LASHLENS: INTELLIGENT SYSTEM RECOMMENDING MAKEUP FOR THE EYE LASHES

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ABSTRACT

Beauty is a power which allows people to express themselves, gain self-confidence and open to others. Usage of beauty products can help this by creating a new look to uplift the character. Choosing the right makeup product is not an easy task in this diverse range of products these days. Intelligent systems for beauty and makeup selection have gained significant research interest in recent years. Most existing models focus on detecting prominent facial features such as skin tone, lip colour, and overall facial structure. However, minor yet impactful areas, such as the delicate regions around the eyes, are often overlooked. These areas play a crucial role in defining facial aesthetics, influencing expressions, and enhancing overall appearance. To address this gap, this system is designed to provide targeted recommendations for eye-focused beauty enhancements, ensuring a more comprehensive and personalized approach to makeup selection.

The proposed system will recommend makeup products considering personal traits of the user such as the length and volume of the eyelashes. A new approach has been devised in calculating the length of the eyelashes aiding the use of advanced computer vision techniques like edge detection, and a regression-based Convolutional Neural Network(CNN) model is trained for prediction. A Support Vector Machine (SVM) is used for the classification task in recommending products for eyelash care.

KEYWORDS

Edge Detection, Contour Detection, Support Vector Machine.

1. INTRODUCTION

Beauty serves as a form of communication that allows individuals to showcase their identities, build self-esteem, and connect with others. Application of cosmetics is a popular method for transforming one's appearance, enhancing a person's character. Choosing the perfect makeup that best suits a person is challenging unless they have years of expertise with cosmetics [1], there are many individuals struggling to find the best makeup products that best suits them out of the vast diversity of the products. Even after COVID-19 restrictions eased, concerns about hygiene persist when sharing beauty products. Research has shown that old cosmetics can harbour harmful germs, leading to second thoughts about testing products before purchasing. This makes it more challenging for consumers to choose makeup products. To help people make informed choices and avoid mistakes, makeup recommendation systems have been developed to predict how a person's face will look after a makeover. This has become a popular area of research, with numerous intelligent systems allowing users to virtually try on makeup and see how products will appear on their face. One popular example is the L'Oréal website [2], a platform where users can apply products in real time and view the results virtually.

Most of the existing makeup recommendation systems [1,8,11,12] focus on the larger, more prominent facial features, such as the lips and skin and other aspects like the clothing and hairstyle. However, smaller but significant areas, like the eyes, often receive less focus. The eyes play a crucial role in facial aesthetics, capable of transforming expressions and conveying emotions, making them an essential part of any makeup routine. The adage that ‘‘beauty is in the eye of the beholder’’ has been challenged scientifically over the past 20 years [3], the authors have examined various aspects of facial attractiveness particularly focusing on the eyelashes, one of the common feature that is missing in the existing systems, how eyelashes contribute to the attractiveness of female eyes and their role in drawing attention to the face is discussed in [4].Studies have revealed how different length of the eyelashes perceive attractiveness [5] and differ among different ethnic groups [6] also the volume of the not only enhance beauty but are also associated with indicators of good health and youthfulness. Apart from the eyelashes having a diverse range of products and treatments the current systems do not consider them. However, only a few systems currently address these finer details.

Recognizing this gap, a web application has been developed to provide more accurate recommendations for the eye area, with a specific focus on eyelashes. Users can upload images of their eyes, and the system will analyse the eyelashes [7] by examining features such as length and volume [8]. Based on this analysis, personalized recommendations will guide users to suitable styles and products tailored to their unique eyelash characteristics, this system works under all lighting conditions and for various skin tones. A novel approach is used to calculate eyelash length through edge detection, as no existing image processing techniques address this task. A custom CNN model is trained to predict the average eyelash length [9], while product recommendations are made using a SVM classifier [10,11]. Additionally, the volume is analysed by considering a Region of Interest (ROI) in the eyelash area of the image.

2. RELATED WORKS

2.1. Existing Systems

Various studies have contributed to the development of makeup recommendations systems, allowing users to virtually try on products like lipsticks, eye shadows and foundations while receiving personalized suggestions. These systems effectively detect larger facial landmarks using existing image processing techniques. However, minor regions, such as the eyelashes, are more challenging to identify with these methods.

The system proposed by Perera et al. [1]features real-time makeup simulation in an Augmented Reality (AR) environment along with personalized makeup recommendations. Deep learning models, including ResNeXt-50, ResNet-18, and VGG-16, were used for Facial landmark detection, with ResNet18 achieving the highest accuracy. The recommendation engine combines Content-Based Filtering (CBF) and Collaborative Filtering (CF), with the hybrid approach yielding the best performance, achieving an accuracy of 83%.

The work by Daram et al. [12] adopts a similar approach for personalized makeup recommendations and virtual trial experiences. By leveraging Generative Adversarial Networks (GANs) trained on a diverse dataset-including various skin tones, lighting conditions, and makeup styles - the system generates synthetic images that enhance skin detection algorithms. In this study, the virtual trial experience and recommendation functions focus exclusively on products such as lipstick, foundation, and eye shadow, achieving an impressive system accuracy of 98%.

Taleb Alashkar et al. [13] developed a Deep Neural Network (DNN) model using database rules and examples to demonstrate the ability to recommend makeup styles. The expanded their research, as presented in [14], by introducing a rule-based model that generates makeup style recommendations based on trends, contexts, and facial characteristics. This was the only notable system capable of producing an output that included an image with synthesized mascara. The system compares the user's input with a database of images and applies predefined rules to generate a synthesized makeup look, without relying on feature extraction or segmentation techniques for personalisation. However, its accuracy remains low, as stated by the authors due to insufficient data.

The Beauty e-Experts system, as part of Liu et al.'s work in [15], utilizes a multiple tree-structured super-graph model analyses feature relationships and aligns recommendations with user images. The systems in [14] and [15]employs SVM classifiers: Alashkar's classifies face shape, skin tone, and eye shape, while Beauty e-Experts targets high-level beauty attributes like makeup styles and facial features.

In the existing systems presented in [1,8,9,10,11] have not focused on the context of eyelashes. However, a few studies, such as[16], consider the user's current occasion, ensuring that recommendations are not only personalized to the user's features but also relevant to their immediate context. Unlike earlier systems that relied on general facial similarity, the system in [17] personalizes recommendations through face style recognition.

2.2. Edge Detection

In Don et al.'s study, the most suitable edge detection methods for face recognition are identified in [18]. A facial image is captured using a mobile phone and processed in MATLAB software with Canny, Sobel, Roberts and Prewitt edge detectors. The image is first converted to YCbCrcolour space, then the edge detector is applied after which the results are analysed. The study concludes that the Canny edge detector outperforms the other three methods, producing comparatively clearer detected faces.

Hu and Zhang proposed a method for more complete and accurate edge detection, as presented in [19].This study introduces an image edge detection method based on Fuzzy C-Means and the Canny operator within the Non-Sub sampled Shearlet Transform (NSST) domain. The image is first decomposed using NSST into high- and low-frequency components. The improved Canny operator extracts low frequency edges from low-frequency bands while high-frequency edgesare extracted from the high frequency band using the modulus maximum. The final image is obtained through a simple weighted fusion of two different frequency edges, followed by edge thinning processing. The results are summarized in Table 1.

Table 1:The Edge detection results of a railway image.[19]

	Sobel	**Canny**	**Wavelet**	**Shearlet**	**Ours**
CEN	47930	55520	54339	62644	106872
TEN	53440	81110	81109	70194	113115
R	0.8969	0.8061	0.9547	0.8924	0.9448

2.3. Feature Extraction and Periocular Recognition

The success of facial recognition systems depends on accurate feature extraction and representation. Singh et al.proposed an algorithm using Sobel edge detection and morphological operations for face and eye detection[20]. Dharma et al employed Canny edge detection and Local Binary Patterns(LBP) features with a Self-Organizing Map(SOM) classifier in [21]but achieved lower accuracy (50% for faces, 25% for eyes) due to a small dataset. Noor et al compared various feature extraction methods like Histogram of Oriented Gradients (HOG), Speeded-Up Robust Features (SURF), Features from Accelerated Segment Test (FAST), and Harris corner detection, as shown in [22]. Their findings indicated that HOG, combined with supervised k-means clustering and SVM yielded the highest accuracy of 90.79%. Liliana et al focused on geometric facial feature extraction using Active Appearance Models (AAM) and fuzzy rule-based classifiers in [23], achieving 93.67% accuracy in facial expression recognition.

The periocular region refers to the region around the eye, encompassing various elements such the sclera, eyelids, lashes, brows, and skin. Hernandez-Diaz applies various pre-trained CNN architectures to periocular recognition as presented in [24]. Pre-trained networks like AlexNet, GoogLeNet, ResNet, VGG, and VGG-Face (trained on millions of ImageNet images) are tested and compared against traditional methods such as LBP, HOG, and Scale-Invariant Feature Transform (SIFT). The results indicate that CNNs outperform traditional descriptors, with ResNet101 achieving the highest accuracy. However, further improvements could be made through additional optimization and fine-tuning

Table 2: Results for the method proposed by Hernandez-Diaz [24]

Method	**Equal Error Rate (EER)**	**False Rejection Rate(FRR)At FAR =1%**
ResNet101(Best CNN)	5.6%	14%
Fusion (ResNet101 + Traditional Features)	5.1%	11.3%
HOG(Baseline)	11.3%	31.2%
LBP(Baseline)	17.8%	48%

Parkavi et al.proposed a periocular recognition method using VGG16 and ResNet50 CNN models with K-Nearest Neighbours (KNN) classifiers in[25]. Periocular images were enhanced using ROI extraction andContrast-Limited Adaptive Histogram Equalization(CLAHE)to improve contrast. ResNet50 achieved 80% accuracy, outperforming VGG16's 75%, though performance may decline with low-quality or non-frontal images. The dataset included 24 subjects with variations in pose, illumination, and expression, aligning with challenges noted by Noor et al in [18].

Kowlagi, Rao and Lakshmeeshaused YOLOv7 in their research in [26] for face detection and EYENET for eye feature extraction, highlighting YOLOv7's superior accuracy and speed over other models. While VGG-16 and AlexNet exhibited slower training times and lower accuracy, YOLOv7 outperformed them in face detection, as detailed in Table 3. EYENET, a CNN-based model, identified 12 critical eye feature points, with colour mapping enhanced eye region visibility, enabling the calculation of attributes like eye area and eyebrow length.

Table 1: Performance results of different modelsused in [26]

Model Name	Accuracy	Loss
MTCNN	85.16%	0.346
YOLO v3	86.233%	0.211
HyperFace	87.01%	0.205
VGG -19	87.86%	0.199
YOLO v5	89.32%	0.016
YOLO v6	90.54%	0.003
YOLO v7	91.72%	0.00092

2.4. Eyelash Segmentation Techniques

Table 4: Methods, Findings and limitations of some existing eyelash segmentation techniques

Authors	Method	Key Contribution/ findings	Limitations
Zhang *etal.'s approach* [27]	Adaptive thresholding and Otsu Algorithms are used to enhance accuracy. It is stated that existing methods often face limitations due to fixed thresholds therefore this paper introduces a method leveraging adaptive thresholds, regional constraints, and inter-class variance maximisation (Otsu algorithm) to improve eyelash segmentation accuracy	There is a significant improvement, preserving more texture information, of the proposed approach.	But the approach struggles in identifying the faint end of eyelashes due to low gradient differences
Gao *et al.'s approach* [28]	A novel eyelash detection algorithm utilizes morphological operations to improve efficiency. It defines an effective search area based on pupil position, reducing computational complexity. Morphological closing and threshold-based segmentation generate a binary image of potential eyelash pixels. The detection process occurs in two stages—rough detection and fine detection—ensuring accurate identification of real eyelashes.	With an average processing time of 0.36 seconds per image, this algorithm outperforms previous methods, such as Gabor filter-based approaches (3.68 seconds) and Gaussian Mixture Models (2.20 seconds).	This method ignored the processing of the eyelash tail.
Aligholizadeh et al.'s approach [29]	Eyelashes are detected using wavelet transform and Hough transform for eyelash modelling. Finally, a neural network is employed for segmentation. The segmentation process is based on two assumptions: first, the pupil position is known; second, the pupil position is unknown.	The results indicate that when the pupil position is known, the proposed system performs reasonably well, and eyelash segmentation is achieved satisfactorily. The accuracy of the proposed method under the first assumption is 97.88%, while under the second assumption, it achieves an accuracy of 91.8%.	The algorithm segmented some iris patterns along with eyelash and eyelid regions but did not show success with non-occluded iris image

Deep Learning (DL) is a class of machine learning algorithms that uses multiple layers to extract high-level features from raw inputs [30]. Among these, CNN are one of the most popular Deep Learning models, as they do not require manual feature extraction. Instead, they learn to recognise features from samples through multiple hidden layers. Ivanda et al.'s work provides a brief overview of several deep learning models applicable to hypers pectral image classification, including CNNs, Stacked Autoencoders (SAE), and Deep Belief Neural Networks (DBN), as indicated in [31].

2.5. Vision Transformers

Vision Transformers (ViTs) are a class of deep learning models primarily used for image recognition and other computer vision tasks. While initially developed for Natural Language Processing (NLP), the Transformer architecture has recently gained traction in image classification [32]. According to [33], a common feature across studies is that transformer-based architectures, or their combination with CNNs alone achieve a better accuracy than CNNs alone. The self-attention mechanism in ViTs is particularly advantageous, as it enables the model to capture and integrate information from the entire image from the highest to the lowest layers. [34] explores the robustness of ViT models, noting that they generally outperform ResNets and scale better with model size when trained on sufficient data. It was also observed that ViTs exhibit a high degree of robustness to removing individual layers. This makes ViTs a reliable option for tasks like defect prediction through image classification. ViTs have proven effective across a diverse range of classification tasks such as Hyperspectral and LiDAR Data Collaborative Classification [35], Classification of brain tumours[36] and Traffic Sign Classification [37].

3. METHOD

Our system considers two attributes of the eyelashes-the length and volume, in recommending personalized products to the user. Since no existing methods accurately measure eyelash length, a new approach is proposed to calculate the average length Additionally, eyelash volume is determined using Edge detection as a foundation.

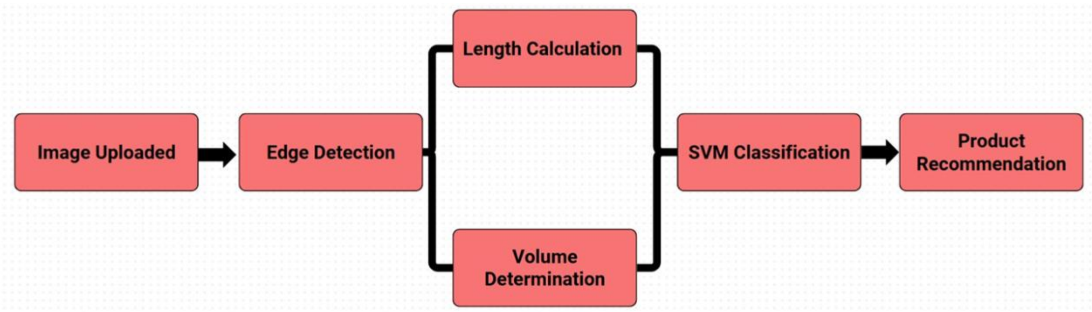

Figure 1:Flow diagram of the proposed Methodology

3.1. Data Collection

There are limited datasets available in this area of research. While a dataset of periocular regions is available on Kaggle [38], it contains a higher proportion of male images compared to female images. To avoid bias in the system, this dataset was not used. Instead, a customised unbiased dataset was created with images from different skin tones and genders. The images used for length calculation and model training are of high quality. If an image is unclear or contains blurry eyelashes, making them less visible, edge detection will struggle to accurately identify the eyelashes.

3.2. Pre-Processing

To ensure accurate analysis, all inputs underwent preprocessing before feature extraction and classification. Each image was resized to 128*128 to ensure uniformity across the dataset. The images were then converted to grayscale conversion to enhance effectiveness of edge detection. To minimize unwanted details while preserving significant features such as eyelashes, Gaussian blur was applied to reduce noise.

The extracted features, the eyelash length and volume, were stored in a CSV file. The CSV file contained the following columns:

- Image Filename: The name of the processed image.
- Eyelash Length (pixels): Measured average pixel length
- Real Length (mm): The real eyelash length of the eyelashes
- Eyelash Volume (Edge Density Score): Ratio of the edge pixels to total pixels in the defined ROI.

Feature scaling and normalization ensure consistency in input data for model training. In this approach, the pixels values of images are normalized to a range of [0,1] by dividing by 255, enhancing model convergence and preventing large-scale variation from affecting learning. The preprocessing step ensures that only high-quality, standardized input is fed into the deep learning model, improving the accuracy of length estimation and product recommendations.

3.3. Eyelash Length Calculation

The image is loaded and pre-processed by setting it to a fixed size, converting it to Grayscale, and applying Gaussian Blur to reduce noise. Edges are then detected using Canny edge detection, which is identified as best predefined edge detection algorithm in[18]. Contours are detected in the edge-detected image using OpenCV's contour detection functions [39], and the three longest contours are selected by sorting them based on their perimeter. Next the contour points are extracted, and the top-most and bottom-most points are identified. The shortest path between these points is calculated using graph theory, with Dijkstra's algorithm employed for the computation. This method is applied to several eyelashes to determine their length from which an average length is derived. The method calculates the pixel length of the eyelashes, which is later converted to real-world measurements.

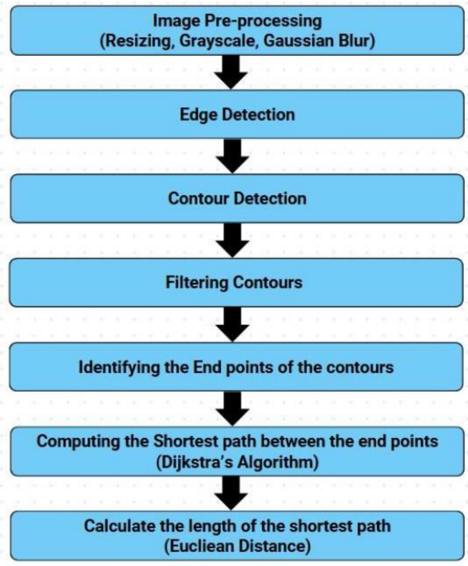

Figure 2: Flow diagram shows the length calculation method explained in 3.3

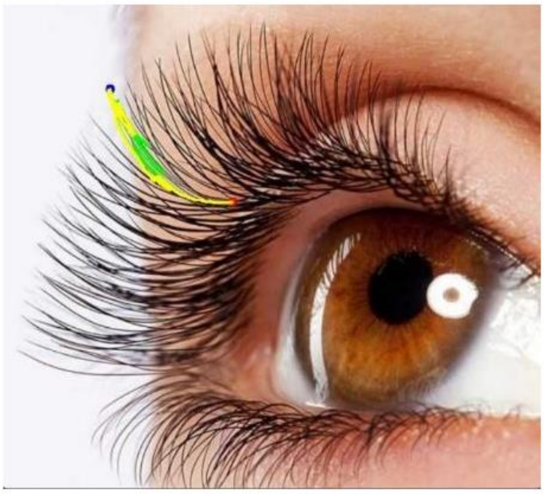

Figure 3: The blue point indicates the starting point, and the red point indicates the end point. The green line is the original length identified by the contour and the yellow is the shortest path between the two points

3.4. Volume Determination

Canny edge detection is applied to images to identify edges. A specific ROI is defined in the eyelash to analyse the upper eyelash region. The edge pixels within the ROI are counted, along with total number of pixels and the edge density is calculated. Higher edge density values indicate denser eyelashes, while lower values suggest sparser eyelashes. The edge density is given by:

$$Edge\ Density = \frac{Number\ of\ Edge\ Pixels}{Total\ ROI\ Pixels} \tag{1}$$

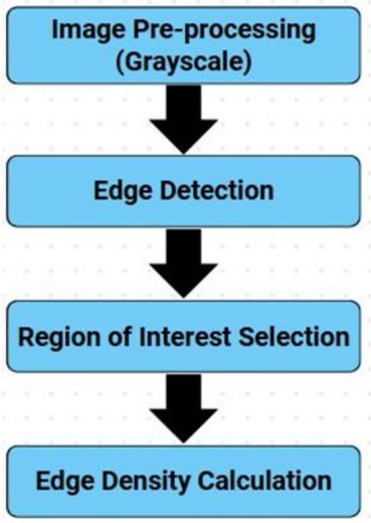

Figure 4: Volume Determination Approach

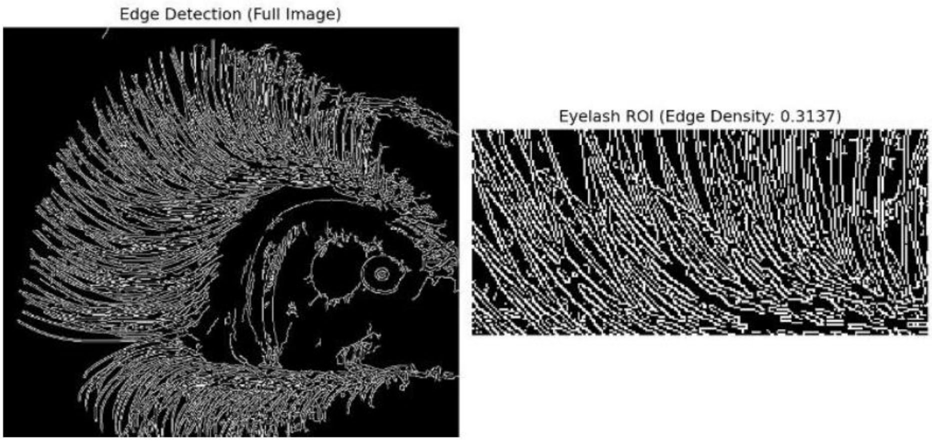

Figure 5: The original edge-detected image and the ROI extracted from the eyelash region.

3.5. Model Training

A Custom CNN for Image-based regression of eyelash lengths is trained to estimate eyelash lengths from images using deep learning techniques. For the model training, a customised dataset was used by collecting a diversity of images. The corresponding length values were calculated using method in 3.3 and stored in a CSV file. The images were resized to 128*128 pixels [40,41] to ensure uniformity across the dataset. To improve the CNN's learning efficiency, pixel values were normalised (scaled between 0 to 1) using MinMaxScaler enhancing model convergence.

The dataset is split into training (80%) and validation (20%) sets to assess generalisation. Different data split ratios, such as 70:30 and 90:10, were tested, and the results showed that the 80:20 split provided best balance between training efficiency and generalization performance. The model is optimised using the Adam Optimiser with a learning rate of 0.001 for efficient weight updates. Training is conducted for 20 epochs with a batch of 32. A total of 200 images were used for training, while 50 images were used for validation.

As part of the evaluation, a ResNet50-based CNN is trained. The model leverages transfer learning by using the pre-trained ResNet50 architecture as a feature extractor. The extracted features are passed through fully connected layers with ReLU activation and Dropout for regularization, with the final output is a single continuous value representing the predicted eyelash length. The model was trained for 20 epochs with a batch size of 32, using the Adam optimizer with a learning rate of 0.001, the same as our custom CNN model.

Table 5: Custom-CNN Architecture

Layer	**Number of Nodes**	**Kernel Size**	**Activation Function**	**Other Details**
Input Layer	-	-	-	Image Input (128*128*3)
Conv2D	32	(3,3)	ReLU	Feature Extraction
MaxPooling2D	-	(2,2)	-	Reduces Dimensionality
Conv2D	64	(3,3)	ReLU	Extracts More Features
MaxPooling2D	-	(2,2)	-	Further Down sampling
Conv2D	128	(3,3)	ReLU	Deeper Feature Extraction
Flatten	-	-	-	Converts Feature Maps to 1D
Dense	128	-	ReLU	Fully Connected Layer
Dense	64	-	ReLU	Fully Connected Layer
Dense (Output Layer)	1	-	Linear	Regression Output (Eyelash Length)

3.6. Product Recommendation

The classification model recommends appropriate eyelash care products considering two attributes - length and volume. It utilizes a SVM classifier, as the dataset is relatively small, and the decision boundary is well-defined for cosmetic recommendations. SVM uses Radial Basis Function (RBF) kernel to handle non-linearity, the independent variables are Eyelash Length (px) and Eyelash Volume, while the dependent variable is Product Recommendation. For classification, eyelash length is categorized into three classes: short, medium, and long, while volume is classified as thick or sparse'. The dataset is split into 75% for training and 25% for validation. Unlike neural networks, SVM does not use epochs but instead determines the optimal decision boundary for classifying eyelash length and volume.

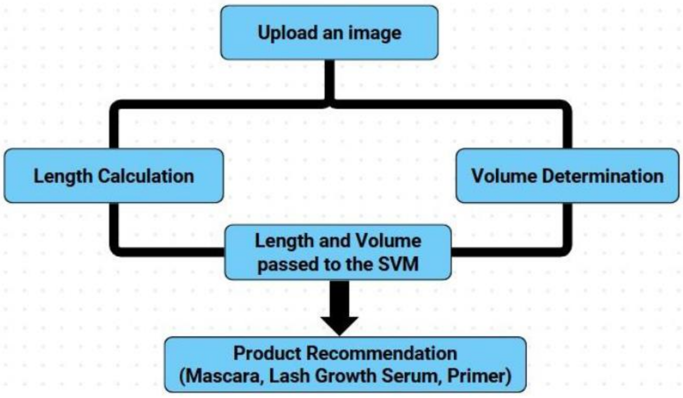

Figure 6: Flowchart depicting the Product Recommendation using an SVM Classifier in 3.6

4. EXPERIMENTAL RESULTS

The proposed method for calculating the average length of the eyelash is applied to multiple images. Using the Python Matplotlib library, the contour-drawn image is visualised to verify whether the contours are correctly mapped onto the eyelashes. The pixel length of the eyelashes is manually measured using the ImageJ software. A comparison between the manually measured length and the length calculated by our method for a few sample images is shown in the Table6.

Table 6: Comparison of Pixel Length using Manual and Our Method

Images	**Manual Calculation Length/pixels**	**Our Method Calculation Length/pixels**
1	108	140
2	183	174
3	145	116

Figure 7: Edge detected images with the extracted ROI

Figure 7 shows the edge detected images along with the ROI extracted for determining the volume of the eyelashes. The right image has a sparse volume of eyelashes with an edge density of 0.1121 but the left image has a thick volume of eyelashes and has edge density of 0.2847.

Selecting the appropriate evaluation metrics for predictive modelling is a crucial decision influenced by the objectives and characteristics of the dataset. Muraina et al.’s study in [42]explores various classification and regression evaluation measures including accuracy, confusion matrix, precision. Several metrics are used to assess model performance. The Mean Absolute Error (MAE) is computed to measure the average absolute difference between expected and actual values [43], while the Mean Squared Error (MSE) quantifies the mean squared difference between expected and actual values [44].Mean Absolute Percentage Error (MAPE), acommonly used metric for evaluating the accuracy of predictive models, particularly in regression tasks. Is given by:

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2}$$

where n represents the number of summation iteration happens, A_t denotes the actual value, and F_t represents the forecast value.

Table 7: Performance Comparison of Custom CNN and ResNet50 for Length Prediction

Model	**Mean Absolute Error (MAE)**	**Mean Squared Error(MSE)**	**MAPE(%)**
Custom CNN	25.29	877.91	25.29%
ResNet50	34.12	1747.53	34.12%

The Table 7 compares the performance of our custom CNN model with ResNet-10. The evaluation indicates that our model outperforms better compared to the ResNet-10, as it achieves lower MAE and MSE values. Additionally, the Mean Absolute Percentage Error (MAPE %) of the CNN is 25.29%, which is lower than that of ResNet-10, suggesting better overall accuracy.

The graph illustrates the training and validation MAE over the epochs. The initial drop in training MAE indicates a significant model improvement, while the validation MAE also decreases, though at a comparatively slower rate. Both lines remain close to each other, indicating that the model is generalizing well and not overfitting. During the training, the rate of improvement diminishes, with both lines flattening after a few epochs. This suggests that the model has learnt most of the patterns available in the data. Further improvements could be achieved using techniques such as data augmentation and learning rate adjustment. The backend is developed using Fast API, the attribute calculation and the product recommendation is shown in Figure 9 and 10.

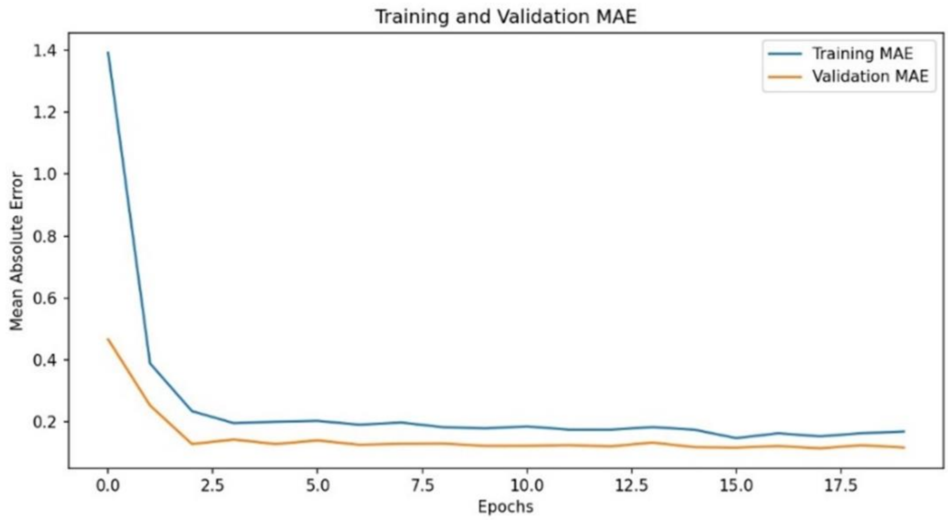

Figure8: Graph showing the training and validation MAE for the Custom-CNN model

Figure 9: The image inputted for recommendation

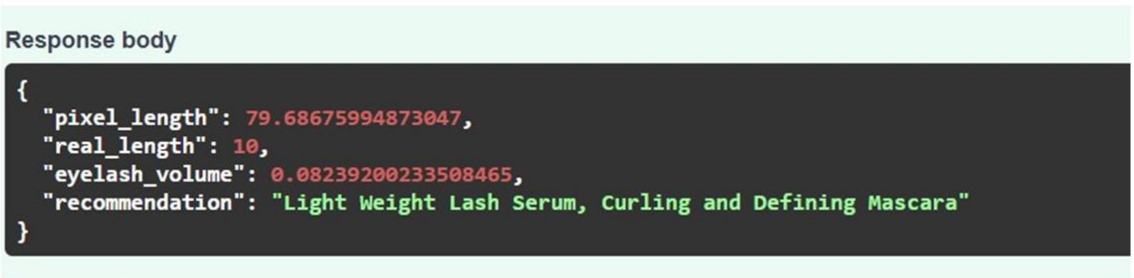

Figure 10: The response from the backend for the inputted image

Table 8: SVM performance metrics

Precision	**Recall**	**F1-Score**
0.97	0.98	0.97

The accuracy of the SVM is 75%, indicating a reasonably reliable recommendation of products. However, accuracy alone does not fully determine whether a model is good or poor. A more comprehensive evaluation requires considering additional metrics such as precision, recall, and the F1-score, which together provide a better understanding of the model's performance.

Table8 summarizes key evaluation metrics:

- A precision of 0.97 indicates that the model effectively minimizes false positives across all classes.
- A recall value of 0.98 demonstrates that the model is highly effective at identifying instances from all categories.
- An F1-score of 0.97 highlights that the model performs well in terms of both precision and recall across all classes [42].

5. Discussions

When examining the contours identified in the images, as shown in Figure 3,it is evident that they do not extend to the very base of the eyelashes (near the root). This region consists multiple lash endings, making it challenging to accurately determine the termination point of an individual lash.lash. This limitation may contribute to the differences between the manually calculated values and those obtained using our method. The pixel length is then converted to the original length in millimeters (mm).

The volume of the Region of Interest (ROI) extracted by this approach is validated through visualization, which provides an indication of the eyelash density. While this visualization does not represent the actual volume of the eyelashes, it serves as a method to assess whether they appear thick or sparse. An edge density value of 0.01 edge indicates sparse eyelashes, whereas a value of 0.30, suggests denser eyelashes (refer to Figure 7).

This approach to calculating the average eyelash length or training a custom CNN is entirely novel, with no prior research available for direct comparison. To evaluate its performance, a ResNet-50 model—known for performing well compared to other pre-trained architectures in [24]—was trained. However, the evaluation indicates that the custom CNN outperforms ResNet-50.Since ResNet-50 is a very deep network (50 layers) designed for extracting hierarchical features in classification tasks, it may not be well-suited for this specific problem. Given the small dataset and lack of complex patterns, ResNet-50 is prone to over fitting, leading to poor generalization on new data.

The SVM Model is trained for product recommendation performs well, achieving good accuracy. Unlike deep learning models, SVM is effective even with limited data. The length and the volume of the eyelashes are considered in recommending products as shown in Figure 6 and 10, the attributes are passed to the classifier and it provides personalised recommendations such as the right Mascara, Curler and removal products etc.

Currently, the system does not store user-uploaded images, ensuring a level of privacy protection. However, in future implementations where real-time image capture is integrated, security measures will be crucial to safeguard user data. Secure storage methods, such as encrypted databases or temporary session-based storage, will be employed to prevent data misuse. Furthermore, privacy-preserving AI techniques, such as on-device processing or edge computing, will be considered to minimise risks associated with storing sensitive biometric data on external servers.

6. CONCLUSION

This paper presents the development of a makeup recommendation system specifically designed to suggest personalized products for eyelashes, addressing the lack of systems that focus on eyelashes when recommending makeup. The proposed method calculates the average length of eyelashes by training a CNN model to predict this length, while also determining the volume of the eyelashes. Users provide an image to receive personalized product recommendations and eyelash care tips, generated using the SVM classifier.

For future work, the dataset could be expanded with more images, potentially improving the accuracy of the CNN model. Additionally, the method for calculating eyelash length could be refined to work with standard images, or a technique to upscale images before applying the method could be explored. And with the integration of multi-modal learning techniques, leveraging transformer-based architectures and sensor fusion methods to enhance the accuracy of eyelash analysis and personalized beauty recommendations.

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