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Advancements in Hairstyle Recommendation Systems using CNN Model

Abhinav Rathi[1], K. Prakash Jayant[2], Ananaya Lal[3], Akshit Rastogi[4], Abhinav Kumar Srivastava[5]

[1,2,3,4,5]*Department of Computer Science Engineering, Raj Kumar Goel Institute of Technology, Ghaziabad, UP, India*
abhinavrathi08102002@gmail.com, kpjayfcs@rkgit.edu.in, learn.ananayalal@gmail.com, akshitrastogi0404@gmail.com,
abhinavsrivastava681@gmail.com

ABSTRACT—

Choosing a suitable haircut is an integral part of one's appearance. It has a big impact on how someone looks, feels and presents themselves. Technological developments in the last few years have resulted in the creation of several hairstyle recommendation systems that categorize faces and helps providing best suited hairstyle. These tools are meant to help people of all gender to select haircuts that highlights their best face characteristics. This paper takes in consideration of several approaches that are helpful in the development and application of such facial and hair recommendation systems. With the collaborative integration of Machine learning algorithms, specialized knowledge and facial recognition technology, it focuses on achieving precise face shape classification. The study also looks at how these systems affect the beauty and grooming sector, emphasizing how they can improve user experience and expedite procedures. Through this, the emphasis is on examining of the overall efficiency of algorithms and methods like support vector machines and strategies like VGG-face. In order to increase classification accuracy, the research also addresses the fusion of several descriptors and optimisation strategies. This paper highlights the possibility of combining several representations of data to improve the performance of expert systems in advising hairstyles based on face shape and provides intriguing directions for future research through a thorough evaluation of current approaches.

Keywords-- Convolutional Neural Networks (CNN), Machine learning, Facial recognition technology, Facial analysis, Flask framework, Base64 encoding, Recommendation System.

1. INTRODUCTION

Today we are in a fashion-conscious society, where a person's hairstyle greatly contributes to their sense of self. More and more individuals consider hairstyle as an essential component of their entire appearance, because of which the hairstyle business has experienced a meteoric rise in popularity. Finding a perfect hairstyle can be difficult for the people who are not sure which look best suits their own set of face traits.

Selecting a haircut has a big impact on one's appearance and self-confidence; it's not only a question of personal preference. The correct haircut may completely affect a person's appearance and attitude, whether it's a dramatic adjustment or a slight one. But selecting a hairstyle can be difficult; people frequently rely on the internet or publications to help them decide which style best fits their face.

Acknowledging the importance of matching haircuts to facial features, scientists and programmers have worked to develop creative algorithms for recommending hairstyles. By offering individualised hairstyle recommendations based on each person's unique facial features, these systems hope to help people make well-informed selections. These technologies, which make use of image processing and artificial intelligence, provide a quick and easy method to look at many haircut options [1].

Hairstyle suggestion systems rely heavily on facial shape classification. Specialists have always stressed how crucial it is to know one's facial form in order to choose a haircut. Every face shape, whether it be oval, rectangular, square, round, or heart shaped, has unique qualities that affect which hairstyles works best for them. Hairstyle recommendation algorithms provides a customized idea that improves our appearance and confidence by precisely identifying facial types [2].

Systems that recommend hairstyles have been developed using a variety of techniques. While some systems use complex artificial intelligence algorithms for face identification and analysis, others use human image processing approaches to identify facial features and categorize face forms. Developments in deep learning techniques made it possible to extract complex facial traits, techniques such as convolutional neural networks (CNNs), which have improved the accuracy of hairstyle recommendations even more [3].

There are still a number of issues with hairstyle recommendation systems despite of their widespread use. One of the major issues is accurately identifying and categorizing facial forms, it becomes more difficult when there is a varied cultures with a wide range of facial features. Furthermore, constant optimization and verification of the underlying algorithms are necessary to guarantee the dependability and efficacy of hairstyle recommendations [4].

In this study we are giving a thorough overview of the current state of the art facial feature-based hairstyle suggestion systems. We will look at the many approaches used in these systems, from sophisticated artificial intelligence algorithms to image processing techniques. We will also study each approach's advantages and disadvantages as well as possible directions for further study and advancement.

This study provides important insights about the field of hairstyle recommendation system with the help of collected knowledge and information from the existing literature. We want to study more about the technologies and approaches used in existing systems and develop a more accurate hairstyle recommendation systems by carefully examining existing approaches and developing trends.

In summary, the quest for the perfect hairstyle is driving continuous innovation in both fashion and technology. Systems for recommending hairstyles integrate artificial intelligence, image processing, and professional knowledge have the power to drastically alter how people experiment and explore with their hair, ultimately enhancing their sense of style and confidence.

2. LITERATURE REVIEW

Abdullah et. al. [5], highlighted the value of facial classification in the fashion and cosmetic industries in addition it also illustrates the usefulness of facial analysis in the number of other fields. Recent advancement in deep learning specifically convolutional neural network (CNN) have been applied alongside more conventional techniques like active appearance model (AAM) and fisher face approach have been applied alongside more conventional techniques like active appearance model and fisher face approach. Ling and wang created an automatic recommending system that takes into account variables like gender age and occupation. The goal of the propose work was to develop a hybrid Computer based phase shape categorisation model that takes into account a variety of facial features and improve accuracy this research also highlights the importance to have reliable algorithm that can recognise and suggest appropriate haircuts based on unique facial traits.

Xing et. al. [6], highlighted how crucial it is to use machine learning algorithms and facial recognition technology to provide personalised recommendation. The potential for such system is demonstrated by already existing solutions like face it and hair colour of modiface which helps consumers choose appropriate hairstyles based on face traits. However, a lack of consideration for user preferences and current haircuts makes it difficult to achieve high accuracy rates. This study also emphasizes the need of ongoing development and proposes directions for future research including the addition of user feedback loops flexibility in responding to fashion trends and optimisation of input variables and learning algorithms. With these initiatives, hairstyle recommender systems will be better able to cater to the unique demand and tastes of the users.

Rajapaksha et. al. [7], Presents a new hairstyle recommendation system that makes use of image processing techniques and expert knowledge based on face shapes. It also highlights cruciality to choose hairstyles that are appropriate for one's facial type in order to boost once appearance and confidence. This process consists of data gathering, facial landmark detection, face shape identification, hairstyle selection, and face detection. It's evaluations finding shows that the system performs well and receives positive user comments on its usability and accuracy in identifying facial shapes. Altogether this study ads to the recommendations for customised hairstyle and identifies potential areas for future system capability development.

Pasupa et. al. [8], Introduces a modern system for the recommendation of hairstyles based on face shapes, it utilizes a support vector machine (SVM) model and combined handcraft in deep learning teachers through multiple kernel learning (MKL) results emphasize the Synergy between different data representation and indicate a significant accuracy improvement to 70.33%. Highlighting the effectiveness of multiple kernel learning (MKL) in leveraging both hand-crafted and deep learned descriptors, also provides practical implications for the beauty industry. It also gives some future research directions including announcing of geometric feature extraction and exploring direct hairstyle suggestions without face shape classification. This study carefully addresses dataset collection, feature engineering, and model optimization, which demonstrate a comprehensive approach. Overall, the paper contributes valuable inside into developing a more personalized and accurate hairstyle recommendation.

Liu et. al. [9], draws attention for customised recommendation systems growing demand, specifically for the fashion and beauty industries. Previous researches have investigated various method of combining technologies like picture recognition and machine learning techniques to provide customised advice, some of them address the difficulty of making hairstyle recommendation based on facial traits. In an effort to minimise this gap this research expands on the previous work in face recognition and recommendation algorithms by putting forth a recommendation system for hairstyle that integrates the technologies to offer individualised hairstyle recommendations.

Sarakon et. al. [10], discussed the problem of identifying face shapes from 3D data, which is also important for applications for designing spectacles. There are very limited applications of existing approaches as they frequently presuppose segmented head data and known frontal phase direction. They utilised support vector machine approaches, suggested non-contact methods integrates shape classification, face plane recognition and head segmentation. Their method eliminates the requirement for presumptions by using total 3D body data and provides a fully autonomous system. With 73.68% accuracy rate their approach shows potential for wider use in the disciplines of 3D face analysis and related work.

Yang et. al. [11], suggests an example-based framework that emphasizes on facial shape analysis and statistical learning in order to automatic hair style retrieval. As to address the arbitrary nature of appropriateness, hairstyle suggestion algorithms see too much facial shapes with appropriate haircuts. Current methodologies involve human selection or shows in educate specificity. To achieve realistic hairdo synthesis, it requires the integration of image processing techniques. The effectiveness of the approach is confirmed by evaluation trials, which also present fortuities for various applications. They also showed that this paradigm could we extended in the future to additional fashion sectors like attire recommendations based on body shape.

Razavian et. al. [12], investigates how well generic descriptors from CNNs, specifically the OverFeat network performs in a variety of recognition tasks. It performs better on tasks including attribute identification, fine-grained recognition, and image categorization, when compared to earlier techniques. IT also achieves competitive results in visual instance retrieval tasks. In the conclusion they acknowledge NVIDIA's support and the work of important personnel, but recommends CNN features as the top option for visual recognition jobs.

3. TECHNOLOGY USED

A recommendation system is referred to a technology that analyses user data, provided either in real time or uploaded manually to suggest relevant options like products, services, items and more. These systems are mostly utilised in various online applications such as e-commerce platforms, fashion brands, music streaming platforms and more to provide customer with relatable and most relevant to their choice products.

Recommendation system is very important and integral part for enhancing user experience by helping them discover new items they might like and make decision making easier and effective for the user. Recommendation systems are constantly evolving with advancements allowing users to simplify decision making and understanding trends.

Convolutional Neural Network (CNN): It is referred to a deep learning model trained to classify images into different face shape categories, done by providing rigorous training on large datasets. A pre-trained model is used by loading it on system for prediction. The model functioning includes taking in images and analyses the raw pixels, leading to finding the best matching face shape class.

For the Hair Style Recommendation System, the CNN model uses deep learning algorithm designed for image classification. Because of the great ability to learn hierarchical features from raw pixels, CNN models are best suited for Visual data processing.

A basic CNN architecture consists of convolutional layers, pooling layers and fully connected layers which work together to provide in depth filtered output. A set of filters or kernels are applied on image's pixel values (input) to extract features from the input image through convolutions. To sample down the feature maps, pooling layers come in action. Pooling layers work after the convolutional layers and takes the output of convolutional layers as it's input. This whole process decreases the computational complexity without compromising with the important features.

In the following steps, the normalized exponential function is used. This function converts a vector of K real numbers into a probability distribution of K possible outcomes. This method here is used for multi-class classification and is utilized through fully connected convolutional layers. The final output is calculated by the summation of the features that were collected from the previous layers. The fully connected layers take in the output of the previous layer as an input in order to provide the final output.

The model is taught to differentiate between different hairstyles. This training is based on backpropagation combined with gradient descent optimization techniques. GD optimization techniques include Adam or stochastic gradient descent to update the model parameters using repetition method and minimizing errors. Further adjustments are done in the weight of convolutional filters in order to provide more accurate output based on training data.

A major factor to avoid on the surface is overfitting. To deal with overfitting, techniques are used such as dropout regularization in which deactivation of certain number of neurons (randomly) while training and forcing the CNN model to learn robust features. In addition, it also leads to improvement in generalization performance.

Flask Framework: It is a lightweight Python web framework working on the backend. Flask provides routes that handle user interactions. When the user captures an image, the /predict route receives the image data. Using the TensorFlow, communication is set up between Flask and the pre-trained CNN model for prediction. At last, a JSON response containing the predicted face shape and recommended hairstyles is generated before sending it back to the user's browser for update.

Base64 Encoding: Used for converting image data into a text format suitable for transmission within the JSON response between the frontend and backend.

4. PROPOSED WORK

The hair style recommendation system utilises an integration of frontend and backend. Distinct functionalities are utilised on user's browser and server-side Flask application. This setup creates a client-server architecture.

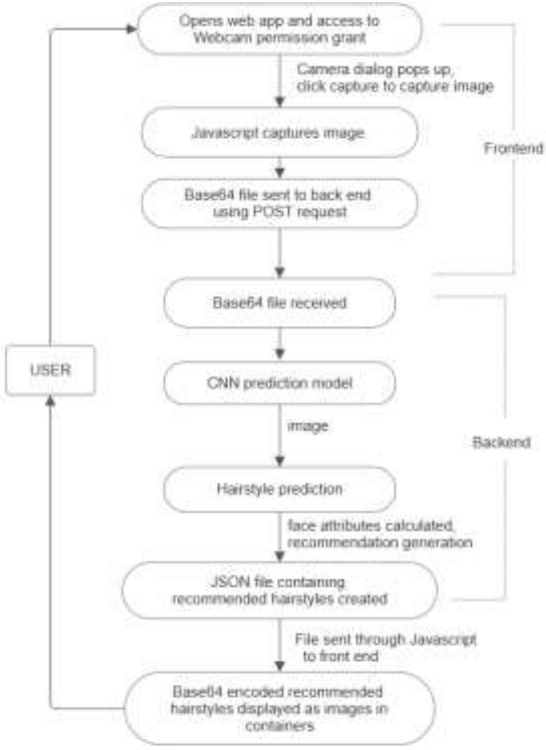

Fig 1: Data flow diagram of implementation

Frontend: The user interacts through the web interface, which displays instructions for getting the required recommendation and a capture functionality is provided using a Capture button on the interface. User first need to provide web application the access to their webcam. To capture image of the user for further recommendation "Capture" button is clicked. Following the action, the JavaScript code accesses the user's webcam, captures an image, and converts it to a base64-encoded format. A POST request is then used. The request is used to send the user image to the backend for further processing.

Backend: The backend receives the image data, decodes it, and preprocesses it for the machine learning model. A pre-trained convolutional neural network model predicts probabilities for each face shape class in the dataset. The class with the highest probability is identified as the predicted face shape. Based on this prediction, the backend retrieves information about recommended hairstyles (filenames or paths) from a folder structure corresponding to the predicted class. These images are then encoded to base64 format for efficient transmission.

Response and Display: The backend sends a JSON response containing the predicted face shape and a dictionary of recommended hairstyles with filenames/paths as keys and base64-encoded data as values. The frontend receives this response, displays the predicted face shape, and replaces any previous recommendations. Finally, it utilizes the base64-encoded data to display the recommended hairstyles as images within the designated section of the user interface.

```
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(64, activation='relu'),
    Dense(7, activation='softmax')
])
```

Fig 2: CNN model architecture

```
loss: 2.1196 - accuracy: 0.0968 - val_loss: 1.9632 - val_accuracy: 0.1368
loss: 1.9515 - accuracy: 0.1720 - val_loss: 1.9408 - val_accuracy: 0.1895
loss: 1.9442 - accuracy: 0.2043 - val_loss: 1.9295 - val_accuracy: 0.2105
loss: 1.9330 - accuracy: 0.2258 - val_loss: 1.8770 - val_accuracy: 0.2105
loss: 1.8998 - accuracy: 0.2151 - val_loss: 1.8516 - val_accuracy: 0.2000
loss: 1.9446 - accuracy: 0.2043 - val_loss: 1.8329 - val_accuracy: 0.2211
loss: 1.8593 - accuracy: 0.2258 - val_loss: 1.6881 - val_accuracy: 0.4737
loss: 1.7233 - accuracy: 0.3226 - val_loss: 1.4422 - val_accuracy: 0.4842
loss: 1.6485 - accuracy: 0.3978 - val_loss: 1.5748 - val_accuracy: 0.3789
loss: 1.5581 - accuracy: 0.4624 - val_loss: 1.2615 - val_accuracy: 0.6526
```

Fig 3: Model trainging output

This methodology highlights the collaborative effort between the user's browser and the server to capture an image, predict the face shape, retrieve recommendations, and present them to the user in a visually appealing way.

5. CONCLUSION AND FUTURE SCOPE

The article delves into the pivotal position of facial shape category within the style and cosmetics industries, providing a entire analysis of the evolving panorama surrounding customized coiffure suggestion systems. It emphasizes the importance of facial assessment and identification technologies in turning in tailor-made tips, thereby improving purchaser pleasure and contentment. A dynamic research environment is portrayed, showcasing the combination of superior deep getting to know strategies, substantially Convolutional Neural Networks, with conventional strategies which includes the Active Appearance Model.

Looking beforehand, identified studies trajectories and improvements offer promising avenues to enhance the effectiveness and software of hairstyle recommender systems. Strategies together with group strategies integration, deep learning version optimization, and interactive person comments mechanisms maintain ability to raise recommendation first-rate and consumer satisfaction. Moreover, the prospect of turning in extra precise and well-timed personalised pointers in response to evolving trends in face characteristic extraction techniques underscores the capability for recommendation systems to remain relevant and efficient in assembly consumer possibilities.

In order to extra exactly seize minor facial developments, future studies may also focus on developing facial feature extraction methods. The system's capacity to understand complicated facial bureaucracy and tendencies might be improved with the aid of utilising sophisticated picture processing strategies or by using including 3-d facial modelling, which might bring about more accurate hairstyle suggestions.

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