Abstract

In Taiwan, the "Beauty Technician Certification" serves as an essential professional benchmark in the beauty industry. However, its reliance on subjective human evaluations introduces inconsistencies, leading to regional disparities and potential unfairness. This project aims to address these issues by leveraging machine learning techniques to develop an objective and standardized evaluation system, with a focus on the smoothness and cleanliness of lip makeup as an initial target.

The project employs basic machine learning classifiers and begins with lip contour extraction through techniques such as image cropping, masking, and edge detection. Two features were explored:

(1) the area difference between contours under hue and saturation channels, and

(2) the Mean Squared Error (MSE) from polynomial regression fitted to lip contours.

Unfortunately, the features were not sufficiently distinguishable—either due to imprecise contour detection or the selection of ineffective features. While achieving precise contour detection across all photos under both the hue and saturation channels proved challenging, I observed that contours with smaller areas were often accurately identified as lip boundaries. This observation suggests that the fitting curve of these contours could be utilized in the future to calculate another potential scoring criterion for lip makeup: symmetry.

Introduction

1.1. Motivation

Beauty standards vary significantly among individuals, influenced by factors such as nationality and gender, which shape personal perceptions of attractiveness. Surveys often reveal general trends; for instance, facial contrast positively correlates with perceived femininity in female faces and negatively with perceived masculinity in male faces. Consequently, makeup is found to exaggerate femininity, making women appear more attractive [1]. However, the precise criteria underlying judgments of "beautiful" or "unattractive" remain elusive.

With technological advancements, the quantification of beauty has become possible through methods like deep learning. Unlike traditional techniques using handcrafted features, deep neural networks (DNNs) learn high-level features from large datasets of facial images, enabling more precise predictions [2]. Moreover, research found that DNNs can simulate human visual processing stages across both time and space [3].

These technologies not only offering insights into human cognition, but also provide innovative and rather fair evaluation methods for certification examinations. This is particularly important in Taiwan. In our country, the "Beauty Technician Certification" serves as a critical benchmark for professional qualifications in the beauty industry; however, its reliance on subjective human evaluations often leads to inconsistencies among evaluators, resulting in vagueness and unfairness. For example, individuals may find it easier to pass the exam in one region but harder in another or feel compelled to pay for expensive courses offered by evaluators. This project aims to address these issues by leveraging machine learning techniques to create an objective and standardized evaluation system.

1.2. Previous Works

The Beauty Technician Certification evaluates makeup techniques for individual facial features separately (Fig. 1.2.1). However, previous studies on human aesthetics have primarily focused on overall facial attractiveness, such as putative ratios of facial features [4]. Research specific to assessing techniques for individual features remains underdeveloped.

To address this gap, this project aims to develop a novel machine-learning-based solution. As an initial target, I focus on evaluating the smoothness and cleanliness of lip makeup.

分級說明　級別「1」60分以下…未達標、級別「2」60~69分…低標、級別「3」70~79分…中標、級別「4」80~89分…高標、級別「5」90分~100分…頂標

項目	1. 粉底			2. 眉型						3. 眼影			4. 眼線				5. 假睫毛		
技法	適當性	對稱	流暢度	適當性	對稱				流暢度	對稱	色彩漸層	無分界線	適當性	對稱		流暢度	適當性	對稱	
	配合臉型	立體感	色彩均勻	配合臉型	形狀	角度	粗細	長短	深淺均勻	修飾眼型	色彩調和	自然潔淨	配合眼型	形狀	線條	線條順暢	配合眼型	長度	位置
單項分數	5	5	5	5	5				5	5	5	5	2	3		2	3	4	
項目配分	15			15						15			7				7		
項目	6. 鼻影				7. 腮紅				8. 唇型					9. 整體感			總分	級別	
技法	適當性		對稱	流暢度	適當性	對稱	流暢度		適當性	對稱		流暢度		整體性					
	配合臉型	鼻型修飾	形狀線條	順暢自然	臉型修飾	位置	自然均勻	無界線	唇型修飾	左右對稱	上下厚薄	自然均勻	無界線	色彩搭配	美感	潔淨			
單項分數	3		2	2	2	2	3		2	3		2		10	5	5	100	5	
項目配分	7				7				7					20					

Fig. 1.2.1 Evaluation form of Level B Technician for Beauty.

1.3. Research Methodology in this project

Given my limited technical experience, I chose to implement one of the most fundamental concepts in machine learning: classifier. The research began with extracting lip contours and gradually identifying distinguishable features.

How to accurately detect the lip region became the first obstacle. Most existing research on lip contour analysis focuses on lip-reading recognition, where minimal anchor points describing lip shape features are required. This approach diverges from the goals of this project. In order to draw the whole contours of lips, I implemented several image-processing techniques, including image cropping, filtering, masking, and edge detection.

To further extract distinguishable features, I explored two potential characteristics for classifying lip makeup quality:

1. Area Difference: Calculating the area difference between contours under the saturation and hue channels.

2. Fitted Contours: Applying polynomial regression to fit lip contours and calculating the Mean Squared Error (MSE) between the contours and their fitted lines.

Observation → Image Processing → Feature Extraction → Classification

Fig. 1.3.1 Project process.

1.4. Results and Conclusion

Although the concept of a classifier is straightforward, significant challenges emerged in the stages of image processing and feature extraction. I experimented with various methods to improve contour detection, such as combining masking and edge detection results using XOR operations. Unfortunately, the features I identified were not sufficiently distinguisha-ble—either due to imprecise contour detection or the selection of ineffective features.

Nonetheless, a detailed inspection of the data revealed that lip contours were generally captured accurately across both the hue and saturation channels, despite minor distortions caused by shadows or lighting variations. These distortions were often mitigated by the curve-fitting process, which suggests that the fitted results reliably represented the lip shapes observed in both channels. However, the extracted features still failed to produce meaningful separability in classification, indicating that distinguishing makeup quality us-ing these features alone might be inherently challenging.

While achieving precise contour detection across all photos under both hue and saturation channels proved challenging, contours with smaller areas were often accurately identified as lip boundaries. Future research could leverage the fitting curves of these contours to compute additional scoring criteria, such as symmetry, for lip makeup evaluation.

Review and reflections

現有研究中，關於唇形的機器學習多應用於輔助唇語判讀的唇形辨識。這些研究通常著重於如何以最少的錨點來描述不同唇形特徵，而對於唇形流暢度的探討則較為罕見。由於缺乏相關文獻參考，實作前我花了大量時間探索可行的研究方法。過程中曾經歷許多天馬行空的想像，但礙於學習到的知識有限，最終還是選擇以最基礎的分類問題和迴歸問題作為研究方向。

剛開始以少量樣本進行影像處理測試與觀察特徵時，一切還很順利。通過分析圖片的 HSV 色彩空間，可以發現：色相值高的區域涵括了模特兒本身的嘴唇範圍加上口紅塗抹區域，而飽和度高的區域則代表實際塗抹口紅的部分。進一步偵測邊緣後，發現如果唇形畫得較好，色相和飽和度下的輪廓會比較一致，飽和度的線條也更加流暢，且嘴角部分也塗得較俐落。

然而，想將相同的方法推廣至其他樣本時，卻遇到許多挑戰。使用邊緣偵測圈選唇形輪廓時，適用於每張圖片的參數各異，很難找到適用於所有照片的閾值。後來又改用建立遮罩的方式來偵測輪廓。由於嘴唇與皮膚之間的色相差異較大，換方法後的確能較準確地圈出色相通道下的唇形。可惜飽和度的分析仍受光線與陰影影響，無法得到穩定的結果，將參數正規化（normalize）也無法解決此問題。單純使用邊緣偵測常出現只有部分邊緣被留下的狀況，建立遮罩又找不出恰當的參數，最終，我將遮罩和邊緣檢測的結果結合，進行 XOR 運算，才改善了唇形輪廓的偵測效果。

在這次研究中，我深刻體會到，機器學習分類和迴歸問題的邏輯雖然簡單，但在實際應用中，要找到合適的特徵是非常困難的挑戰。過程中，我一度過於執著地尋找能精準圈選每個唇形輪廓的方法，卻偏離了最初的研究目標：找到一個能夠反映唇形流暢度的評分方式，這導致我花了過多時間在精進影像處理的步驟，而沒把重心放在解讀數據上。直到試著將圈選好的輪廓疊加到原始影像上查看時，才發現有些圈選不清晰的地方恰好反映出口紅邊界模糊或暈開的部分。這讓我深刻體悟做完實驗要檢查結果，並思考結果是否合理的重要性。整體來說，本次實作加深了我對機器學習的理解，為了理解人工評審的評分標準，我從不會化妝到成功通過美容丙級考試也是研究過程中的一個意外收穫。