**RESEARCH PROPOSAL**

**PERSONALIZED FASHION SHOPPING PLATFORM:**

**DEVELOPING A HYBRID FASHION RECOMMENDATION MODEL**

**1. Introduction**

Fashion recommendation systems have become a cornerstone of modern e-commerce platforms, enhancing user experiences by providing personalized product suggestions. Despite significant advancements, existing systems face limitations such as a lack of diversity in recommendations, scalability challenges, and cold-start problems. This research addresses these limitations by developing a hybrid fashion recommendation model that leverages vast datasets and combines multiple algorithms to improve predictive accuracy for different fashion classes.

**2. Research Problem**

While hybrid recommendation systems represent the current state-of-the-art, significant gaps remain. Current literature reveals:

1. A reliance on either content or user-based approaches leads to a lack of diversity in recommendations (e.g., only visually similar items are suggested).
2. Difficulty in scaling models for large datasets while maintaining high accuracy.
3. Limited handling of the cold-start problem, where new users or products lack sufficient data for effective recommendations.

**Research Aim**

This research aims to develop a hybrid recommendation model that leverages large datasets to accurately predict and recommend fashion items based on their relatedness, thereby addressing limitations in diversity, scalability, and cold-start handling.

**Research Objectives**

1. To review existing literature and identify the limitations of current fashion recommendation systems.
2. To preprocess and augment a secondary fashion dataset to enhance model performance.
3. To design and implement a hybrid model integrating content-based and collaborative filtering techniques.
4. To evaluate the model using metrics such as accuracy, precision, recall, and F1-score.

**Research Questions**

1. What are the limitations of current fashion recommendation systems?
2. How can data preprocessing and augmentation improve model accuracy?
3. How does the proposed hybrid model perform compared to existing models in terms of accuracy, precision, recall, and F1 score?

**2.2 Dataset**

* **Source**: A publicly available secondary dataset will be obtained from Kaggle. The dataset will include images, metadata, and user interaction data to simulate real-world scenarios.
* **Preprocessing**:
  + Data cleaning to remove inconsistencies.
  + Label encoding to handle categorical data.
  + Data augmentation techniques (rotation, flipping, zooming, etc.) to make the model less sensitive to potential overfitting.

**2.3 Hybrid Model Design**

* **Architecture**: A combination of content-based filtering (using CNNs for visual feature extraction) and collaborative filtering (based on user interaction data).
* **Model Selection**:
  + Pre-trained CNN models such as ResNet or VGG for feature extraction and transfer learning.
  + Collaborative filtering models, such as matrix factorization, to address cold-start problems.
* **Integration**: These models will be combined into a hybrid system that leverages the strengths of both approaches to provide diverse and accurate recommendations.

**2.4 Implementation**

* **Platform**: Google Colab will be used for model training and evaluation, leveraging freely available GPUs to handle computational demands.
* **Frameworks and Tools**:
  + TensorFlow/Keras for deep learning implementation.
  + OpenCV for image preprocessing.
  + Scikit-learn for evaluation and statistical analysis.

**2.5 Evaluation**

* The model will be evaluated using the following metrics:
  1. **Accuracy:** Measures the global accuracy of the predictions.
  2. **Precision:** Evaluate the appropriateness of the recommended items.
  3. **Recall:** Check the system’s effectiveness in identifying the relevant items.
  4. **F1-Score:** Offers an average of both precision and recall, thus providing a fair assessment of the results.

**3. Justification for Techniques**

1. **Hybrid Model**:
   * Content-based filtering provides the user with the visual consistency of items that are being recommended, which is particularly important in the context of fashion.
   * Collaborative filtering offers variety and customization because it takes into account user controls and interests.
2. **Transfer Learning**: It helps reduce the training time and enhances performance by utilizing the features that the network has learned from a large set of images.
3. **Data Augmentation**: Contributing to the stability of the model by creating variations of the dataset to prevent the model from being too specific to the current data.
4. **Evaluation Metrics**: Precision, recall, and F1-score guarantee that the model's recommendations are not only correct but also useful and fair in terms of various criteria.
5. **Google Colab**: Facilitates access to advanced computational resources free of charge and is ideal for dealing with intricate deep-learning models

**4. Expected Outcomes**

1. A hybrid recommendation model that can effectively classify fashion classes and offer a variety of recommendations.
2. Identifying the key characteristics and limitations of existing systems has contributed to developing a framework that addresses issues of extensibility and applicability.
3. A system assessed by industry-standard metrics and its application to actual e-commerce settings.

**5. Conclusion**

This research will significantly contribute to developing fashion recommendation systems by proposing a scalable and effective hybrid model. The results and approaches are expected to serve as a basis for future work and innovations in personalized recommendations.

GIT HUB LINK <https://github.com/UCJAYY/Fashion-Store>