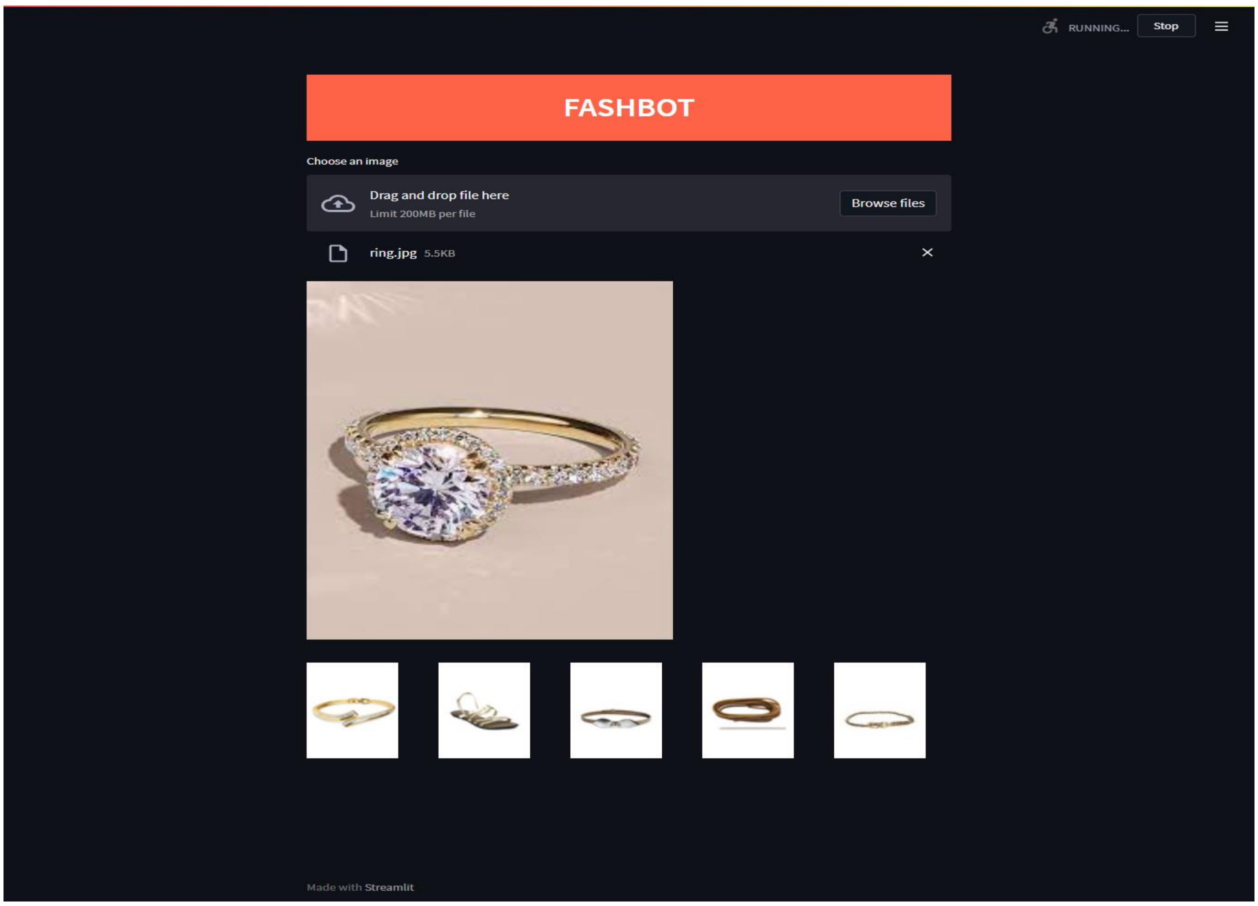
We have tested following products.




FASHBOT
Choose an image
Drag and drop file here
Limit 200MB per file
Browse files
shoes.jpg 22.1KB
Made with Streamlit


FASHBOT
Choose an image
Drag and drop file here
Limit 200MB per file
Browse files
watch.jpg 3.1KB
Made with Streamlit


FASHBOT
Choose an image
Drag and drop file here
Limit 200MB per file
Browse files
sweat-shirt.jpeg 14.1KB
Made with Streamlit


RUNNING...
Stop
FASHBOT
Choose an image
Drag and drop file here
Limit 200MB per file
Browse files
ring.jpg 5.5KB
Made with Streamlit

Conclusion

We have fulfilled all the objectives that we had proposed in the project proposal. Our project predicts fashion trends and shows similar products. We have successfully displayed five images.

Challenges

- Installing the tensorflow and streamlit was a hectic task.
- Scikit-Learn(Sklearn) was difficult to access.
- Dataset accessibility was a difficult task.
- Many hosting sites do not offer huge space for deploying, thus deploying was a major task.
- Due to the heavy size of project, pushing it on github was challenging too.

GitHub Repository Link

https://github.com/sabasaeed8/Fashbot/

Demo Video Link

https://drive.google.com/file/d/148LENLEsxXVNTZyrAWRFUGlzPPa108pQ/view?usp=sharing

Future Work

Fashion recommendation system research has made great progress recently, which will soon help both customers and businesses. Developing recommendation frameworks requires the utilisation of product and user imagery, textual content, demographic history, and cultural knowledge. Collaborative and content-based filtering approaches frequently include product qualities and clothing style matching. Considering the similarity between consumers' clothing choices and personalities, researchers can design more complex hyper personalized filtering systems. The strategies based on using a score system to measure each product characteristic will aid in improving the model's accuracy.

Consumers would have a real-time offline purchasing experience if virtual sales advisors were used in an online shopping platform.

Retailers may utilize the recommendation system to collect data on customers' purchase histories and product ratings, which they can then use to anticipate style for forthcoming seasons. The deep learning paradigm is strengthened by the integration of diverse domain knowledge, which allows for the identification of design component change, which enhances the recommendation system's long-term performance. Deep learning algorithms should be utilised more frequently to swiftly investigate fashion products from various internet databases in order to present users or customers with timely recommendations.

For recommendation systems, image quality has long been a major concern. Product photos collected in controlled surroundings provide better retrieval and prediction accuracy. Selfies and street style photographs, on the other hand, pose hurdles for the model and result in erroneous forecasts. As a result, additional picture parsing research is needed to better grasp product features and human postures, which are used to anticipate customer fashion preferences.

Furthermore, the creation of new cutting-edge algorithms to evaluate randomly obtained social media or street images will be beneficial in overcoming many technological challenges such as image resolution, backdrop, and other technical elements.

Image analysis for online fashion suggestion is indeed a slow process. When product photographs from internet stores are combined with street snapshots, a massive dataset is created that may be used to parse body and garment images and detect apparel properties like textures and styles. Therefore, future study on social media should incorporate a comprehensive analysis of users' photographs, messages and facial expressions to make the recommendation system more successful.

Potential Algorithmic Models for the Future

- Multi View Deep Neural Network

The multi view deep neural network (MV-DNN) is a cross-domain recommendation system that considers people as a pivot view and each domain to be an auxiliary view. The core model is based on the assumption that users with specific likes in one domain would have stuff in common in many other areas as well. As a result, this model may be unproductive in some circumstances when it is required to have some prior knowledge about cross-domain correlations. A MV-DNN or MV-CNN can be used in a FRS along with a MLP, which could potentially learn from features of items from cross-domains and user features as well as map users and items to a latent space where the similarity between users and their preferred items can be maximized. Moreover, it can be a great addition to a highly scalable fashion recommendation system to attain rich, feature-based user representation by reducing the dimension of the inputs and the amount of training data required.

- Neural Collaborative Filtering

To focus the recommendation system, it was proposed to create a two-way communication between user preferences and item features. To describe the two-way communication between users and items, a dual neural network was proposed. Combining the neural interpretation of matrix factorization (MF) with multilayer perceptron (MLP) to create a new extended model that takes advantage of both MF's linearity and MLP's non-linearity may improve recommendation quality. Customer satisfaction is not tracked in most fashion suggestion systems, and there is a dearth of negative feedback. By using the outcome of one layer as that of the input of another to provide feedback for the projected recommendation, using such a neural collaborative network during last phase of the system can lessen this. Furthermore, it can improve any user's performance, such as colour and style choosing confidence, based on correct feedback about the product.

References

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