B.Tech Computer Science Engineering

CS3007 - Pattern Recognition and Machine Learning

Facial Feature Analysis And BMI Prediction: OpenCV and DLIB

REPORT

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1. Introduction

In recent years, advancements in machine learning and computer vision have enabled novel approaches to health analytics. Predicting Body Mass Index (BMI) plays a crucial role in assessing an individual's health and identifying potential risks. Traditional BMI calculation methods rely on weight and height measurements. However, image-based models offer a promising alternative, leveraging facial and body features to enhance prediction accuracy. This project investigates the application of convolutional neural networks (CNNs) for BMI prediction and gender classification, aiming to bridge the gap between conventional methods and modern computational techniques.

2. Data Preprocessing

Data preprocessing is a crucial step in ensuring the model receives clean and standardized inputs. The images were resized to a uniform dimension of (128x128x3) to maintain consistency across the dataset. Additionally, normalization techniques were applied to scale pixel values, and data augmentation strategies were considered to enhance the model's ability to generalize. Missing or incomplete data points were addressed to improve the reliability of the dataset.

3. Model Architecture

The team utilized a **Convolutional Neural Network (CNN)** with the following components:

Architecture Breakdown

Branch	**Layers**
Front Image Branch	Conv2D (32 filters) → MaxPooling2D → Flatten → Dense (128 units)
Side Image Branch	Conv2D (32 filters) → MaxPooling2D → Flatten → Dense (128 units)
Combined Branch	Concatenate branches → Dense (128 units) → Output Layer (Softmax activat

Table 1: Model Architecture Overview

Input Details: Two images: Front and side views, resized to dimensions (128x128x3). The use of separate branches for each input ensures that unique spatial features are independently extracted before combining them for final classification.

4. CNN Structure

- **Front Image Branch:** Conv2D (32 filters) → MaxPooling2D → Flatten → Dense (128 units). This branch captures essential facial features such as contours and skin texture from the front perspective.

- **Side Image Branch:** Conv2D (32 filters) → MaxPooling2D → Flatten → Dense (128 units). The side perspective helps the model recognize depth-related attributes such as profile structure and facial angles.
- **Combined Branch:** Concatenation of the front and side image branches. Dense Layer (128 units) → Output Layer (Softmax activation for BMI categories). The combined features provide a holistic representation for robust classification.

5. Model Training and Evaluation

Training the CNN involved splitting the dataset into training, validation, and testing subsets. The Adam optimizer was utilized for its adaptive learning rate capabilities, coupled with categorical cross-entropy loss for multi-class classification. Early stopping criteria were employed to prevent overfitting. Evaluation metrics such as accuracy, precision, recall, and F1-score were calculated to assess the model's performance comprehensively. Hyperparameter tuning was performed to refine the architecture for optimal results.

6. Results

Preliminary results indicate that the CNN model achieves promising accuracy in BMI classification, surpassing older models used for comparison. Key findings include:

- High classification accuracy for balanced datasets.
- Enhanced performance with data augmentation techniques.
- Lower accuracy observed for underrepresented BMI categories, highlighting the need for more diverse data.

Visualization of training and validation loss curves indicates stable convergence during training. Future evaluations aim to incorporate additional metrics for deeper insights.

7. Conclusion

The project successfully demonstrates the feasibility of using image-based CNNs for BMI classification. The model effectively processes spatial features from both front and side images, combining them for enhanced classification accuracy. Despite its success, the project faced several challenges, including:

- Limited availability of high-quality labeled datasets for training and validation.
- Balancing the trade-off between computational efficiency and model accuracy.
- Addressing variability in images due to different lighting conditions and camera angles.

Future Work:

- Incorporating more diverse datasets to improve the generalizability of the model.
- Exploring alternative architectures such as transformers or hybrid models.

- Adding a gender classification module for dual-task learning.
- Investigating techniques to reduce computational overhead for real-time applications.

The insights gained from this project provide a strong foundation for further advancements in health analytics using deep learning techniques. The proposed approach not only advances BMI prediction methodologies but also opens new avenues for integrating facial analytics into broader health assessment frameworks.