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ChromaLipSense: Lipstick-Based Biosensors for Metabolic Monitoring

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ChromaLipSense: Lipstick-Based Biosensors for Metabolic Monitoring

Lipstick as a ubiquitous beauty product is an ideal substrate for the encapsulation of biosensors due to its direct contact with saliva, food and drinks, frequent use, and discrete nature. This article introduces ChromaLipSense, a lipstick that seamlessly embeds a colorimetric biosensor whose colors change in response to pH levels. This project addresses limitations in existing biosensor technologies, such as transdermal patches and temporary tattoos, which often pose challenges related to adhesion, invasiveness, and frequent calibration requirements. Saliva is a readily-available bodily fluid for biosensing applications due to its transparent, regenerative nature and rich composition that indicates health-related information. The main contributions include the use of a lipstick as a biosensing form factor, a DIY fabrication process for biosensor lipstick using medical-grade commercial products, and the integration of machine learning algorithms for on-body biosensor detection. The data collection process involved five pH calibration solutions, six distinct lighting conditions, the use of two devices for photo capturing, and four participants. The results presented an accuracy of 96.88% in detecting the pH levels. ChromaLipSense as a novel biosensing platform offers continual metabolic monitoring through everyday beauty products in wellbeing and healthcare sectors.

Keywords: Lipstick; biomaterials; colorimetric biosensors; deep learning; color detection; machine learning; biosensors

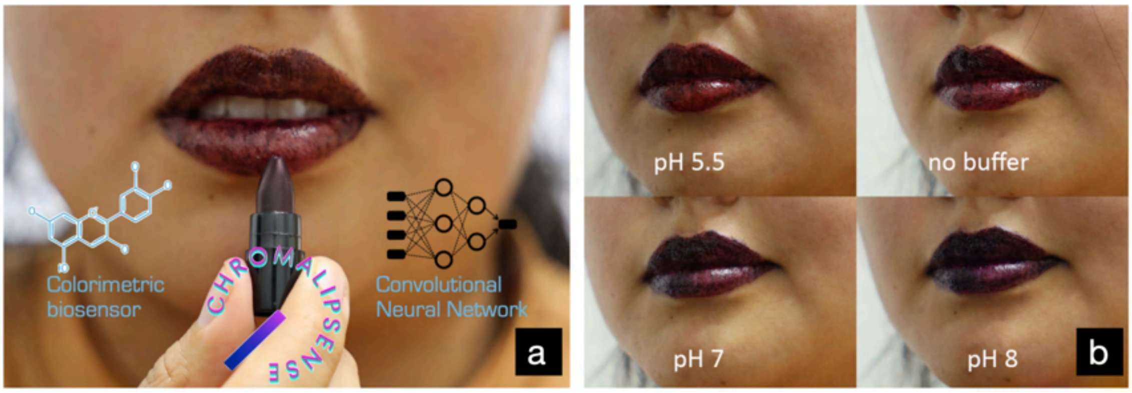


Figure 1. ChromaLipSense: Detecting color changes in a lipstick biosensor with Machine Learning. a) User applying biosensor; b) Colorimetric demonstration across pH levels and control.

1. Introduction

Colorimetric biosensors, whose colors change to indicate specific analyte concentrations such as pH, sodium, or glucose, play a crucial role in illness detection and health monitoring. This sensing method opens up new possibilities for exploring biosensors that can detect analytes in various body fluids, including blood, interstitial fluid, saliva, sweat, and tears (Yetisen et al. 2018).

While transdermal sensors interacting with interstitial fluid are prevalent in commercial products such as diabetic patches (Vaquer, Barón, and de la Rica 2021a) and novel research such as biosensor tattoos (Vega et al. 2017; He et al. 2021), they often present challenges related to invasiveness and tissue damage (Shaji and Varkey 2012). Non-invasive alternatives involve measuring sweat using skin-worn patches (Nyein et al. 2018; Yang et al. 2020), jewelry (Young-Ng et al. 2022; Sun et al. 2023), and fabric (Zhu et al. 2023). However, these sweat sensors as patches or fabric present certain drawbacks, including the need for frequent calibration and the potential to induce contact dermatitis, which restricts their practicality in continuous analyte monitoring (Nakata et al. 2017). Additionally, maintaining the long-term stability and durability of the colorimetric components is essential for sustained functionality.

Securing the patches or temporal tattoos on the skin poses challenges, as they tend to lose adhesion, particularly in moist conditions. Moreover, the need for replacement arises when they become wet, limiting their usability to a single application or requiring a process for biosensor restoration.

As another non-invasive alternative for colorimetric biosensors, saliva stands out for its transparency, regenerative nature, and rich composition of crucial health-related information. With a complex composition featuring enzymes, hormones, antibodies, and metabolic byproducts, saliva proves invaluable for assessing diverse physiological levels (Zhao et al. 2018). Due to its easy collection process and direct correlation with systemic processes, saliva is an attractive medium for monitoring various health parameters, including pH (Moonla et al. 2022), which is associated with periodontal disease such as enamel decalcification (Maheshwaran et al. 2020), glucose (Bordbar et al. 2023) and lactate (Pomili, Donati, and Pompa 2021a). However, the current method involves collecting human saliva in a container and pouring it onto a paper substrate, which is inconvenient for people to use in their daily lives.

Lipstick serves multiple roles, enhancing cosmetic appearance by adding color and definition to the lips, while also acting as a form of self-expression, confidence boost, and hydration. Historically, lipstick has evolved from being associated with cultural, religious, and wealth status symbolism to becoming a polarizing yet iconic symbol in the marketplace (Gurrieri and Drenten 2021). In the United States, the popularity of lipsticks is evident, with over 22.62 million women using them in 2023—a number projected to soar to 124.68 million in 2024 (Statista, n.d.). While lipstick has traditionally served as a means to draw attention to the lips, making them stand out and enhancing self-esteem and confidence, recent trends have witnessed a phenomenon where people actively pursue specific lipsticks endorsed by celebrities. This pursuit has led to a somewhat standardized appearance among individuals. Consequently, there is a growing desire to shift away from this trend, with the hope that each person can have a lipstick uniquely tailored to their own color—a shade that is exclusively theirs. This reflects an emerging call for more personalized and diverse expressions of individuality through cosmetic choices.

Lipstick, a widely-used beauty product, becomes an optimal substrate for biosensors given its direct contact with lip interactions involving saliva and the consumption of food or drinks. Its common features, such as portability, constant routine reapplication throughout the day, and discreet nature, align with the convenience desired in wearable biosensing devices. Furthermore, the natural color variability found in lipsticks provides a visually intuitive representation of pH changes, transitioning from pink to purple.

This study presents ChromaLipSense: a novel Lipstick Biosensor capable of displaying pH levels through color variation, offering a visually intuitive representation of saliva's biochemical information. The developed lipstick biosensor is shown in Figure 1. User interactions involve common lip gestures like mouthwatering or lip smacking, as well as interactions with foods and drinks. The main contributions include:

1. **ChromaLipSense Biosensor:** Introducing ChromaLipSense, a novel form factor of colorimetric biosensors in the shape of a lipstick designed to interact seamlessly with saliva and respond to the ingestion of food or drinks.
2. **DIY Fabrication:** Detailing a DIY process for biosensor lipstick with natural pigments and skin-safe buffers for technical and user evaluations.
3. **Machine Learning for on-body colorimetric biosensor detection**: Employing deep learning models for pH levels detection on lips.

4. **Lighting conditions:** considering diverse lighting conditions when generating the dataset, enhancing robustness and applicability of the model.

2: Related Works

2.1: Saliva in Metabolic Diagnostics

Saliva is gaining recognition as a valuable diagnostic fluid due to the presence of diverse biomarkers that signal various diseases. These salivary biomarkers accurately mirror both normal and diseased conditions in humans (Baliga, Muglikar, and Kale 2013). The advantages of saliva sampling, in contrast to blood sampling and other body fluids sampling, include its non-invasive and cost-effective collection methods (Malon et al. 2014; Chiappin et al. 2007). As an example, salivary pH was more alkaline for patients with generalized chronic gingivitis and whereas patients with generalized chronic periodontitis had more acidic pH, due to *P. gingivalis* growing at a pH of 6.5-7.0, *P. intermedia* at a pH of 5.0-7.0 and *F. nucleatum* (Baliga, Muglikar, and Kale 2013) at a pH of 5.5-7.0. Salivary analysis extends beyond traditional diagnostic approaches, offering insights into metabolic, hormonal, and immunological aspects (Chiappin et al. 2007; Zhao et al. 2018). Though mostly present in the mouth, saliva is occasionally exposed to the external environment, which is how it can serve as a potential vector for transmitting infectious diseases (Zhao et al. 2018).

The examination of salivary pH, for instance, provides valuable information about the body's acid-base balance; maintaining an average pH of 6.7, deviations indicate potential systemic abnormalities like gingivitis (Baliga, Muglikar, and Kale 2013; Narasimhan et al. 2023). Salivary pH, regulated by both the sympathetic and parasympathetic nervous systems, has the potential to function as a stress biomarker

(Cohen and Khalaila 2014). BraceIO introduces biochemical ligatures for dental braces that respond to variations in saliva concentration levels, including pH, nitric oxide, and uric acid. These ligatures exhibit color changes that can be conveniently interpreted by an external device (Vasquez, Yetisen, and Vega 2020).

2.2: Biosensors

Biosensors contribute to personalized medicine, tailoring treatment plans based on individual responses and variations. Microneedle dermal tattoo patches (He et al. 2021), laser cut paper sensors (Pomili, Donati, and Pompa 2021b), and more techniques are used to create color-changing biosensors to detect multiple biomarkers like pH, glucose, uric acid, and temperature. Changes are visible to the naked eye or a camera for semi-quantitative measurement. It works in various settings, including in vitro, ex vivo, and in vivo, and can monitor biomarker concentrations for at least 4 days, promising for long-term health monitoring (He et al. 2021; Maheshwaran et al. 2020; Zhu et al. 2023).

Continuous monitoring of glucose levels has revolutionized diabetes management, allowing individuals to make informed decisions about insulin administration and lifestyle choices (Cappon et al. 2019). A laser-engraved sensor that enables simultaneous sweat sampling, chemical sensing, and vital-sign monitoring, showcasing continuous detection of temperature, respiration rate, and low concentrations of uric acid and tyrosine, which are associated with conditions such as gout and metabolic disorders (Yang et al. 2020). The integration of biosensors into wearable devices enhances their accessibility and usability, empowering individuals to actively participate in their health management (Bhatia et al. 2024; Nyein et al. 2018). Biosensor technologies promise to redefine healthcare practices, offering a comprehensive and data-driven approach to monitoring health and managing illnesses.

Smartphone-based colorimetric sensors enable on-site diagnostics and point-of-care testing. Image quality impacts detection sensitivity, and users can optimize it by adjusting accessories and parameters (Geng et al. 2023; Vasquez, Yetisen, and Vega 2020). Colorimetric sensing establishes a relationship between sample content and color data to determine single or multiple samples accurately. Smartphones enhance portability and accuracy by capturing images through customized accessories for various platforms. Embedded smartphone apps enable real-time colorimetric detection and sensitive result output (Geng et al. 2023). Drawing inspiration from these works, the paper presents the creation of a lipstick with skin pH biosensing capability.

2.3: Color Sensing Techniques

Traditionally, colorimetric sensing can be done by naked eye-based detection and is limited to reactions with significant color changes. Instrument-based detection is usually conducted in controlled lab settings with specific lighting environments and a bulky spectrophotometer. This method faces challenges in its application under various conditions. Thus, machine learning provides a promising avenue for improving the accuracy and applicability of colorimetric sensing technology.

In the realm of artificial intelligence (AI), machine learning (ML) has made remarkable strides, especially with the advent of advanced methods like deep learning, renowned for its applications in image analysis, facial recognition, and speech recognition. Notably, the spotlight is on deep learning techniques, particularly the convolutional neural network (CNN) (Anwar et al. 2018) and recurrent neural network (RNN) (Mou, Ghamisi, and Zhu 2017), which work well in image analysis. This assists in detecting and calibrating biosensors, turning electrochemical biosensors, fluorescence biosensors, and colorimetric biosensors into intelligent biosensors (Cui et al. 2020). In colorimetric biosensors, the color change in a colorimetric biosensor requires visual interpretation under various lighting conditions. Variations in ambient light may impact the perceived color, making it essential to use in certain environments for consistent and accurate results. Using machine learning could provide more accurate pH values in different situations because it allows us to gather data from various lighting conditions.

In the realm of early colorimetric biosensors, the support vector machine (SVM) frequently serves as the preferred machine learning classification algorithm. SVM, a supervised learning model, intricately devises an optimal hyperplane to discern data pertaining to distinct classes (Hearst et al. 1998). Leveraging inequality-type constraints, SVM optimizes the quadratic function of variables. However, under dual lighting conditions, the accuracy of SVM is constrained, reaching only up to 80% accuracy (Solmaz et al. 2018). Consequently, in recent studies on biometric biosensors, the introduction of deep learning (DL) methods has emerged as a promising avenue to address these limitations. Besides SVM, deep learning, particularly the Convolutional Neural Network (CNN) model, has proven highly effective, yielding an impressive accuracy rate of 99%. CNNs exhibit robust computational efficiency in image classification due to their utilization of convolution and pooling operations, coupled with parameter sharing. A pivotal component of CNNs is the convolutional layer, which applies a convolution filter to the input data, generating a feature map. This process allows the incorporation of nearby pixels in the prediction, enhancing accuracy and enabling adaptation to varying conditions or positions for the target (Mercan and Kılıç 2020).

Since the biosensor is intended for use in challenging conditions, including varying lighting conditions, high/low light illuminations, and reflections, addressing these challenges becomes crucial. Prior research has presented a computer vision framework to tackle such issues (Sivakumar et al. 2022). Similar challenges were encountered in previous approaches involving machine learning algorithms (Mutlu et al. 2017), where the model's sensitivity to specific lighting conditions posed a limitation. To mitigate the impact of ambient light interference, incorporating a diverse set of input data that includes adverse effects, such as varying ambient illumination conditions, can enhance the machine learning algorithm's robustness under more versatile conditions (Yüzer et al. 2022).

3: Implementation

3.1:Design Considerations for ChromaLipSense

In order to ensure maximum colorimetric biosensing capabilities, the introduced lipstick biosensor formula uses a tested balance of water resistant, water soluble, and absorbent cosmetic grade materials. The design considerations include safety of materials, availability, and functionality. For example, it was crucial to ensure that the applied lipstick adhered to the skin and itself, as to not run when liquids were applied, functioning properly as a cosmetic product. At the same time, the lipstick should not be so hydrophobic as to prevent the sensing function of the biosensor, reacting with fluids. Our detailed design considerations are as follows for maximizing and balancing lipstick and biosensing quality:

- **Lipstick:**
    - ***Safety:*** usage of food-grade and skin-safe materials during the lipstick fabrication process to ensure user safety.
    - ***Lipstick Integrity:*** performance of the lipstick as a cosmetic product

        - *Hydrophobicity:* waterproofness and resist dissolving or running when applying
        - *Adhesion:* lastingness on lips once applied
    - ***Appearance:*** the visual result of the lipstick when applied on lips
        - *Intensity:* vividness, opacity, and finish
        - *Color:* desirability of the biosensor colors as a colors are in a range of tones of commercially available lipstick colors
    - ***Texture:*** smoothness, moisturizing of skin, and comfort during and after application
- **Biosensor:**
    - ***Efficacy:*** colorimetric sensing performance of the biosensor
        - *Accuracy:* comparability of results to original form factor (powder, prior to implementation in lipstick) and other biosensors
        - *Speed:* time needed reach readable result and lastingness of result
        - *Range:* visual hue variation range of biosensor color changes
        - *Reactivity:* sensitivity to the targeted analyte without reacting to other chemicals
    - ***Biosensor Performance:*** physical durability and capability of the biosensor. This consideration directly correlates with lipstick integrity, that means that changing the formulation could impact the biosensor performance.
        - *Hydrophobicity:* ability to function effectively in presence of applied liquids while maintaining the integrity of the lipstick layer on the lips

- *Reusability:* number of times the biosensor can be reused and time it takes after each use to return to original state of color or pH level

3.2:ChromaLipSense Fabrication Process

To maximize the quality of the lipstick biosensor, different variations are tried to balance benefits and drawbacks of the considerations, as advantages to one contradict desired results for the other in many cases, as mentioned above. Our chosen ingredients based on the balancing of all criteria are detailed in Table 1 and Figure 2 b). The listed considerations are considered when determining materials, the form factor of the materials, and units. Additionally, if any specific design considerations are notably targeted by the material, it is listed in the targeted criteria column of Table 1.

The design considerations not only influenced material selection but also procedures of the fabrication process. The fabrication process is diagrammed in Figure 3. Fabrication of lipstick biosensor starts with combining 4 portions of a commercial lipstick base, 1 portion of cetyl octanoate, 1 portion of non-nano titanium dioxide, and 1 portion of a skin safe primer adhesive (containing stearic acid, octyldodecanol, and PVP). The wax base used for the lipstick is from TKB 1. The ingredients are Ricinus Communis (Castor) Seed Oil, Cetyl Stearyl Alcohol, Olive Fruit Oil, Cera Alba (Beeswax), Hydrogenated Castor Oil, Glycine Soybean Lipids, Lauryl Laurate, Copernicia Cerifera (Carnauba) Wax, Euphorbia Cerifera (Candelilla) Wax. Cetyl octanoate, stearic acid, and octyldodecanol are emollient with waterproofing properties. Non-nano titanium dioxide helps form a film or a barrier on the skin. PVP is a soluble skin safe adhesive.

Table 1. The ingredients of a Lipstick Biosensor

Ingredients	Targeted Considerations	Usage & *Additional Effects*	Units (%)	Detailed Ingredients
commercial lipstick base [1]	safety, intensity, texture	provide shape and a spreadable texture	33.3	Castor Seed Oil, Cetyl Stearyl Alcohol, Olive Fruit Oil, Beeswax, Hydrogenated Castor Oil, Glycine Soybean Lipids, Lauryl Laurate, Carnauba Wax, Euphorbia Cerifera Candelilla Wax
cetyl octanoate	adhesion, hydrophobic, texture	waterproofing, emollient and texture enhancer. Skin conditioning agent	8.3	
non-nano titanium dioxide	intensity, hydrophobic	waterproofing, provide opacity to products such as paints, plastics, papers, inks. *H*elps protect the skin from ultraviolet light	8.3	
skin safe primer adhesive	adhesion, texture	forms a film or a barrier on the skin, acts as thickening agent for improving the texture of formulations, and acts as a soluble skin safe adhesive	8.3	stearic acid, octyldodecanol, PVP
clear silver mica powder	intensity, range, color	lightweight, long-lasting color effect, reflect light. Create a pearlescent effect	8.3	Mica, Titanium Dioxide
red cabbage powder	range, color, efficacy	pH sensing coloring agent	33.3	

[1] https://tkbtrading.com/products/lip-stick-base

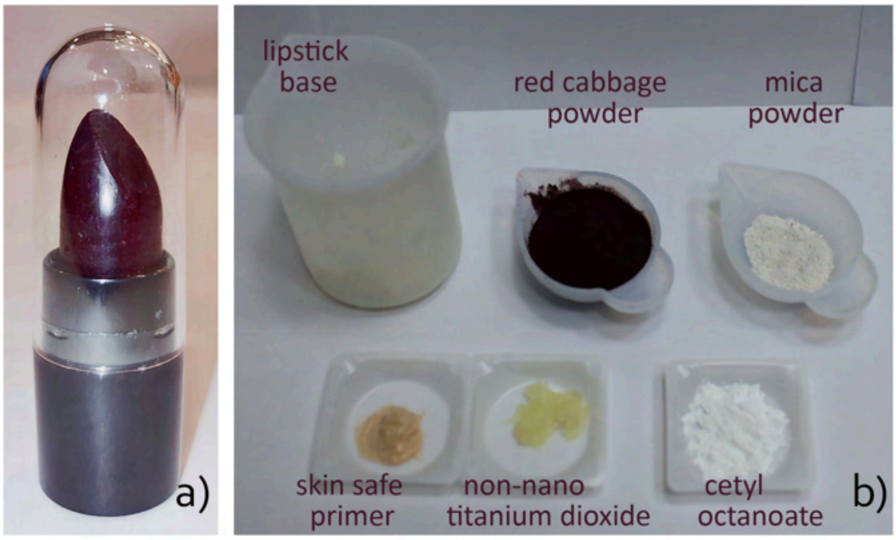


Figure 2. ChromaLipSense form factor and materials: a) form factor of the biosensor lipstick; b) ingredients used in the biosensor fabrication process

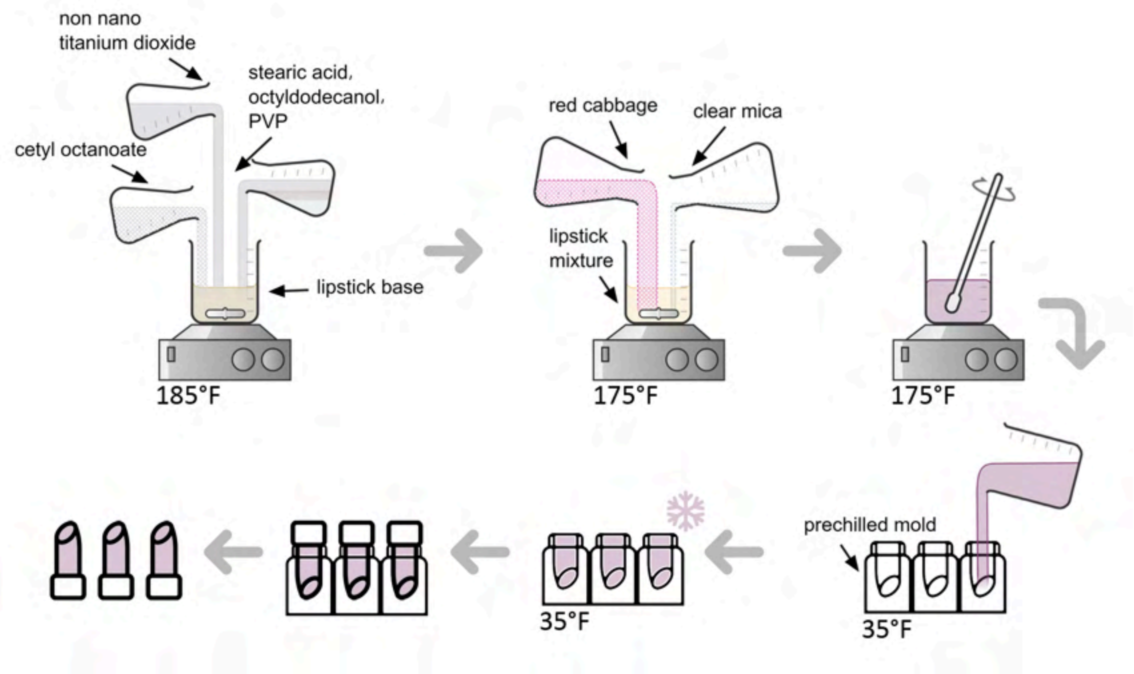


Figure 3. Lipstick fabrication process, from mixing ingredients on a heated magnetic stirrer to molds and to the lipstick tubes.

The above formula is magnetically blended till it is fully melted and heated till the temperature reaches 185ºF, this process takes around 10 minutes. It is then stirred in

1 portion of acrylate copolymer, another barrier former, powder and blend for an additional minute. Next, while still stirring, the temperature decreases to 175ºF. When the target temperature is reached, 1 portion of clear silver mica powder and 4 portions of red cabbage powder are added to the mixture. The temperature remains to be decreased to accommodate the integrity of the color changing cabbage powder and to ensure the proper manufacturing of the lipstick. The mixture is blended for another 5 minutes. The formula is poured into the silicone molds to make bullet shaped 9mm wide lipsticks. These molds are pre-chilled at 35°F, and chilled at 35°F immediately after pouring to preserve desired final texture. After 10 minutes, the mold is removed from the lipsticks and they are inserted into the lipstick containers to continue chilling for another 15 minutes. They are then stored at room temperature till usage, as a non-sensing lipstick would be. The finished product is shown in Figure 2 a).

3.2.1: Red Cabbage pH Biosensing Properties

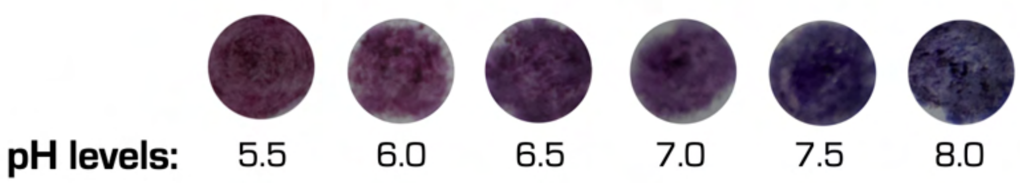


Figure 4. The red cabbage powder, before fabrication, exhibits a color change from red to blue across pH levels ranging from 5.5 to 8.

Red cabbage contains a pigment molecule called flavin (an anthocyanin). This water-soluble pigment is also found in apple skins, plums, poppies, cornflowers, and grapes. Very acidic solutions will turn anthocyanin into a red color (Figure 4). Neutral solutions result in a purplish color. The hue of the juice undergoes alterations corresponding to variations in its hydrogen ion concentration. Acids within an aqueous solution tend to release hydrogen ions and exhibit a lower pH level (typically below 7).

3.2.2: Preparation of pH Solutions

A buffer solution,used to help check that your pH meter or electrode is calibrated, is created by mixing weak acids with their corresponding salts. Food safe ingredients were used to meet the OSHA Hazard Communication Standard. The solutions used for testing are created with sodium dihydrogen phosphate dihydrate (H2NaO4P) and acetic acid (C2H4O2). The pH of a freshly prepared solution is kept at 72ºF. The solution is kept in a sealed container to keep it stable. Each solution is tested with a freshly calibrated digital pH meter during preparation and right before testing. In this experiment, 5.5, 6, 6.5, 7, and 8 pH values were prepared (Table 2). This was chosen based on human saliva pH range and the sensing range of our biosensor. The ratio is adjusted till the precise pH value is obtained on a digital pH meter

Table 2. Estimated proportions of pH solution preparation using sodium dihydrogen phosphate dihydrate (SDPD) and acetic acid.

pH Value	SDPD (mmol)	acetic acid (mmol)
5.5	40	10
6	45	5
6.5	5	0
7	50	5
8	50	0

3.3: Evaluation on Artificial Lips

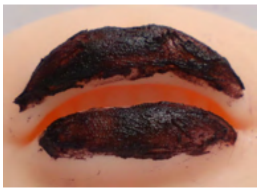
The evaluation of the ChromaLipSense on artificial lips aimed to test the application procedure of our lipstick biosensor before testing on actual human subjects, specifically targeting the design considerations from Section 3.1. Moreover, artificial lips were used to ensure stable conditions during photo capture in the Lighting Lab. This choice guarantees consistency in camera angles and the precise application of lipsticks and solutions. To best simulate human testing, we used artificial lips for three different skin colors with a special application protocol.

Application Protocol: Protocol begins by sanitizing the artificial lips (silicone-based lips) with alcohol for 5 seconds, and followed by a 3-second patting to maintain a moist (but not wet) state. The lips are weighted and tared on the scale to zero for precise measurements. Using a sterile silicone applicator, 0.05 grams of lipstick is evenly applied, continuing weighting them with the scale to ensure consistency between lips. Initial photographs capture the lips with lipstick before applying any testing solutions; this step is performed only once. After reweighing and zeroing the scale, a paper-based stencil is placed over the lip models to reveal only the area with lipstick. Three full squeezes of the testing solution (between 0.02 to 0.06 grams) are then sprayed in an upright position onto the lips from a bottle held 3 inches away. Any excess is corrected as necessary, ensuring the desired quantity is achieved without overspray. A gentle pressure is applied on the artificial lips for 5 seconds to simulate a lip smack.

During the pH testing procedure, powder-free gloves are used to prevent smearing, avoiding excessive product pickup, and restarting if the lipstick on the lips is damaged to ensure precision. To allow potential color changes, we wait for 15 seconds before proceeding. Capturing photos occurred within 5 minutes of applying the testing solution. After each test, the artificial lips are cleaned with a wet makeup remover wipe.

A tripod was used to ensure that all photos were captured at the same location and angle for each lighting condition to ensure data uniformity. Due to the artificial lips material, testing solutions may evaporate, potentially causing color reversal, particularly in a setting with a temperature of approximately 70°F. Being mindful of these factors enhances the accuracy and reliability of the pH testing procedure, as well as providing consistent images for the dataset when capturing images with human subjects.

Table 3. Silicone lips with ChromaLipSense in five pH value solutions

	Artificial Lip 1	**Artificial Lip 2**	**Artificial Lip 3**
pH = 5.5			
pH = 6.0			
pH = 6.5			
pH = 7.0			
pH = 8.0			

The evaluation of artificial lips involved testing the proposed application procedures and design considerations prior to human participant involvement. We examined the lipstick's appearance across several lighting conditions, diverse skin tones, its color-changing properties with various buffer solutions, and the ease of following procedures. We captured 240 images involving silicone-based artificial lips with three skin tones, eight light color temperatures and five pH buffer solutions. Visual assessments were conducted to gauge color-changing intensity and speed accurately. The results in Table 3 shows that the lipstick biosensor's color changes over the three artificial lips under 5700K lighting condition. The color changes align with different buffer solutions, ensuring reliable analyte detection. The procedures were observed to be straightforward, contributing to the ease of use for both participants and evaluators. These findings validate the efficacy of the designed testing protocol and provide valuable insights for further refinement. The color changes of the lipstick across different skin tones, demonstrates its suitability for a range of users, and a future work that must involve the use of machine learning to identify the colors of biosensors independently of the skin tone of the user.

3.4: Implementation with Deep Learning and Biosensors Colors Detection

The study focuses on the development of a deep learning model for color detection based on the pH value of saliva in the context of ambient lighting conditions. The model aims to classify lipstick colors corresponding to different pH values, considering the influence of ambient lighting conditions on color perception. To enhance model robustness, our dataset encompasses diverse lighting conditions to provide comprehensive information for training and evaluation.

3.3.1: Overview of Deep Learning Process

The process of building the deep learning model for ChromaLipSense involves five crucial steps: Prepare Dataset, Split Dataset, Crop Image, Training, and Test & Evaluation. Figure 5 illustrates the overview of the process.

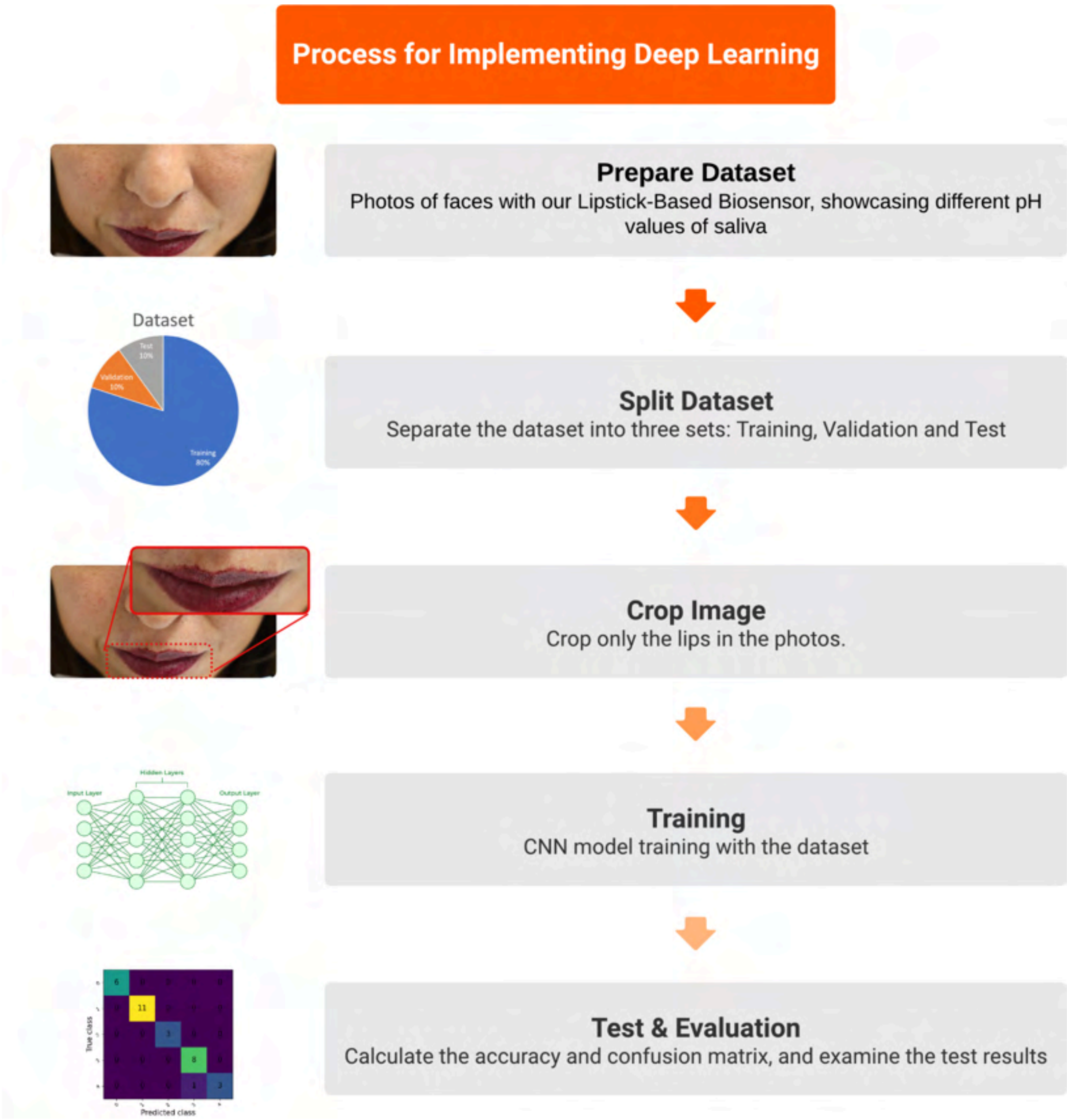


Figure 5. Implementing Deep Learning for Biosensor Color Detection

The implementation of the Deep Learning model for detecting the biosensor colors includes the preparation of a comprehensive dataset containing photos of lips with ChromaLipSense with different pH values of saliva, training the model and testing it with unseen data. To account for the potential impact of ambient light on color, data collection is conducted under various lighting conditions. A Convolutional Neural Network (CNN) is used for training the model. The model learns the intricate relationship between the pH value of saliva and the resulting color of the lips. The model is tested with previously unseen data to evaluate its performance and assess its ability to accurately predict pH values based on lip color. This iterative process allows for refinement and improvement of the model's accuracy and effectiveness.

1. Prepare Dataset: The dataset comprises 40 images, considering five pH categories, eight lighting conditions, and two camera brands. Human lips are included in the dataset with different data collection methods. Which will be detailed in their protocols in the Human Lips subsections.
   - Participants: Four participants (3 females, one male) participated in the data collection. They were healthy participants without skin allergies. Three of them had previous experience with lipstick and other makeup products.
   - pH Categories: To represent the saliva with different pH values, 5 solutions with different pH values were prepared: 5.5, 6.0, 6.5, 7.0, 8.0. These solutions make the lipstick show different colors.
   - Lighting Conditions: In previous works, different lighting conditions simulated specific color temperatures using halogen (H), fluorescent (F), and sunlight (S) bulbs set at 2700 K (warm), 4000 K (neutral), and 6500 K (cold), respectively (Yüzer et al. 2022). Other studies activated different light sources in various sequences to recreate real-life scenarios, however, the color temperature was not accurately represented. Consequently, our evaluation took place in the Lighting Lab at the California Lighting and Technology Center, allowing the research team to select a specific controlled

color temperature for precise lighting. The dataset incorporates eight color temperatures: "2200K", "2700K", "3000K", "3500K", "4000K", "5000K", "5700K", and "6500K". Illuminance level and color rendering index (CRI) are consistent among these different lighting color temperatures. By capturing photos within this controlled environment, the project aims to create a more reliable dataset.

- Cameras: Two camera devices were used for photo capture: the Canon DS126721 EOS R and the Pixel 6 smartphone. The Canon camera was chosen for obtaining high-resolution images, while the Pixel 6 was selected for capturing images with normal resolution and without focusing. Incorporating a smartphone in our camera choices allows us to simulate the shooting settings of users' daily lives. The setup of the testing space placed the cameras directly in front of the object to avoid light obstruction. Manual settings were employed for both cameras to capture original colors and ensure consistent image quality. Smartphone images were captured in automatic mode to replicate typical user behavior.

Additionally, the data is labeled with the corresponding pH values of the solution on the lips, creating a fully labeled dataset for supervised learning. In addition, we include data augmentation techniques, including horizontal flipping and random cropping in each batch, to address the limited dataset size and prevent biases related to lip shape.

2. Split Dataset: The dataset is randomly split into training (80%), validation (10%), and test (10%) sets. The training set is used for model training, the validation set monitors performance and updates loss during training, and the test set evaluates the final model.

3. Crop Image: After collecting all the images and creating the three datasets, an object detection model (Jiang et al. 2022) is used to detect and crop the lips. Specifically, the Ultralytics yolov8 model is implemented. This step enables us to focus on the primary target, which is the lips in the images.
4. Training: For our learning architecture, ResNet for the CNN model is used, drawing inspiration from previous work (Yüzer et al. 2022). ResNet has demonstrated outstanding performance, and its architecture is renowned for its effectiveness in image analysis. This choice serves as a solid foundation for future improvements. ResNet-18 and ResNet-50 are used to explore the model's capabilities. The number after ResNet indicates the sum of the hidden layers. While ResNet-50 boasts additional layers, potentially enabling it to capture more intricate features, it also requires a longer training time. This comparative analysis helps us understand the trade-offs and benefits between the two models. Model training comprises 50 epochs with a batch size of 8, a learning rate of 0.0001, and ADAM optimizer. Cross-entropy loss, suitable for classification tasks, is employed. The model is trained under Apple M1, which is a series of ARM-based systems-on-a-chip.
5. Test & Evaluation: The model's accuracy will be calculated using the test dataset, and a confusion matrix will provide detailed insights. We've got overall near 97% accuracy. The detailed results will be shown in the next section.

3.4.2: Dataset with Human Lips

Human lips were incorporated into our dataset to simulate real-life use cases, which will be used for the training. Four participants, three females and one male took part in the study. Participants were asked to position their heads on a head-chin rest bracket to ensure consistency in the alignment of their lips. The equipment setup for capturing images is illustrated in Figure 6. A partial dataset is depicted in Table 4 and Table 5. Table 4 presents human lips under various conditions, including raw lips, with ChromaLipSense, and different pH value solutions. Table 5 showcases lips with ChromaLipSense under different lighting conditions.

Application Protocol: The procedure lasted approximately 30 minutes per participant. Participants were instructed to apply the lipsticks in a manner that felt most natural to them. The procedure involved spraying solutions onto the participants' lips and asking them to compress their lips to ensure thorough mixing of the solution and lipstick. This process simulated how users might apply saliva to their lips. After a 15-second wait, the lips were photographed in various lighting conditions.

Figure 6. Equipment setup for collecting human lips dataset

Table 4. Human lips under different conditions: without makeup, with ChromaLipSense, and with ChromaLipSense in five pH value solutions.

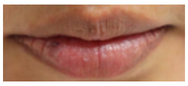
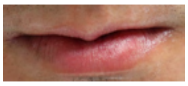
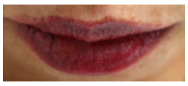
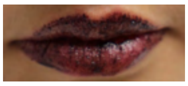
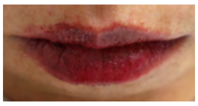
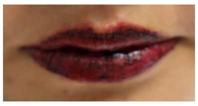
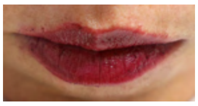
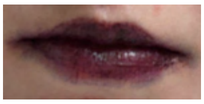
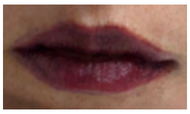
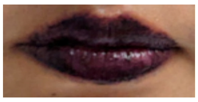
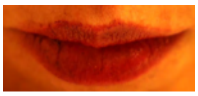
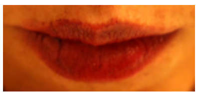
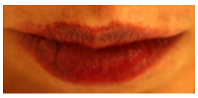
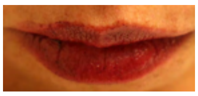
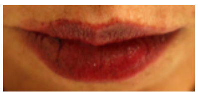
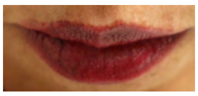
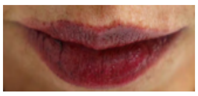
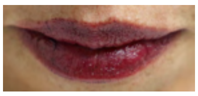
	Participant 1	**Participant 2**	**Participant 3**	**Participant 4**
Without makeup				
With Lipstick				
pH = 5.5				
pH = 6.0				
pH = 6.5				
pH = 7.0				
pH = 8.0				

Table 5. Lips with ChromaLipSense in eight lighting conditions for participants P2.

Lighting	2200K	2700K	3000K	3500K
				
Lighting	4000K	5000K	5700K	6500K
				

3.4.2: Test and Evaluation Results

The validation set is defined during the midpoint of the training process to calculate accuracy, providing insight into the model's learning progression. The test set is used for evaluating the final trained model. To evaluate the test set, the images within it serve as input for the model to predict the corresponding class (in our case, the pH value). Accuracy is determined by the percentage of images for which the predicted class matches the ground truth label. Since the test dataset contains data that is excluded from the training process, it serves as a valuable simulation of real-world scenarios. The results in Table 6 indicate a validation accuracy of 100%, signifying proper learning during the middle stages of training. However, there is a slight decrease in test accuracy. Notably, both ResNet-18 and ResNet-50 present the same performance. To gain further insights from the test results, a confusion matrix (see Figure 7) is employed to assess the model's performance across different classes, which represent pH values. The numbers within the confusion matrix represent the count of images classified correctly and incorrectly. In a confusion matrix, colors represent the intensity of values in each cell. Brighter colors indicate higher values, while darker colors indicate lower values. Additionally, Figure 8 displays partial test images labeled with both their ground truth pH values and predicted pH values. The red frame highlights a test image where the model made an error. Specifically, the model incorrectly predicted the image to have a pH value of 7.0, whereas the ground truth value is actually pH value of 8.0. This misclassification is the only error in the test case, corresponding to the purple cell with the number "1" in the confusion matrix (Figure 7).

Table 6. The validation accuracy and test accuracy of the two deep learning models, namely ResNet-18 and ResNet-50.

Model	Validation Accuracy	Test Accuracy
ResNet-18	100%	96.88%
ResNet-50	100%	96.88%

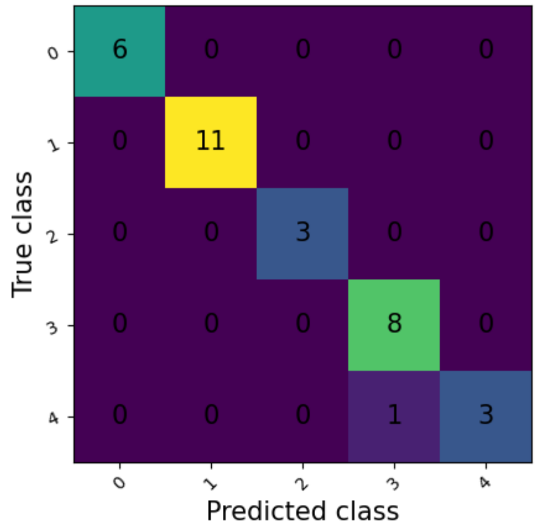


Figure 7. Confusion matrix depicting the test results, with classes [0, 1, 2, 3, 4] corresponding to pH values 5.5, 6.0, 6.5, 7.0, and 8.0, respectively.

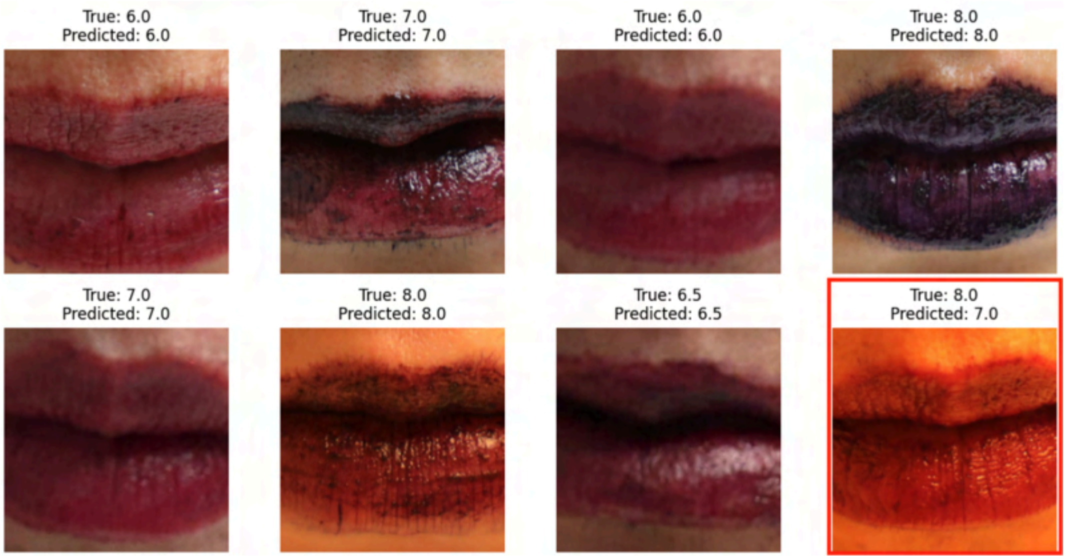


Figure 8. The predicted pH values and the ground truth pH values of the test data.

4: Discussion and Future Works

4.1: Interpretation of the Technical Evaluation Results

Upon reviewing the results obtained from the analysis of human lips, it seems that the presented model demonstrates strong accuracy, effectively detecting color changes and accurately predicting pH values. However, a noteworthy observation arises in the case of the test results, where the model achieves a seemingly flawless accuracy. This perfection may be attributed to overfitting, a consequence of limited data, posing a potential challenge when dealing with new datasets or images. The model might be overly specialized for the collected dataset, potentially struggling with diverse raw lip colors encountered in real-world scenarios.

When comparing the two models, ResNet-50 performs similarly to ResNet-18 in terms of accuracy. This can be attributed to the deeper architecture of ResNet-50, enabling it to capture more intricate details in the images. However, this may indicate that ResNet-18 is sufficiently complex for the dataset. Considering that ResNet-50 requires more time to train, ResNet-18 could serve as a more practical base model for future improvements.

4.2: Comparison with other pH monitoring methods and technologies

To the best of our knowledge, there has been limited research on Lipstick-Based Biosensors incorporating machine learning to detect color changes for assessing the pH value of saliva. In comparison, the results of this study are benchmarked against digital pH meters and test strips (Yüzer et al. 2022), achieving a comparable accuracy of nearly 97% in the test data. While the outcomes align closely with the referenced study, opportunities for future enhancement exist. Potential refinements in model architecture and the augmentation of dataset size could further improve the robustness and performance of the proposed approach.

4.3: Future Works

4.3.1: Beyond Lipstick-Based Biosensing

The application of machine learning methods, as demonstrated in the context of lipstick-based biosensors, presents an exciting opportunity for extending health monitoring to various cosmetic elements. A similar procedure and model training approach can be employed to detect health-related indicators associated with other cosmetic products such as eyeliner, eyeshadow, and temporary tattoos on the skin.

Beyond lipsticks, other materials and fabrication methods can be explored to produce other cosmetic biosensors for other analytes. Certain biosensors for other analytes may behave differently and require more manipulation. For example, glucose biosensors are usually composed of an enzyme activator and a color reagent (Vaquer, Barón, and de la Rica 2021b). Chemical interactions among the targeted biomarker and other solutions that the body part may come in contact with will also influence the biosensor and substrate material and fabrication process.

For the matter of chemical interaction, in addition to altering design, other studies must be conducted to evaluate the interaction of the biosensor with other non-salivary factors such as foods, drinks, skin pH level, or other fluids/particles in contact with the lips.

Expanding the scope of machine learning-based biosensing beyond lip products offers the potential to unveil diverse health status indicators associated with different parts of our body. This holistic approach could contribute to a comprehensive and non-invasive health monitoring system, providing valuable insights into various physiological parameters through the analysis of cosmetic adornments or other skin-based biosensors such as in temporary tattoos and bandages.

4.3.2: Dataset Augmentation with Generative AI: A Time-Efficient Approach

Since the collected dataset has a low amount of data, the model often overfits the dataset. Once the number of participants increases, a more comprehensive model can be developed to fit real-world cases.

The process of creating a comprehensive dataset for this study is undeniably time-consuming, requiring significant effort and resources. With the additional challenge of finding suitable participants, this procedure demands considerable dedication. To address these challenges and enhance the diversity of our dataset, the integration of generative AI models should be considered.

By utilizing generative AI, it is possible to efficiently generate additional data by saving valuable time and resources. This approach holds immense potential in providing a more extensive and diverse set of human data, particularly encompassing various skin tones. The augmentation of the dataset through generative AI not only accelerates the data creation process but also promises to improve the robustness and performance of our model.

4.3.3: Smartphone App for Seamless User Experience

Upon receiving the lipstick-based biosensors, providing users with a convenient and accessible way to obtain real-time health status results is crucial. Introducing a dedicated smartphone app emerges as an ideal solution, leveraging the device's embedded camera for seamless interaction. This real-time feedback mechanism not only enhances user experience but also caters to the diverse needs of all users.

5. Conclusion

This paper introduces ChromaLipSense, a novel form factor for biosensors that seamlessly integrates colorimetric biosensors into a lipstick. Due to the ubiquity and routine reapplication of lipstick, coupled with its direct interaction with saliva, drinks, and food, a lipstick emerges as an optimal substrate for biosensors. As an initial exploration, red cabbage extract was used as a pigment for the lipstick through its color matches common lipstick colors. Saliva, recognized for its transparency, regenerative properties, and diverse analytes, stands out as a valuable alternative for non-invasive biosensing, offering a wealth of health-related information.

The key contributions of ChromaLipSense encompass its innovative form factor, the do-it-yourself fabrication process, and deep learning models (specifically ResNet-18 and ResNet-50) for on-body biosensor detection. The comprehensive data collection, involving four participants, five pH calibration solutions, two cameras, and eight lighting conditions, resulted in an accuracy of 96.88% in detecting pH levels. Beyond its cosmetic appeal, we aim that ChromaLipSense provides a new possibility for dermatology, health monitoring, and even food tracking through everyday beauty products.

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