StyloScope

Report

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Abstract:

This project explores the development of an outfit recommendation system that predicts suitable combinations of clothing based on body type and wardrobe features using machine learning and real-time pose detection. Two Random Forest models are trained on wardrobe data to suggest top and bottom clothing combinations, while body type is classified using Mediapipe's pose detection in real-time. The project aims to enhance personal styling systems by integrating machine learning, pose recognition, and real-time webcam feed. The results demonstrate a practical system for personalized wardrobe recommendations, showcasing the potential for broader applications in fashion and personal styling.

Introduction:

Background

Personal styling applications have become increasingly popular as people look for tailored clothing recommendations based on their preferences, occasions, and body type. Traditional styling advice often lacks personalization, particularly for factors like body shape and real-time outfit recommendations.

This project leverages machine learning to predict outfit combinations and Mediapipe's pose detection system to classify body types. By combining these technologies, the system provides personalized outfit suggestions based on body type, clothing style, color, occasion, and season.

Problem Statement

Existing outfit recommendation systems do not consider body type in real-time, limiting their ability to provide personalized suggestions. This project addresses that gap by integrating real-time body type detection with a machine learning model that predicts outfit combinations.

Objective

- Develop a machine learning model to predict suitable outfit combinations.
- Use real-time body type detection with Mediapipe.
- Provide personalized clothing recommendations based on the user’s body type, preferences, and occasion.

Related Work

Wardrobe recommendation systems typically rely on static data input from users. Systems like Stitch Fix use machine learning for clothing recommendations but do not account for real-time body detection. Mediapipe is often used in applications for pose estimation but has rarely been integrated with a wardrobe recommendation system. This project uniquely combines these technologies to enhance user experience.

Methodology

Data Collection

The dataset consists of wardrobe information, including item type (shirt, pants, etc.), color, style, occasion, and season. The target variable is the recommended clothing combination for tops and bottoms. The features used for prediction include:

item_type: The type of clothing (e.g., shirt, jeans).

color: The color of the clothing item.

style: The style (e.g., formal, casual).

occasion: The type of occasion (e.g., daily, office).

season: The season for which the item is appropriate.

body_type: The user’s body type.

Label Encoding

Since the data contains categorical variables, Label Encoding is used to convert features like item_type, color, and occasion into numerical values. This transformation is necessary for feeding the data into machine learning models.

Model Design

Two Random Forest classifiers are trained:

- One for predicting the bottom (e.g., jeans, skirt) based on the input top (e.g., shirt, tshirt).
- Another for predicting the top based on the input bottom.

Random Forest was selected due to its robustness in handling categorical data and its ability to prevent overfitting. The model is trained on the encoded features, with hyperparameters tuned to achieve a balance between model complexity and accuracy.

Body Type Detection

The system uses Mediapipe's pose detection to classify body types in real-time. The width of the shoulders, hip measurements, and other landmarks are used to classify body types into categories such as athletic, average, etc. This body type is then used as an input feature in the clothing recommendation system.

Training and Testing

The dataset was split into training (80%) and testing (20%) sets. The training data was used to fit the Random Forest models, and the test data was used to evaluate model performance.

Implementation

Outfit Recommendation

The system allows users to input their clothing preferences (e.g., top, color, style). The trained model uses these inputs along with the user's detected body type to predict the most suitable bottom.

Code:

```
predicted_combination = predict_outfit(item_type='shorts', color='white', style='casual', occasion='daily', season='summer', body_type='athletic')
```

Pose Detection

Using a webcam , the Mediapipe library detects body landmarks to classify body type. The system tracks pose landmarks like shoulder width and hip distance, using this information to determine body type dynamically.

Code:

```
with mp_pose.Pose(min_detection_confidence=0.5, min_tracking_confidence=0.5) as pose:
    body_type = classify_body_type(results.pose_landmarks.landmark)
```

Results:

Model Accuracy

Top Model Accuracy: 85.75% on the test set.

Bottom Model Accuracy: 84.22% on the test set.

The models performed consistently across training and test datasets, with minimal overfitting due to the limited depth of the decision trees in the Random Forest classifiers.

Predictions / Output:

Top: T-shirt

Color: White

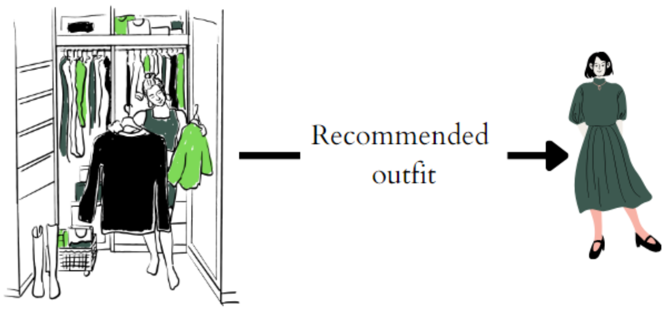
Style: Casual

Occasion: Daily

Season: Summer

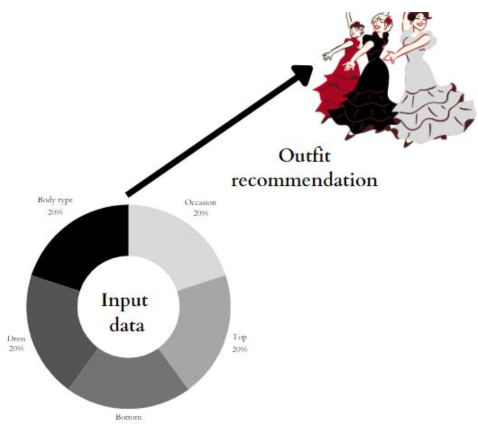
Body Type: Athletic

Predicted Bottom: Jeans



Discussion

The model successfully predicts suitable clothing combinations based on both wardrobe features and body type. The integration of real-time body type detection enhances the system's personalization capabilities, making it stand out from traditional static recommendation systems. However, the body type classification could be improved by incorporating more detailed body landmarks, and future models could consider the inclusion of accessories and footwear.



Workflow Diagram

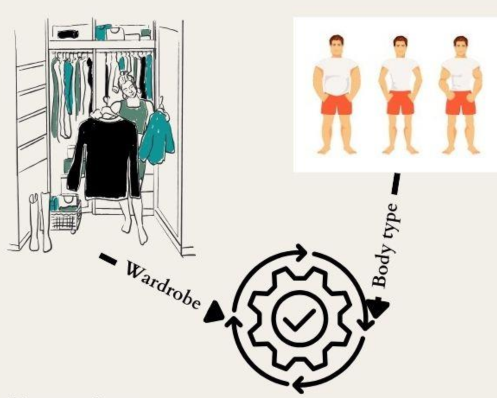
1

User Input:
"Top, Bottom, Style, Occasion, Season"

2

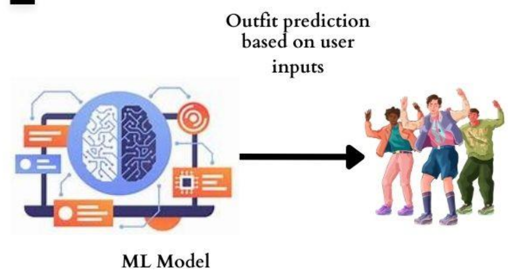
Body Type Classification:
"Real-Time Body Type Detection"

3



Data Processing:
"Combining Wardrobe & Body Type Data."

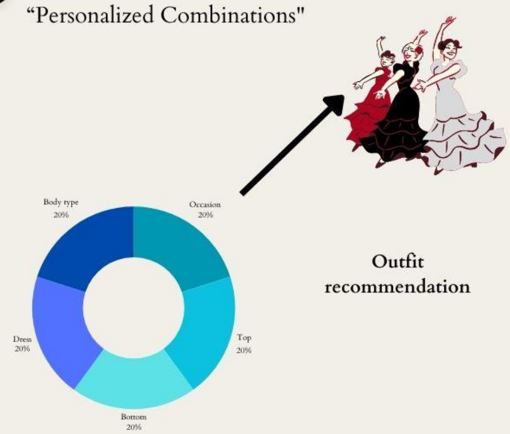
4



Machine Learning Model:)
"Random Forest Model: Predict Top & Bottom Clothing."

5

Outfit Recommendation:
"Personalized Combinations"



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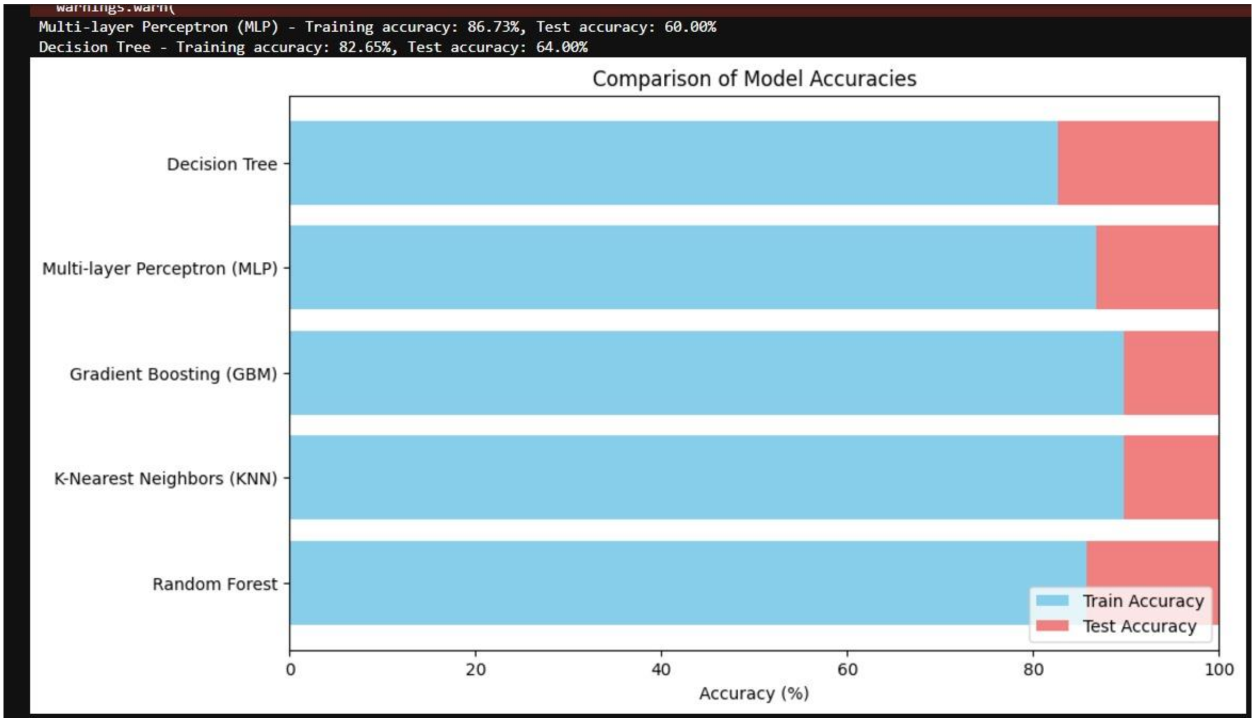
Final Output:
"Personalized Clothing Recommendation"

Analysis



Challenges

Limited Dataset: The dataset size was relatively small, limiting the diversity of possible outfit combinations.

Pose Detection Accuracy: The accuracy of body type classification may vary with different camera positions or lighting conditions.

Future Improvements

Incorporating more body types and making the classification more granular.

Expanding the dataset to include more diverse styles and clothing categories.

Using more advanced machine learning models like Neural Networks to capture complex relationships between features.

Conclusion

This project demonstrates the feasibility of integrating machine learning with real-time pose detection for a personalized outfit recommendation system. The combination of Random Forest classifiers and Mediapipe body detection creates a robust and dynamic system for personalized wardrobe recommendations. Future improvements in data size and classification techniques could make this system highly applicable in the fashion industry.