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Machine Vision Based Intelligent Eyeglass Recommender

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***Abstract*—**Nowadays, people find it difficult to select the better-looking Spectacles for their face. It was noticed that manual selection of frames may take time and may not satisfy customers. It is leading to Customer's dissatisfaction and a decline in their optical business. To address this issue and satisfy Opticians and Customers, we have planned to develop an intelligent tool called Machine Vision based Intelligent Eyeglass Recommender. This task of recommending eye frames based on people's appearance is quite hard and there are no similar projects available at the moment. This system takes into account over 20 facial attributes, maps them into eyeglasses features with the help of expert module created by us. Our Expert module apply written beforehand rules to get necessary mappings. High interpretability of such an approach guarantees user's understanding and loyalty towards the system. To get necessary attributes from the photo this system uses bunch of machine learning algorithms and existing free services, i.eBetaFaceAPI and Face++. Face++ allows to locate bounding boxes of faces in images, while BetaFace uses various classifiers to get most of the secondary-importance features. So, we should have access to the internet. To detect face shape probabilities, iris color, forehead size, jaw type type, skintone this system uses its own pre-trained convolutional neural networks (CNNs). These models run on local machines on CPU. To get all necessary eye frames attributes, the large dataset (>8k records) of eye frames was parsed and processed. Because in real life there are not so many eyeframe models available in the local shop, the generation of unique eyewear by given features was implemented. The system uses a conditional GAN followed by Super Resolution GAN to create non-existing high-definition images of the eye frames.

Keywords*—Age,gender prediction, Deep neural networks, Generative Adversarial networks, face shape identification, Facial features detection, cosmetic; deep learning; facial image; decision support system, Multilayer perceptron, retraining Inception V3, training GAN, Eye frames Recommendation. (key words)*

I. INTRODUCTION

(AGE AND GENDER PREDICTION)

Age and gender prediction has become one of the more recognized fields in deep learning, due to the increased rate of image uploads on the internet in today's data driven world. Humans are inherently good at determining one's gender, recognizing each other and making judgements about ethnicity but age estimation still remains a formidable problem. To emphasize more on the difficulty of the problem, consider this - the most common metric used for evaluating age prediction of a person is mean absolute error (MAE). A study reported that humans can predict the age of a person above 15 years of age with a MAE of 7.2-7.4 depending on the database conditions. This means that on average, humans make predictions off by 7.2-7.4 years.

The question is, can we do better? Can we automate this problem in a bid to reduce human dependency and to simultaneously obtain better results? One must acknowledge that aging of the face is not only determined by genetic factors but it is also influenced by lifestyle, expression, and environment. Different people of similar age can look very different due to these reasons. That is why predicting age is such a challenging task inherently. The non-linear relationship between facial images and age/gender coupled with the huge paucity of large and balanced datasets with correct labels further contribute to this problem.

Very few such datasets exist, majority datasets available for the task are highly imbalanced with a huge chunk of people lying in the age group of 20 to 75 or are biased towards one of the genders. Use of such biased datasets is not prudent as it would create a distribution mismatch when deployed for testing on real-time images, thereby giving poor results. So, we used a Cloud based face Feature classifying service Providers to do this job. (Face++ and Betaface) Face++ allows to locate bounding boxes of faces in images and Betaface uses various classifiers to get most of the secondary-importance features.

(FACE SHAPE CLASSIFICATION)

The human face plays an important role in daily life. Pursuing beauty, especially facial beauty, is the nature of human beings. As the demand for aesthetic surgery has increased widely over the past few years, an understanding of beauty is becoming increasingly important for medical Thus, the cosmetic industry has produced various products that target to enhance different parts of the human body, including hair, skin, eye, eyebrow, and lips. Not surprisingly, research topics based on the face features have a long track record in psychology, and many other scientific fields. During recent decades, computer vision systems have played a major role in obtaining an image from a camera to process and analyze it in a manner similar to a natural human vision system. Computer vision algorithms have recently attracted increasing attention and been considered one of hottest topics due to its significant role in healthcare, industrial and commercial applications. Facial image processing and analysis are essential techniques that help extract information from images of human faces. The extracted information such as locations of facial features such as eyes, nose, eyebrows, mouth, and lips, can play a major role in several fields, such as medical purposes, security purposes, cosmetic industry, social media applications, and recognition. Several techniques have been developed to localize these parts and extract them for analysis.

The landmarks used in computational face analysis often resemble the anatomical soft tissue landmarks that are used by physicians. Recently, advanced technologies such as artificial intelligence and machine/deep learning algorithms have helped the beauty industry in several ways, from providing statistical bases for attractiveness and helping people alert their looks to developing products which would tackle specific needs of customers . Furthermore, cloud computing facilities and data center services have gained a lot of attention due to their significant role for customers' access to such products by building web-based and mobile applications. In the literature, there have been many facial attribute analysis methods presented to recognise whether a specific facial attribute is present in a given image. The main aim of developing facial attribute analysis methods was to build a bridge between feature representations required by real-world computer vision tasks and human-understandable visual descriptions. Deep learning-based facial attribute analysis methods can generally be grouped into two categories: holistic methods which exploit the relationships among attributes to get more discriminative cues and part-based methods that emphasize facial details for detecting localisation features. Unlike the existing facial attribute analysis methods, which focus on recognising whether a specific facial attribute is present in a given face image or not, our proposed method suggests that all concerned attributes are present but in more than one label. Furthermore, many automated face shape classification systems were presented in the literature. Many of these published face classification methods consider extracting the face features manually then passing them to three classifiers for classification, including linear discriminant analysis (LDA), artificial neural networks (ANN), and support vector machines (SVM), k-nearest neighbors, and probabilistic neural networks. Furthermore, Bansode et al proposed a face shape identification method based on three criteria which are region similarity, correlation coefficient and fractal dimensions. Recently, Pasupa et al. presented a hybrid approach combining VGG convolutional neural network (CNN) with SVM for face shape classification; however, existing face classification systems require more effort to achieve better performance. Therefore mentioned methods perform well only on images taken from subjects looking straight towards the camera and their body in a controlled position and acquired under a clear light setting. Recently, many approaches were developed for building fashion recommender systems. Conducting a deep search in the literature seeking the existing recommendation systems leads to finding two hairstyle recommendation systems .. Furthermore, virtual consultation and recommendation systems based on facial and eye attributes have secured a foothold in the market and individuals are opening up to the likelihood of substituting Recently, advanced technologies such as artificial intelligence and machine/deep learning algorithms have helped the beauty industry in several ways, from providing statistical bases for attractiveness and helping people alert their looks to developing products which would tackle specific needs of customers. Furthermore, cloud computing facilities and data center services have gained a lot of attention due to their significant role for customers' access to such products by building web-based and mobile applications. In the literature, there have been many facial attribute analysis methods presented to recognise whether a specific facial attribute is present in a given image. The main aim of developing facial attribute analysis methods was to build a bridge between feature representations required by real-world computer vision tasks and human-understandable visual descriptions .

Deep learning-based facial attribute analysis methods can generally be grouped into two categories: holistic methods which exploit the relationships among attributes to get more discriminative cues and part-based methods that emphasize facial details for detecting localisation features. Unlike the existing facial attribute analysis methods, which focus on recognising whether a specific facial attribute is present in a given face image or not, our proposed method suggests that all concerned attributes are present but in more than one label. Furthermore, many automated face shape classification systems were presented in the literature. Many of these published face classification methods consider extracting the face features manually then passing them to three classifiers for classification, including linear discriminant analysis (LDA), artificial neural networks (ANN), and support vector machines (SVM), k-nearest neighbors, and probabilistic neural networks. Furthermore, Bansode et al. [26] proposed a face shape identification method based on three criteria which are region similarity, correlation coefficient and fractal dimensions. Recently, Pasupa et al. [27] presented a hybrid approach combining VGG convolutional neural network (CNN) with SVM for face shape classification. Moreover, Emmanuel [28] adopted pretrained Inception CNN for classifying face shape using features extracted automatically by CNN. The work presented by researchers showed progress in face shape interpretation; however, existing face classification systems require more effort to achieve better performance. Therefore mentioned methods perform well only on images taken from subjects looking straight towards the camera and their body in a controlled position and acquired under a clear light setting. The system developed by Liang and Wang [31] considers many attributes such as age, gender, skintone, occupation and customer rating for recommending hairstyles. However, the recommended haircut style might not fit the beauty experts' recommendations based on face shape attributes. To the best of our knowledge, our proposed eyelashes and hairstyle recommendation system does automatically make a recommendation of a suitable eyeframe type based on computer vision techniques. Facial attributes such as eye features, including shape, size, position, setting, face shape, and contour should be applied. The face and eye features are essential for beauty experts because different types of face shape and eye features are critical information to decide what kind of eye shadows, eyeliners, eyelashes extension, haircut style and color of cosmetics are best suited to a particular individual. Thus, automation of facial attribute analysis tasks based on developing computer-based models for cosmetic purposes would help to ease people's life and reduce time and effort spent by beauty experts.

(EYEGLASS RECOMMENDATION SYSTEM)

A novel recommendation system that accepts a frontal face photo as the input and returns the best-fit eyeglasses as the output. As conventional recommendation techniques such as collaborative filtering become inapplicable in the problem, we propose a new recommendation method which exploits the implicit matching rules between human faces and eyeglasses. We first define fine grained attributes for human faces and frames of glasses respectively. Then, we develop a recommendation framework based on GAN (generative Adversarial Networks) which effectively captures the correlation among these fine-grained attributes. To get all necessary eye frames attributes, the large dataset (>8k records) of eye frames was parsed and processed. Because in real life there are not so many eyeframe models available in the local shop, the generation of unique eyewear by given features was implemented. The system uses a conditional GAN followed by Super Resolution GAN to create non-existing high-definition images of the eye frames.Generative Adversarial Networks (GANs) let us generate novel image data, video data, or audio data from a random input. Typically, the random input is sampled from a normal distribution, before going through a series of transformations that turn it into something plausible (image, video, audio, etc.). However, a simple DCGAN doesn't let us control the appearance (e.g. class) of the samples we're generating. For instance, with a GAN that generates MNIST handwritten digits, a simple DCGAN wouldn't let us choose the class of digits we're generating. To be able to control what we generate, we need to condition the GAN output on a semantic input, such as the class of an image. In this example, we'll build a Conditional GAN that can generate MNIST handwritten digits conditioned on a given class. Such a model can have various useful applications: let's say you are dealing with an imbalanced image dataset, and you'd like to gather more examples for the skewed class to balance the dataset. Data collection can be a costly process on its own. You could instead train a Conditional GAN and use it to generate novel images for the class that needs balancing. Since the generator learns to associate the generated samples with the class labels, its representations can also be used for other downstream tasks.Ranking of the frames (glasses) is done by their similarity to the query facial attributes. Finally, we produce a synthesized image for the input face to demonstrate the visual effect when wearing the recommended glasses.

II. RELATED WORKS

A. Age and Gender Prediction

Initial works of age and gender prediction involved techniques based on ratios of different measurements of facial features such as size of eye, nose, distance of chin from forehead, distance between the ears, angle of inclination, angle between locations. Such methods were known as anthropometric methods. Early methods were based on manual extraction of features such as PCA, LBP, Gabor, LDA, SFP. These extracted features were then fed to classical ML models such as SVMs, decision trees, and logistic regression. Hu et al used the method of ULBP, PCA & SVM for age estimation. Guo et al.proposed a locally adjusted robust regression (LARR) algorithm, which combines SVM and SVR when estimating age by first using SVR to estimate a global age range, and then using SVM to perform exact age estimation. The obvious down-side of such methods was that not only was getting anthropometric measurements difficult but the models were not able to generalize because people of different age and gender could have the same anthropometric measurements.

Face Shape and facial proportions Classification

Published work in face shape classification uses handpicked features computed from facial landmark coordinates to train traditional classifiers. A total of 8 features were used including the height of bounding ellipses, distance of bounding ellipses to facial boundaries, length of the jaw line, and diagonal lines from the chin to the lower ear points. The method uses a k-nearest neighbor (KNN) approach trained using 300 images. A face is said to be a blend of two face shapes if a so-called blending score falls within 40%-60%. The reported accuracy is at 80% if errors due to the failure of a sub-component that outlines the facial boundaries is included. If only cases with correctly identified facial boundaries are considered, the reported classification accuracy is about 90%. 19 features were extracted from facial images including the face height to width ratio, jawline width to face width ratio, chin-to-mouth to jaw line width ratio, and the angles that the chin to one of 16 facial points make with respect to the horizontal. Five classifiers were trained and tested using features obtained from 500 images: linear discriminant analysis (LDA), support vector machines with linear (SVM-LIN) and radial basis function kernels (SVM-RBF), and artificial neural networks or multi-layer perceptron (MLP). Reported training accuracy for a training size of 450 images ranges from 64.9% for LDA up to 70.7% for SVM-RBF with an overall accuracy ranging from 64.2% for LDA up to 70.8%.

Eyeglass Recommendation System

The model named eyeglasses frame selection based in oval face shape using convolutional neural network [7],It presents a solution to the problem to increase users' satisfaction when using an eyeglasses selection application. In order to do that, we performed the User Acceptance Test to eleven people based on how this application can impact their decision to help them choose the right glasses. In this case, the shape of the face is one of the factors that affected it. This research uses the Convolutional Neural Network method to help classify human face shape. The shape of the face which became the object of research is the oval face shape, because there are so many example images that can be obtained through simple search in the Google search engine. In fact, all the data that we used in the experiment were retrieved from the Internet using this search. The data collected in this research contains 1300 images of a human face consisting of 650 images of a human face with oval face shape and 650 images of human face with square face shape.

B. Identified Problems

This model only can be used to recommend the eye frames of the person whose faces were oval in shape.

III. EXISTING MODEL

Eyeglasses frame selection based in oval face shape using convolutional neural network [7]

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1) User can input the image by taking a picture directly from the application.

2) The input image will be detected by the system whether having facial characteristics or not using Viola-Jones algorithm in Face API invented by Google. There are eight points which represent each facial characteristic for the detection of the face on the image that user inputs, and the points are left eye, right eye, left cheek, right cheek, down side of nose, left side of lips, right side of lips and down side of the lips.

3) When the input image detected had characteristics of the face, then the system will identify the face shape using models that were already built before.

4) There are two scenarios which occur after the identification of the face shape, the first, if the face is unidentified oval face shape then the system will give a notification to the user that the face is not oval and the second, if the face identified oval face shape, the system will continue to the next step.

5) In the next step, the user will get four glasses frames recommendation. Glasses frames that are being recommended

6) User can select and try on the glasses frame recommendation in the application. The system will automatically attach the frames on the image input from the user.

IV. PROPOSED MODEL

A. Age and Gender prediction

The Age and Gender prediction information is being predicted by our cloud based service providers (Faceplusplus) it used to bound the boxes on the frontal face of the human and it can send the alignment and cropped facial data back to the api side to reception of the data on the side of our eyeglass recommender, (Betaface) it can Classify faces (age, gender, ethnicity, smile, etc).Detect 22 basic facial points. We used this service provider to get the age and gender data delivered to our intelligent eyeglass recommender. Betaface(Betaface API | Open API for face recognition) uses more advanced CNN and more new techniques to identify facial features and it gives some more features for free usage. For Gender Identification . The deep learning approach developed has been adopted to achieve this task. Convolutional neural network composed of three convolutional layers, each followed by a rectified linear operation and pooling layer is implemented. The first two layers also follow the normalisation using local response normalisation. The first convolutional layer contains 96 filters of 7×7 pixels, the second convolutional layer contains 256 filters of 5×5 pixels, the third and final convolutional layer contains 384 filters of 3×3 pixels. Finally, two fully connected layers are added, each containing 512 neurons. The dataset of the Adience Benchmark is used to train the gender identification model. The Adience Benchmark is a collection of unfiltered face images collected from Flickr. It contains 26,580 images of 2284 unique subjects that are unconstrained, extreme blur (low-resolution), with occlusions, out-of-plane pose variations, and have different expressions. Images are first rescaled to 256×256, and a crop of 227×227 is fed to the network. All MUCT images composed of 52.5% female were used for testing.We Gather the data from the Betafaceapi and retrieve the data in our side and interpret those data with our novel face shape and facial feature extraction CNN models of 256 layers and the rest of the program is left for the next module.

B. Face shape and facial proportions classification

To identify the face shape, our developed model that was designed by merging hand-crafted features with automatically learned features was trained and tested on data from MUCT. MUCT data has been randomly split into 3255 images for training, and 500 images was retained for testing. The developed model achieves the classification as follows: (1) detect the face region and crop it using a model trained on the histogram of oriented gradients (HOG) features with Support Vector Machine (SVM) model as classifier , (2) the detected face is aligned using the detected face landmarks (68 landmarks) by the ensemble of regression tree method (ERT), and Finally, the aligned images are used for training and evaluating Inception V3 convolutional neural network along with hand-engineered HOG features and landmarks to classify the face into one of five classes.

C. Eyeglass Recommendation

At First, the Api request is sent to the Face++ Cloud service provider with the input image and we receive the resulting image with face bounded points and Aligned and cropped image of the Person's face, Then Another Api request is sent to Betaface Cloud service Provider with the output image received from the Face++, Betaface detects the Hair colour, Whether the person is Male or Female, Has beard or not, Face shapes and Facial features and the features s sent to the Dictionary with Facial Features created with the research made with suitable frames for the facial features in that there is our Expert module which can actually predict the final eyeglass features and the suitable Description of the Facial features and calculate cosine distances and it gets the top 6 Eye frames recommendations for the Person's Face.

Here, GAN(Generative Adversarial Networks) were used to Generate the Unique eyeglass frames and Eliminate Asymmetry in This Module (CGAN - Conditional Generative Adversarial Networks), (SRGAN- Super Resolution Generative Adversarial Networks) were used to generate the unique eyeglass frame and to upscale the image of the frame and eliminate the asymmetry and generate the unique Eyeglasses .

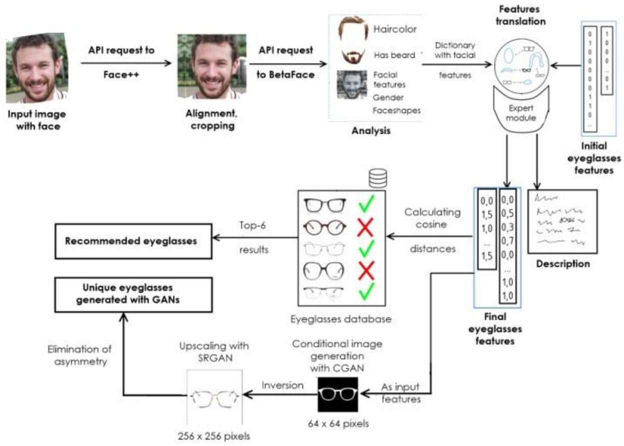


Fig. 1. Architecture Of the System. (*Eyeglass Recommendation*)

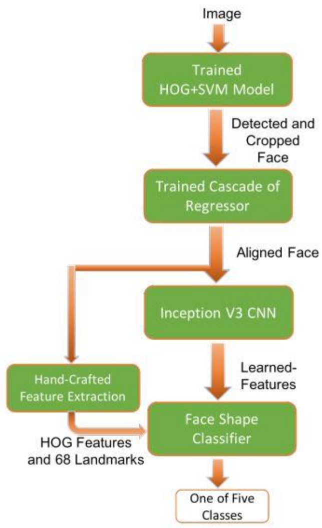
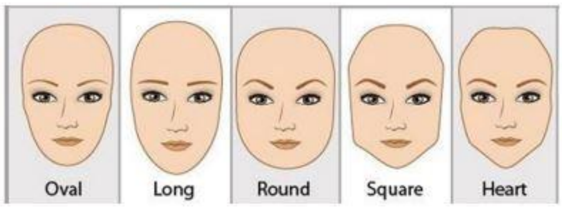


Fig. 2. Face shape Classification

Fig. 3.



Classified Five Face shapes

V. RESULTS AND DISCUSSION

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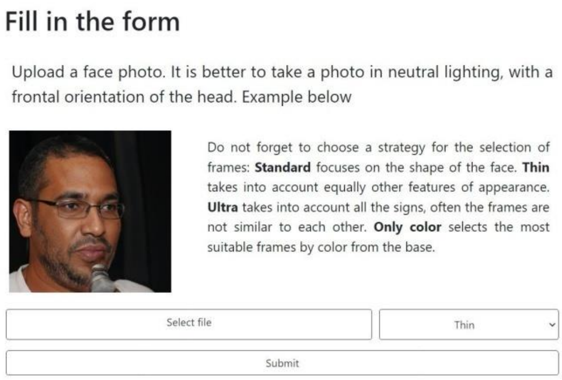
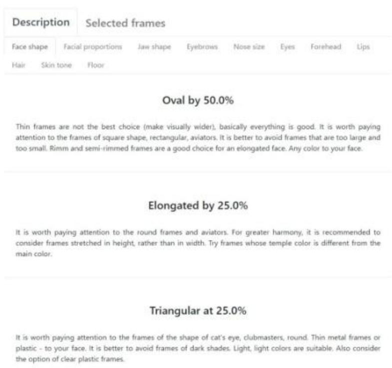


The first option to upload a photo of a person of whom the eyeglass frame has to be recommended and to select the type of the frame whether it is a thin, standard, ultra premium or a color only preferred frame



The Description is the space where all the predicted output will be present on a tab basis. At first the face shape will be selected and then there will be an option of other attributes of facial proportions , Jaw shape, EyeBrows, Eyes, Forehead. Nose size.Lips, hair colour, skin tone and their Gender. The user may select any of the tabs to get the related info which were predicted by the model will be shown over there.

These were the result of the eyeglass recommender, where the eye frames were recommended according to the Age, Gender, Face shape, etc. of the person. According to a survey in a class of 57 students 15 of them were using eyeglass. The 15 students were gone through a survey of using this Machine Vision Based Intelligent Eyeglass Recommender. Out of 15 students, 12 students were satisfied with using this recommending tool for their eyeframe selection. Actually some students were already using the recommended glasses using the Machine Vision Based an Intelligent Eyeglass Recommender.

As the the model can recommend the top 6 Eyeglassesaccording to the Age, Gender, Face shape, Facial Proportions, Jawtype, Skintone, Eyebrows, Forehead, Hair colour and including Nose Size

PERFORMANCE BENCHMARKS

In this section, You can find information of the current Performance of the system,

Speed benchmarks were tested on 2 different machines:

- Windows 10 with 4 cores 2.3 GHz Intel® Core™ i5-4200U and 4 GB of RAM (low spec)
- Linux Ubuntu 16.04 LTS with 4 cores 3.4 GHz Intel® Core™ i7-4770 and 20 GB of RAM (high spec)

Action	Time, low spec	Time, high spec	Standart deviation, low spec	Standart deviation, high spec
Image alignment	4.7s	**3.9s**	2.4s	**0.5s**
Cached image alignment	62.0ms	**39.1ms**	55.0ms	**5.7ms**
BetaFace api request	**1.5s**	1.6s	0.4s	**0.4s**
Cached betaFace api request	2.0μs	**0.7μs**	**0.2μs**	0.3μs
Extraction of facial attributes	2.7s	**2.3s**	1.6s	**1.2s**
Cached extraction of facial attributes	3.0μs	**2.4μs**	**0.1μs**	1.8μs
Features translation	0.78s	**0.11s**	0.62s	**0.54s**
Cached features translation	15.0μs	**3.2μs**	12.1μs	**1.6μs**
Database search with cosine distances	1.1s	**0.8s**	0.4s	**0.4s**
Unique eyeglasses generation	4.2s	**4.0s**	**0.2s**	1.4s
Initialization of class instance	44.7s	**27.2s**	**1.9s**	2.7s

VI. CONCLUSIONS AND FUTURE DIRECTION

Thus the Machine Vision based an Intelligent Eyeglass Recommender uses Faceplusplus cloud services to identify and to locate bounding boxes of faces in images, Betaface uses various classifiers to get most of the secondary-importance features and the Implemented GMMs (Gaussian Mixture Models) for identifying the Iris colour, hair colour, forehead, skin tone and jaw does its job.The Deep Convolutional Neural Network was applied in this study to solving the problem and using Python Language to create the model. This model can make it easier for a person in choosing eyeglasses frame that suits face shape rather than having to try it in physical form one by one. From User Acceptance Test result,

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