Optimizing Dental Crown Shade Selection:

Application of Spectroscopic Color-Standardization and Machine/Deep Learning through an Application Tailored Data-Capture Device

Max A.Vallone

Mr. Luis Felipe & Mr. Robert DuBard

Ransom Everglades School

Abstract

Background:

The dental implant industry is a multi billion dollar industry expected to continue to grow rapidly. The methods for selecting the shade of the crown (the visible artificial tooth), have remained largely unchanged. The reliance on a manual process for selecting the appropriate shade of the crown results in higher costs for providers and longer waiting times for patients. The primary reasons for these inefficiencies are the result of individual human limitations such as color blindness and fatigue, as well as the illumination of the dental provider's room. This research developed a novel solution using a purpose-built image capture device that applies spectroscopy techniques and a deep learning algorithm to attempt to quickly and accurately match the patient's missing tooth or teeth to the optimal available crown color based on predefined selections available in the industry.

Methods:

The research involved the design and manufacturing of a purpose-built device to capture images of the patient's teeth. The device is designed to be easy to use and low cost to produce, leveraging 3D printing technology and readily available components. The device captures 4 images per scan, applying white, red, blue and green pure light to the images. Initially, color based image segmentation is used to create a dataset of segmented images. This dataset is then augmented to increase size and variability. By applying a TensorFlowdeep learning segmentation model to the augmented dataset, reliable segmentation regardless of lighting color and background is achieved. The images are then re-scaled and spectroscopic analysis is applied. Spectroscopic analysis entails looking at the red, green, and blue images for any wavelengths of light that were not emitted by the devices. By subtracting the background from the RGB images and overlaying them a consistent composite image is obtained.

Results:

The device production yielded a highly functional, low cost, easy to manufacture device that fulfills all envisioned requirements. Future research will focus on updates to the device to improve the lighting of the images which will lead to improved image segmentation.

The data science and deep learning research showed that by providing even a small initial dataset of stock images, enhanced with algorithmic augmentation, a deep learning segmentation model could be efficiently trained generating high levels of accuracy. In addition, much of the code has been developed to square all the images, including the training images, the crown shade sample images and the patient tooth capture images, so that both algorithmic or deep learning classification models can be implemented to create effective and accurate comparison between images, resulting in the optimal selection of crown shade based on the pre-manufactured shades that are commercially available.

Conclusions:

Future research will be focused on continuing to train the deep learning models using stock images. Continued research using human subjects will lead to an updated device that solves known lighting issues and will result in higher quality images, making the segmentation and color matching algorithms more effective. Lastly, as the research moves into actual testing with dentists and patients, the predicted datasets produced versus actual patient results will lead to significant improvements in device functionality and data science and deep learning models.

Introduction

Dental prosthetics is expected to grow to a $8.61 billion dollar industry by 2028 (Biospace 2021), with ~ 5.5 million dental implant procedures being conducted and growing by 500,000 per year (American Academy of Implant Dentistry n.d.). Despite the size and growth of this industry, methods of matching the shade (color variation) of the crown, which connect to the abutment attached to the actual dental implant (Delaney, Burke 2016), have remained largely manual processes for the majority of dental practitioners who use pre-made crowns.

Alternative methods of matching crown shade using digital devices, such as intraoral scanners are typically associated with custom crown production, have a high barrier to entry including high cost, and require resources and training that many dental practitioners do not have access to. In addition, these methods are only applicable when a crown is custom colored and not selected from a pre-manufactured range (Chu, Trushkowsky, Paravina (2010).

The most common approach used in selecting a pre-manufactured crown is a manual selection based on sample crown shades held against the patient's teeth. There are a number of problems associated with this process, including the dental practitioner's limitations such as color blindness or retinal fatigue, and the variance based on illumination in the room (Arrowhead Dental, n.d.). Due to the variability of the crown shade selection process, the chosen tooth may not be accepted by the patient, resulting in additional aggravation for the patient and additional cost for the provider (Arrowhead Dental, n.d.).

This research evaluates a novel solution using a purpose-built image capturing device and data science to offer an easy to use, low cost option for dental providers who offer pre-made crowns. The research attempts to select the most accurate standard crown shade for patients based on an available selection of pre-manufactured crowns, while compensating for changing illumination conditions, more accurately and quickly, in comparison to manual methods.

The primary objective of this study is to develop a purpose-built data collection device analysis pipeline that captures images of a patient's teeth and finds the closest crown shade through the application of deep learning and algorithmic models. Additionally, as the product and solution were researched and developed, particular focus was placed on accessibility, ease of operation, safety, ease of repair, reliability and low cost of production, and operation. The device, designed for 3D printing, features standard, accessible, and low cost electronics. 3D printing using thermoplastics and photopolymers exhibit excellent rigidity while being lightweight, which improves the usability of the device and comparative cost. The use of 3D printing coupled with design for manufacturing (DFM) made the device inexpensive to produce and accessible to most dental practitioners and research institutions. The data science pipeline created focused on reliability and consistency regardless of sampling quality. By integrating image segmentation, normalization, color standardization, and algorithmic image comparison, reliable outputs were pursued.

Data Collection Device Development

Requirements:

In order to consistently collect image data for later analysis, it became evident that a custom device was necessary. Although data could have been collected using a device such as a cell phone, the lack of direct hardware control, variable focus cameras, and inability to control the color and brightness of lighting, were reasons for pursuing a purpose-built device. More specifically, the variable focus of cell phone cameras means that light contacting the camera sensor can vary in intensity, and must be corrected by software. This is highly detrimental to consistent image capturing. In addition, a custom-developed device with software to securely capture and transfer the patient images, without requiring direct access to the internet (as does a cell phone), was considered important for the Institutional Review Board (IRB) human subject research. In order to address the outlined issues and maintain reliable data collection, the device had to:

1. Allow for high resolution image capturing
2. Have a means of usable viewfinding for ease of operation when capturing patient images
3. Allow for even lighting distribution from RGB and White light sources
4. Take advantage of fixed focus cameras and optics
5. Have the capability for local image storage and wireless data transmission

The goal of having white, red, green, and blue light sources is not the replication of the white light image, but the creation of a composite image that is consistent regardless of background.

Device Electronics and Components:

These requirements were met through the use of open-source, accessible electronics and hardware, including a Raspberry Pi Zero and Raspberry Pi 5MP Spy Camera. All components utilized are inexpensive, and will continue to be produced for years to come. Table 1 details components utilized.

Component	Price (USD)	Quantity
Raspberry Pi Zero W	10.00	1
Raspberry Pi Spy Camera - 5MP	19.95	1
5” LCD HDMI Display (800x480p)	59.95	1
5mm Bright LEDs (25x)	6.95	1
2.5x5mm Diffused RGB Indicator LEDs (10x)	5.95	1
12.5mm Diameter Dichroic Color Filters (RGB)	55.00	1
12mm Diameter, 24mm FL Double Convex Lens	27.50	1
12.5mm Diameter Borofloat Window	19.00	1
Kaihl Box Navy Switch	0.34	1
AW9532 GPIO Expander and LED Driver	5.90	1
Wiring Components	40.00	1
5V Micro USB Switching Power Supply 2A	7.50	1
Self Threading Screws (100x) (McMaster-Carr #94997A125)	18.81	1
3D Printed Components (Form 3 and Markforged Onyx)	30.00	1

Table 1 - Detailed components list for the data collection device

Design and Manufacturing:

The custom image collection device was designed in computer-aided design (CAD) using Fusion 360, and several versions were created to best incorporate the components listed above, and meet the requirements outlined. Throughout its iterations, the device design focused on ease of manufacturing, assembly, and cost-effectiveness. Specific design choices include the use of loft features in order to create a compact device with all components positioned optimally. Additionally, on the front of the device, the camera is surrounded equidistantly by 4 individual light-emitting diodes (LEDs), and their respective color filters. This allows for even lighting, regardless of the color of light selected. The color filters and camera optics were another carefully selected feature of the device. Dichroic filters were utilized for the color filters, as they provide a specific and consistent range of wavelengths to pass through, which is essential for later color validation. Additionally, multiple camera lens' were tested from 24-72mm Focal Length with the 72mm Focal Length being the one selected, as it maximized the collectable data per image, increased sampling distance from the subject to ~100mm, and decreased the effects of the offset light sources. Additional CAD details include the bumps near the head of the device that protect them if the device is set down on its optics. The nine CAD iterations created are shown below in Figures 1-9:

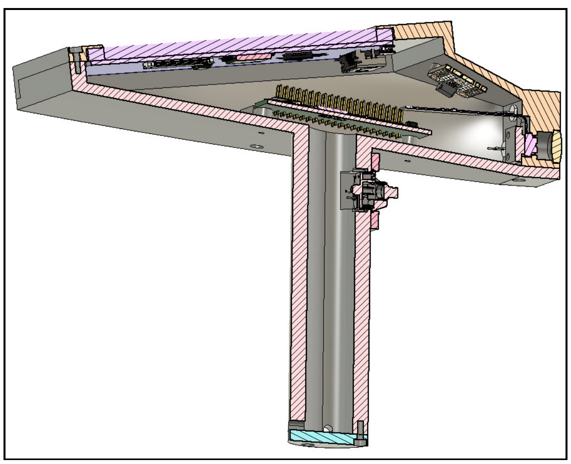
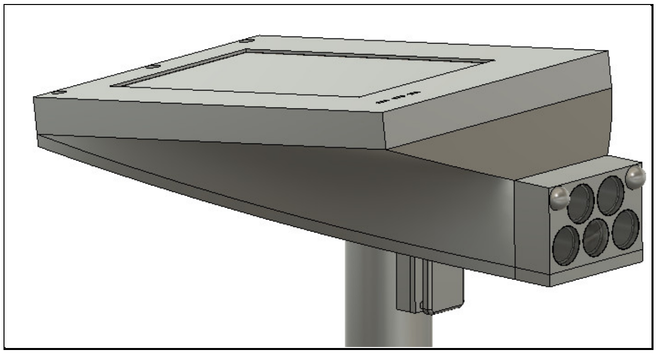


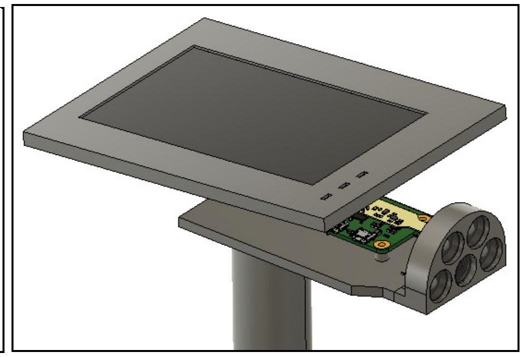

Figure 1 - Above Left - Cross section view of the final CAD iteration (2.2) for the data collection device. This figure clearly shows the mounting of the camera, lens, Raspberry Pi, liquid crystal display (LCD), LED driver, and button.

Figure 2 - Above Right - Final CAD iteration (2.2) of the data collection device showing the lens and optics positioning as well as the use of loft features to make the data collection end less bulky and easier to use.

Figure 3 - Below Left - Iteration 2.1 of the CAD. The major difference between this iteration and the final iteration is the use of a surface-mount device (SMD) button instead of a Cherry MX style switch.

Figure 4 - Below Right - Initial layout testing using a rounded head. This was abandoned, as it complicated the loft features as well as reduced available space for wiring the camera and LEDs.





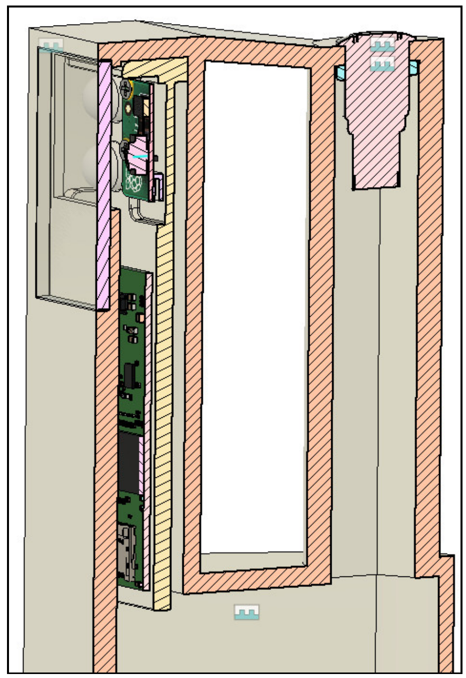
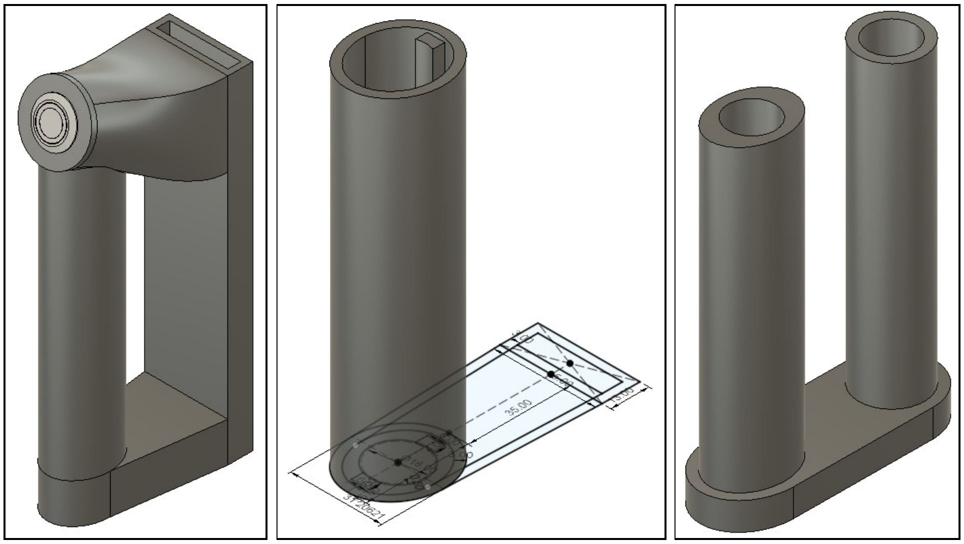


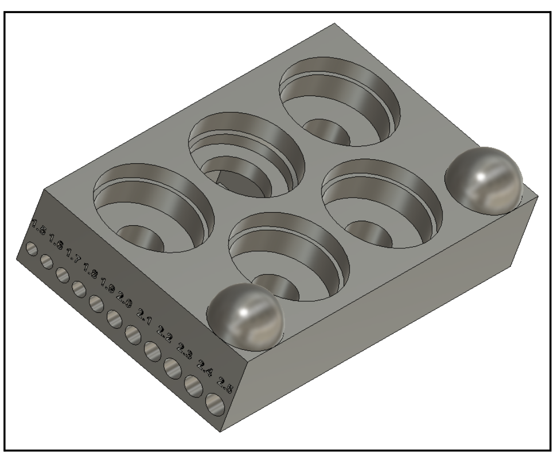
Figure 5 - Above Left - View of CAD iteration 1.3. This iteration was designed before the idea for multiple colored light sources was introduced. This style of component layout was changed, as it made the head of the device very bulky, reduced the ergonomics of the handle, and made the button less accessible

Figure 6 - Above Right - Cross section of iteration 1.3 showing how all electronics were going to be assembled on a frame and slide into place vertically in the device.

Figures 7-9 - Below - Iterations 1.3-1.0 of the device CAD. These iterations served to test component layout, ergonomic handle design, and the use of loft features.



The device was manufactured using both fused deposition modeling (FDM) and Stereolithography (SLA) 3D printing. This allowed for the small features on the data capturing head to be produced, while maintaining rigidity, cost-effectiveness, and durability. A Form 3 and Markforged Onyx printer were used to produce the designed parts. In order to ensure the fitment of optics and screws, a small sample part was produced, which allowed for the fitment to be easily tested and replaced as shown in Figures 10-11. After precision fit testing the part sizes, the full device was 3D printed, assembled, and wired, as shown in Figures 12, 17, and 18.



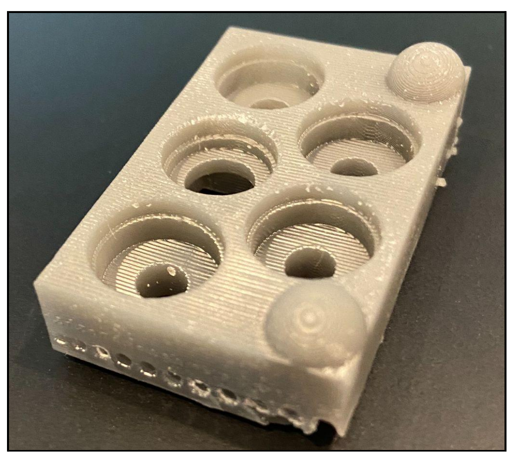
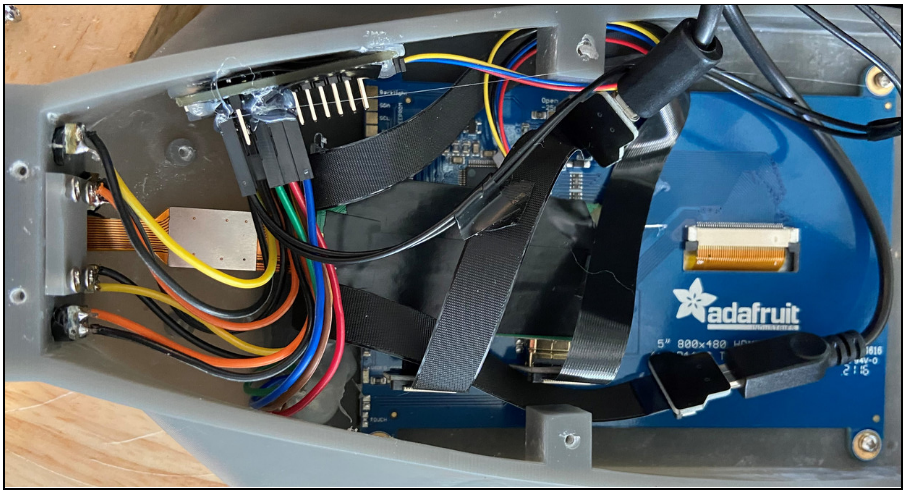
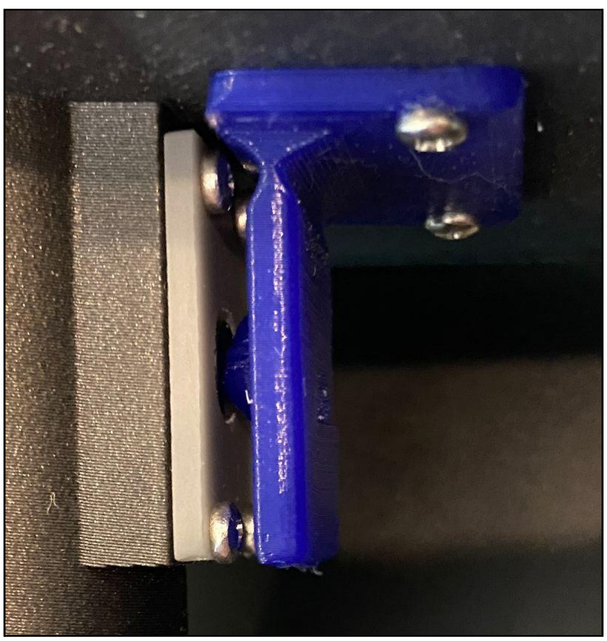


Figure 10 - Above Left - CAD design of fitment test piece. The holes on the side range from 1.5-2.5mm so that the optimal size hole for self threading screws can be identified.

Figure 11 - Above Right - The test piece after printing and testing the hole sizes. Due to the thin walls and brittleness of the material, many of the holes cracked while testing screws, however this was useful in determining the correct fit for the self threading screws so that they wouldn't crack the full printed housing.

Figure 12 - Below - This image shows the device after assembly and wiring. The camera and LEDs are on the left side, the blue printed circuit board (PCB) is the backing of the LCD display, the raspberry pi is mounted above the LCD-PCB, and the LED driver is mounted on the upper wall of the housing.





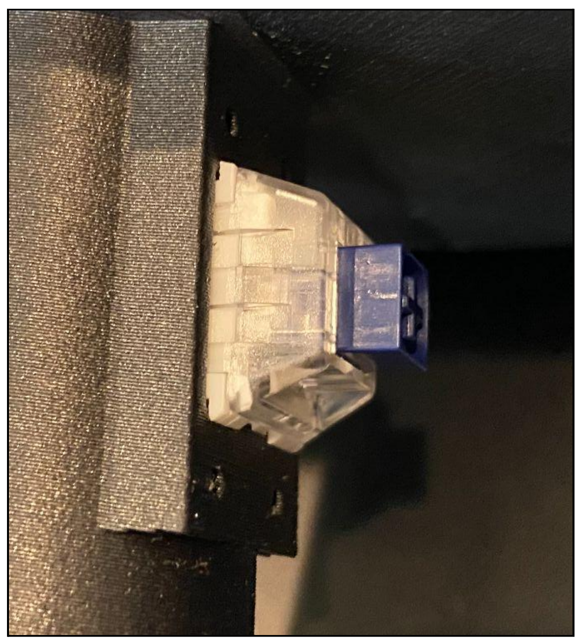


Figure 13 - Above Left - Original trigger design utilizing an SMD button and a 3D printed trigger. This was changed, as the actuation force was too high to keep the device steady when pressed.

Figure 14 - Above Right - Second iteration of the trigger mechanism. The use of a Kailh Box Navy, Cherry MX style switch provides a lighter actuation with a click as feedback.

Figure 15 - Below Left - Dichroic filters, glass window, and camera lens mounted in device assembly.

Figure 16 - Below Right - Optics with all LEDs turned on. The reason that the dichroic filters do not appear their actual color except when the LEDs are on is because they reflect the colors opposite to those they let through, in this case cyan magenta yellow (CMY), as seen in Figure 15.

Figure 17-18 - Above - The fully assembled data capturing device.

Device Code:

Despite having an assembled and functional device, code was needed to facilitate the image capturing process. Code requirements included:

1. Upon trigger press, capture 4 images (RGBW - red, green, blue, white) and store in a time stamped folder
2. Display camera view on LCD
3. Use indicator LEDs to show when device is ready for next scan

These requirements were met using the Picamera and adafruit_AW9523 python libraries. The device begins by initializing the LED pins on the AW9523 driver over I2C. The code proceeds to define the camera resolution (480,480p), framerate (15fps), and start the preview (viewfinder). After initialization is complete, a function “capture” is defined, which creates a time stamped folder, and saves 4 images, one with each LED, as “w.jpg”, “r.jpg”, “g.jpg”, and “b.jpg” when called. After this function is defined, initialization is complete, and a loop that checks for the button position runs. When the user presses the button to capture the images, the software turns off the indicator LED, calls the capture function, and waits for the button to return to its original state. All photos are instantly captured, saved locally, and can be exported when connected to a PC through secure shell (SSH) or virtual network computing (VNC).

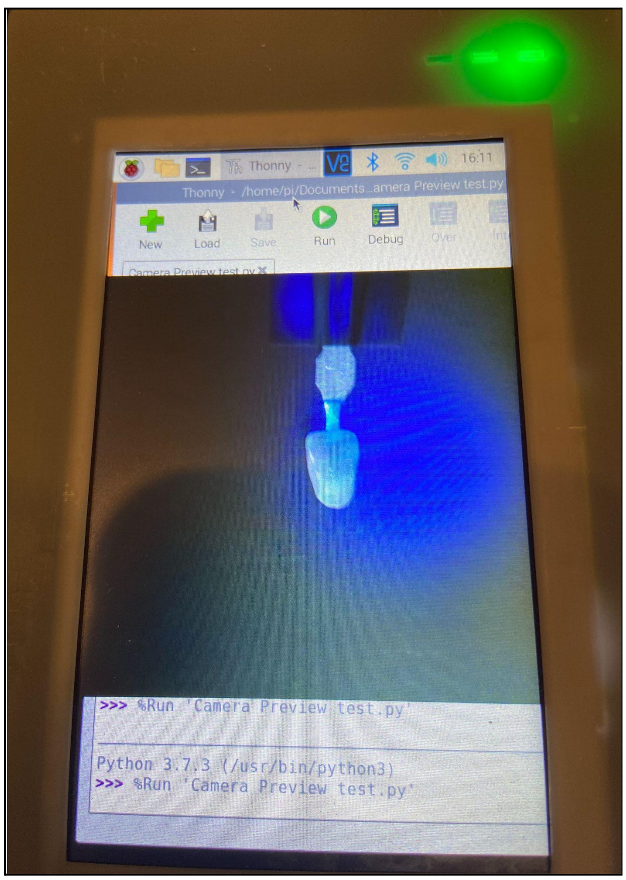


Figure 19 - Above - This image shows the viewfinder user interface (UI) during testing. A large screen covers most of the front of the device, making it very easy and comfortable for a dental provider to capture the best image. The digital display shows the image preview, controls (located above the preview), and the terminal (bottom of the screen), showing the current state or errors of the program. In this example, the subject is one of the premade tooth

samples provided to me by my dentist during this research process. All 16 sample teeth were captured using the device, and used as part of the deep learning and comparison algorithm process.

Device Results:

Once the device was manufactured, assembled, wired and coded, a mixture of testing and data collection was conducted. A series of test images were captured of the 16 crown shade samples I received from my dentist, as seen in Figure 20 below.

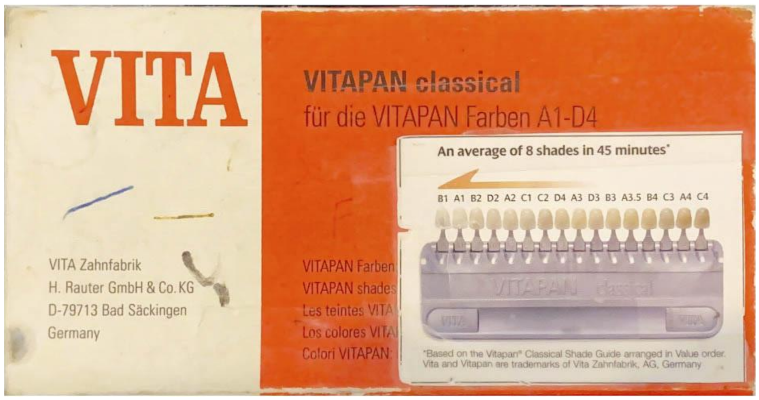
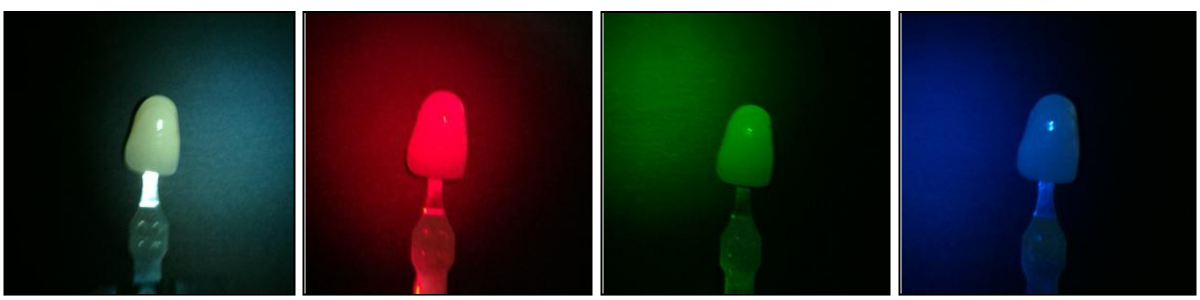


Figure 20 - Above

The device functioned as planned. With a single button press, the device captured and stored a series of images, taken with white, pure red, pure green, and pure blue. Evaluation of the data collected at this stage was purely qualitative and designed to test the functionality of the device, before initiating, human subjects research process.



Figures 21-24 - Above - These four images of the C2 shade were taken using the data collection device on a black background. From left to right, white light image, red light image, green light image, and blue light image. The same process was used to capture human subject tooth samples as part of the IRB approved human trial.

While the device captured the images as expected, the qualitative assessment of the output clearly shows that the lighting was not as consistent as desired. The lighting should be diffused across the entire image, which increases the allowed margin of error during data collection, and should minimize error in spectrographic analysis. This could be improved through a number of methods:

1. The use of RGB (red, green, blue) LEDs instead of color filters
2. A parabolic mirror and fresnel lens to force the lighting to come out of one opening
3. Angling and diffusing the light sources

In a future iteration of the device, RGB LEDs will be tested due to the fact that the exact wavelengths of light emissions are not as important given they remain consistent. The goal of multiple light sources is not the replication of the white light image, but the creation of a composite image that is consistent regardless of background. Additionally, the device image capture software could be improved by automatically running on device start, transfer of the files over an encrypted bluetooth connection, and a crosshair on the camera viewfinder to improve ease of data collection and compatibility with a range of devices.

IRB Human Subjects Data Collection

As part of the research project, I organized an IRB to run a limited human subject research study at Ransom Everglades. The study involved capturing anonymized tooth images of the human subjects, which consisted of both students and faculty. Research consent was captured in writing according to the IRB requirements with parental consent for students. The IRB was deemed to have very low risk, as it involved capturing one or more photos of the subject's teeth from a safe distance, with the entire process requiring less than 5 minutes. The images captured were completely unidentifiable.

In the time allotted, a total of 8 students consented and participated in the research, with a total of 356 images (w,r,g,b) from 89 scans captured from students. My original goal was to collect data from approximately 500 scans, but unfortunately, time and interest of students in participation was limited. This was the first time that Ransom Everglades conducted an IRB study involving human subjects, and the process of organizing the study, coordinating the IRB, and receiving approval and signatures, when added to the limited time remaining to communicate with and gain consent from student participants and their parents, was significantly longer than I expected. This was my first IRB as well, and I learned a lot from the process, in particular, that it is a complicated process. The IRB effort will help pave the way for future students to conduct similar research studies with fewer challenges.

As I continue my independent study and human subjects research throughout this year, I expect to be able to capture significantly more images from students and faculty. In addition, as the testing moves into validation and testing with dental providers, this will enable me to capture larger datasets labeled by dental practitioners that will further improve the accuracy of the deep learning segmentation and classification models, as well as explore the reliability and usability of the developed solution.

Data Science and Deep Learning Models

Through applying data science and machine learning algorithms using Python, the research seeks to leverage deep learning models which will be used to segment the image data and run effective comparisons of a subject's teeth to commercially available crown shades. Algorithmic models including image comparison, color based segmentation, and spectroscopic analysis will also be implemented. The primary use of data science and in customized deep learning algorithms is to achieve the following goals:

1. Reduce or eliminate crown shade matching issues caused by ambient lighting (illumination)
2. Reduce or eliminate the need for subjective selection of the crown shade by a dental practitioner
3. Provide a visual output indicating the best match of crown shade for the patient

Training the Algorithm - Data Science Methods (Pipelines):

Within data science, a pipeline refers to the series of steps that data will be processed through in order to obtain a predicted result. These steps generally include: dataset creation, formatting, augmentation, and encoding, machine learning model parameters, and output scaling. Applying image segmentation techniques allows for other objects in the image to be disregarded. Additionally, individual segmentation is needed for overlaying the RGB images, as minor movements of the scanner or patient between images shift the location of relevant features. Although color based segmentation could be applied to the white light images, the use of RGB images hinders the ability to draw boundaries based on hue, the most reliable method of color segmentation. Four pipelines drafted to test various methods of data analysis are pictured below.

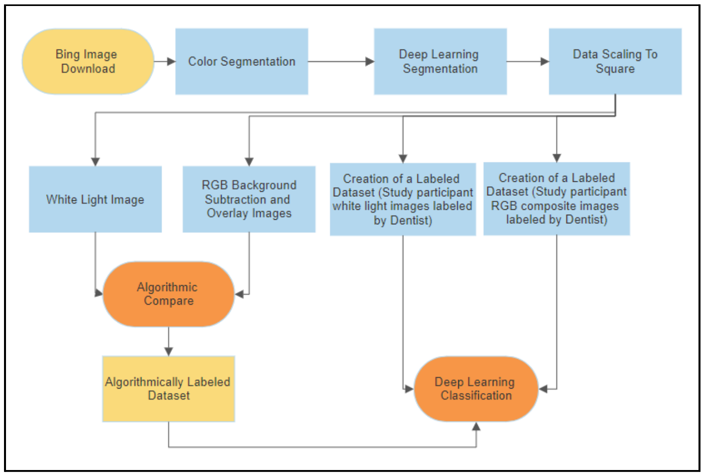


Figure 25 - Above - This flowchart documents the machine learning pipelines used to train the models for evaluation and comparison. By starting with a dataset of stock imagery and using it to train models (now used to create more advanced and effective datasets), the level of analysis can be maximized without requiring significant human intervention.

Pipeline Step Explanations:

Bing Image Download - Through the use of the Azure Bing Image Search API and a public code library, a database of images of teeth was created. Initially, ~400 images were downloaded. These were then manually parsed to remove irrelevant or duplicate images, shrinking the dataset to ~250 images. After attempting color based segmentation of the images, inconducive images were filtered out, leaving 115 images. Using the current 115 image dataset, a deep learning model was trained but showed severe signs of overtraining with training and validation loss values diverging as training progressed. To remedy this issue, brightness, color, and image flip augmentations were applied to the aforementioned dataset to increase the size to 575 images. In the first interactions of the deep learning processing, before augmenting the dataset, the deep learning model showed severe signs of overtraining with training and validation loss values diverging as training progressed

Color Segmentation - To create a dataset for training the deep learning model, color based segmentation using OpenCV was applied. By selecting hue, saturation, and brightness cutoff values, functions create a “mask” which marks all pixels that meet the color conditions. This process begins with the application of a blue effect to the images, improving the quality of the segmented mask. Next, the image is converted into HSV (hue, saturation, value/brightness) format, to allow for cutoffs to be related to specific color attributes. The color segmentation code returns a 2D array; however, to be compatible with deep learning, a 3D array is necessary so that the data type of the image and mask match. This is achieved using a command to add an empty dimension, e.g., (128,128) → (128,128,1). Additional transformations of the mask object were used to adjust the values from 0/255 → 1/3 . This was necessary because TensorFlow datasets read zeros as null values, and the values of the input masks for the sample code were 1/2/3.

Deep Learning Segmentation - Although effective on white light images of teeth, color based segmentation is highly susceptible to background objects and noise. Additionally, color based segmentation is not possible on images taken using red, green, and blue light, as there are no hue variations to distinguish between. Deep learning segmentation requires a dataset of image-mask pairs, which was created using color segmentation and analyzes images using a variety of "layers" that scan for shape, size, color, or texture. While training and tweaking the Deep Learning segmentation model, setting parameters to minimize overfitting was essential. To do this, the batch size was maximized at ~⅓ of the total training data, epochs were set to a middle ground of 20, and validation steps were minimized so the model was minutely influenced by poor test data.

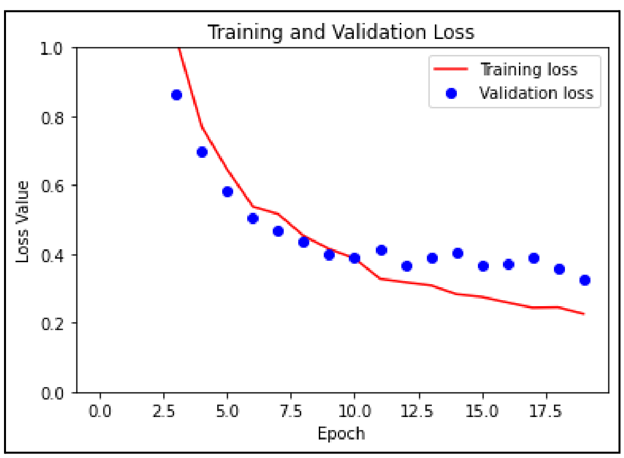


Figure 26 - Above - This figure shows a plot of the training and validation loss. This style of plot is especially useful in spotting overtraining, where the training loss decreases without a significant change to the validation loss. Despite the fact that the training and validation loss diverge around Epoch 10, the difference between the two losses

is minimal. Additionally, the validation loss continues to decrease. In cases where more severe overtraining is present, it is common to see the validation loss begin to increase as the model tailors itself to the training data.

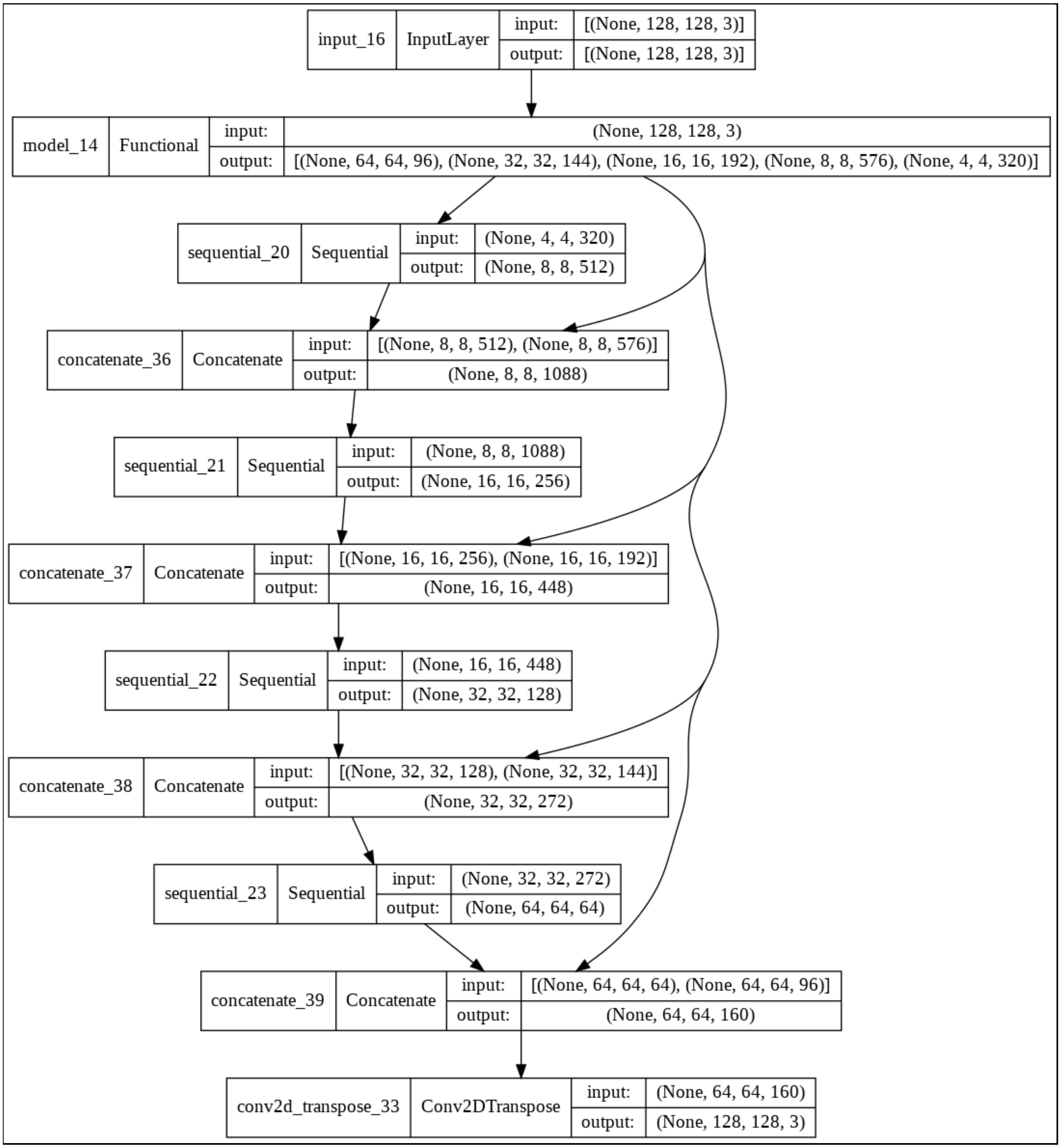
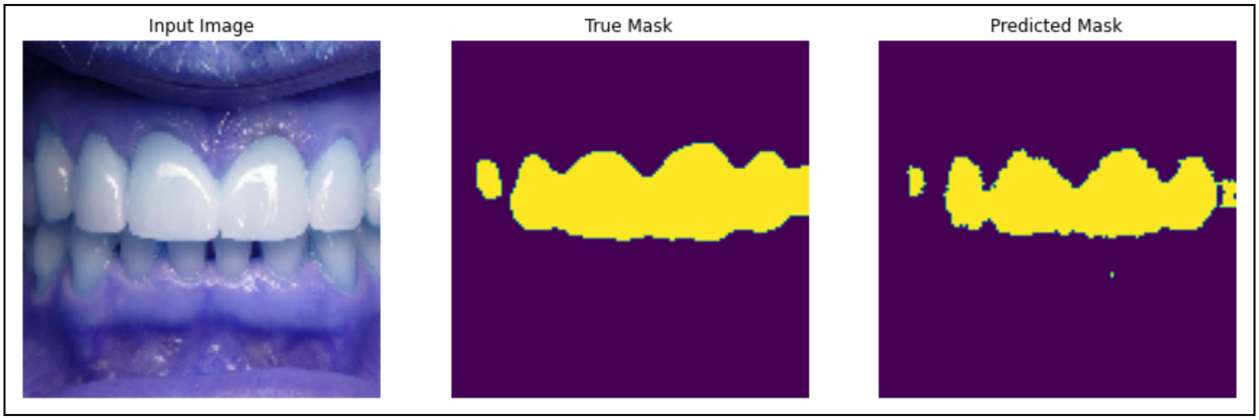
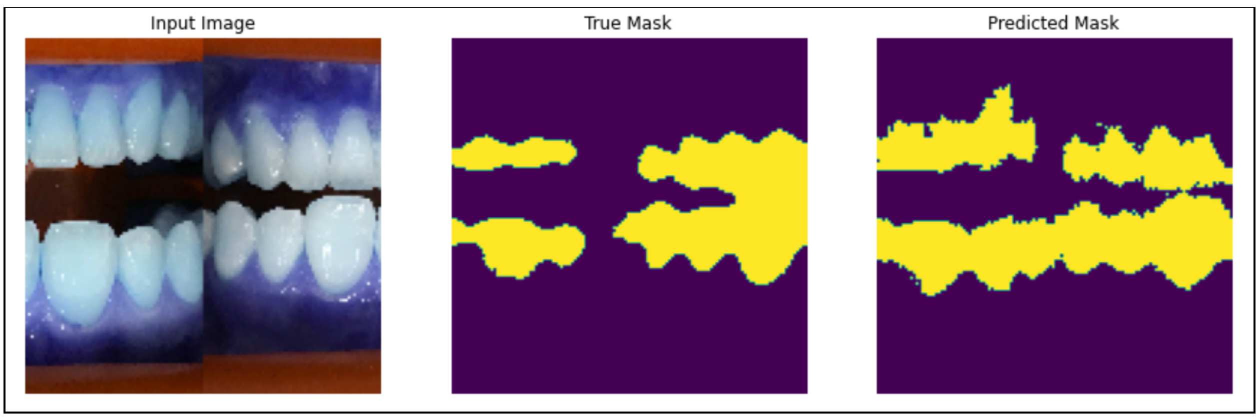


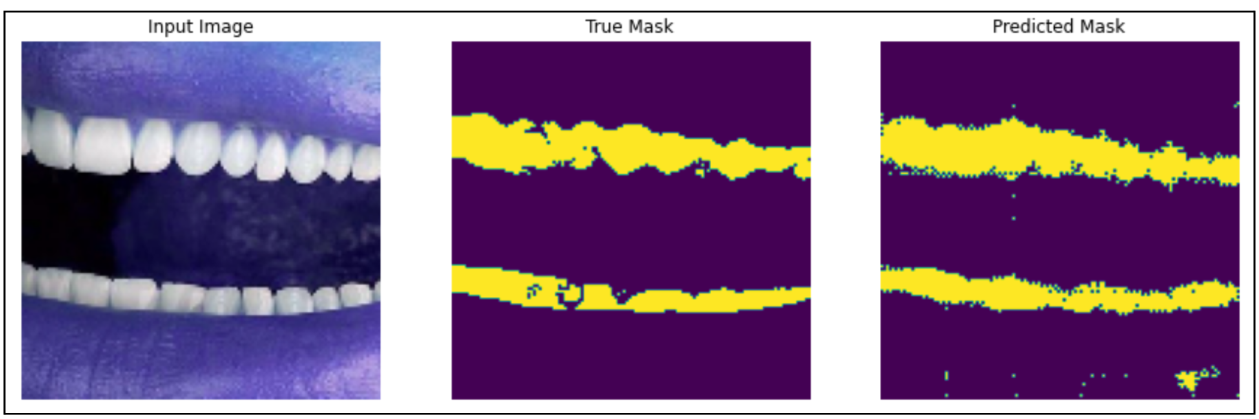
Figure 27 - Above - This flowchart shows the internal structure of the pretrained MobileNetV2 model. This diagram demonstrates the way in which deep learning models use downscaling and analyze the same image multiple times at different resolutions. By analyzing at a range of resolutions, the identification layers of the model can detect both large and small patterns present in the data.

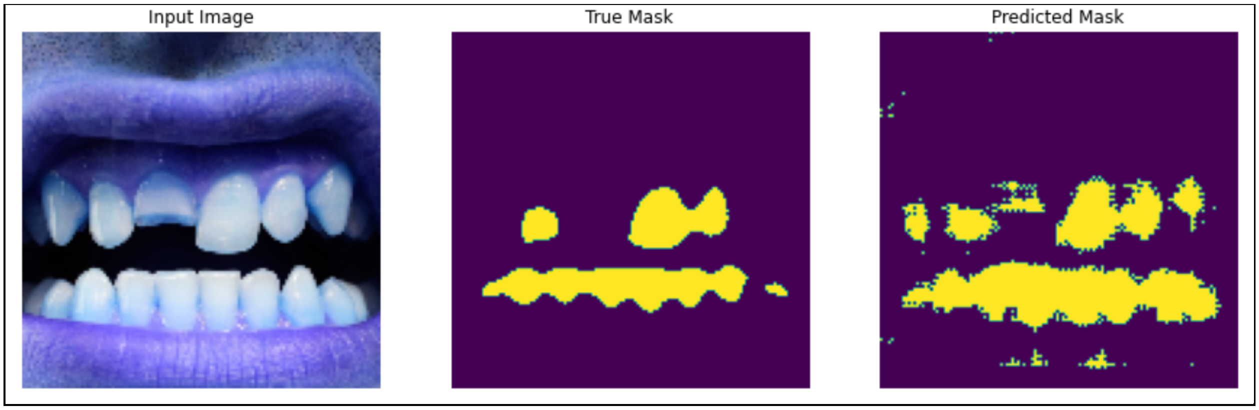


Figures 28-30 - Above - These images from post-training predictions demonstrate the issue of overfitting in a deep learning model. Due to the fact that the machine learning model trained over the data too many times, it learned to match the desired output without actually being able to identify and segment the teeth in the image.

Figures 31-39 - Below - The images displayed below demonstrate the power of a well trained deep learning model. Despite the fact that the input data mask does not do a good job of identifying the teeth, the deep learning model is still able to detect and segment all of the visible teeth in the provided image.







Data Scaling To Square - After segmented data is produced, the groups of outlined pixels vary in shape and size. To maintain consistency across scans, the images must be rescaled back to a square. This will be achieved by applying 1D, rotary, or 2D image size normalization:

- 1D Normalization takes every row or column of pixels in the tooth, stretches them to be as wide as the longest row, and after recombining the rows into a rectangular image, scales the image to be a square of the desired size.
- Rotary Normalization begins by finding the center of the image and splitting it into many slices from the center. By scaling each slice until it reaches the edge of a bounding box and finally reprocessing the pixelation of the image, a square image can be achieved.
- 2D Normalization is a cross between 1D and Rotary, the main difference being the image is scaled by pixels instead of by slices. After identifying the center of the image and the distance between the border and boundary box at every pixel, the pixels themselves can be scaled so the outer edge comes into contact with the boundary box. Despite its apparent complexity, this method has the advantage of customizability in terms of how the scaling is conducted.

Algorithmic Comparison to Sample Shades - The consistently-sized images output from the scaling step above can be directly compared pixel by pixel in order to find an average error. By comparing the input data piece with all the shade standards, the best match (piece with lowest average error) can be identified. This process can be implemented using both white light and RGB composite images. The advantages of an algorithmic comparison model are mainly that no labeled training data are required which decreases the effort required for effective training.

RGB Background Subtraction and Overlay - Although mentioned earlier in this Data Science Pipelines section, one innovative component of this research is the test of background elimination/color standardization through the use of a composite image created from individual red, green, and blue scans. This composite image is based on the concept that in any one image, the red, green, and blue pixel values are based on the sum of the background and device lighting. Through this reasoning, it can be determined that the 3 images can be treated as a system of equations. In the red light image, any blue or green light can be assumed to be background light, despite not knowing what part of the red light is background. If the same is done for blue and green, all unknown values can be found. After the background of each color is determined and subtracted, the images can be overlaid to form an RGB composite. The relative intensity and wavelength of light is not important to the function of this method. The only determining factors are consistency of wavelength and lighting intensity.

Creation of a Labeled Dataset - By working with local dental firms, the current IRB approved data collection will be continued on a broader scale. After collecting a significant library of subject images, they will be labeled by a professional dentist through comparison with shade samples. This labeled dataset is necessary for training deep learning classification models that would be able to even take the way in which materials behave under different lighting conditions into account. Alternatively, a labeled dataset can be created using the Algorithmic Matching outlined above. Although this method would likely be less accurate, a temporary dataset could be created to help when building a Deep Learning or Neural Network classifier model.

Train Deep Learning Model (White or RGB composite images) - By utilizing the labeled dataset created in the previous step, a model will be trained to match white light or RGB composite images to the closest available crown shade. The model will offer flexibility and make methods such as inputting unsegmented white light images a possibility. This could allow the model to develop layers that focus on background lighting and take it into consideration.

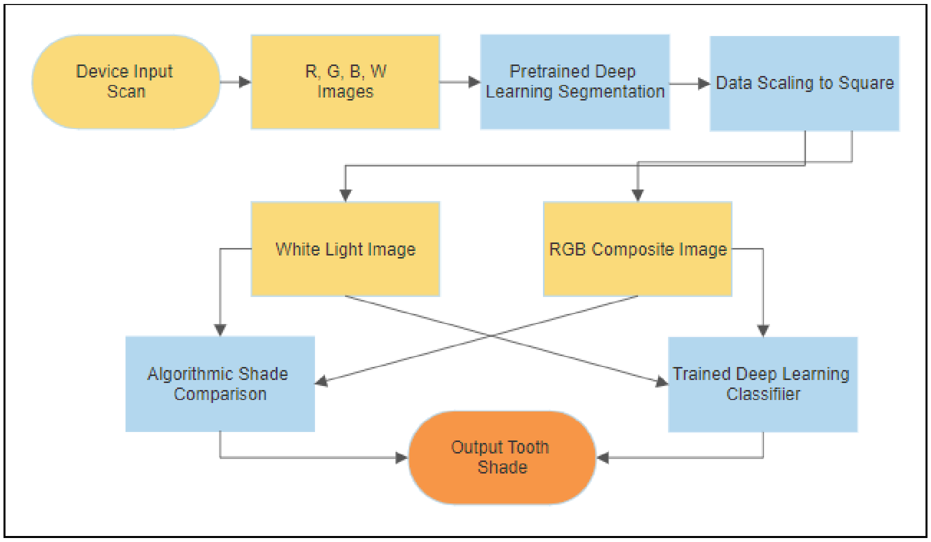


Figure 40 - Above - Shows the pipeline of the use of the device. Beginning with the images taken by the device, data is passed through all of the analysis steps. Finally, this pipeline will output the predictions done by the algorithmic comparison, as well as deep learning classifier. Having multiple outputs allows for some patient choice as well as helping to offset error.

Data Science Codebase:

The following github repository contains the code for all data science and device code including both major data science pipelines including the training algorithms and the image comparison and matching algorithms.

Conclusions

Future research will be focused on continuing to train the deep learning models using a combination of stock images, public datasets, and collected data. As the study progresses, minor changes will be made to the device to improve the quality of the data capture and usability in a professional setting. Continued human subject research will provide a larger dataset of consistent high-quality images. By increasing data quality and dataset size, the deep learning models will be able to train at greater depths with larger batch sizes, leading to more consistent and accurate predictions when matching available crown shades to patients' teeth.

Bibliography

Agarwal (2020, May 12). *Complete Image Augmentation in OpenCV.* https://towardsdatascience.com/complete-image-augmentation-in-opencv-31a6b02694f5

American Academy of Implant Dentistry (n.d.). *Tooth Implant vs Bridge: What Top Dentists Are Recommending.* https://marketplace.ada.org/blog/dental-business/tooth-implant-vs-bridge-what-top-dentists-are-recommending/

Arrowhead Dental (n.d.). *Common Dental Shading Problems and Solutions* https://www.arrowheaddental.com/blog/common-dental-shading-problems-solutions/

Arrowhead Dental (n.d.*). Shade Taking / Color and Cosmetics* [Video]. Vimeo. https://vimeo.com/68618215?embedded=true&source=video_title&owner=2379328

Biospace (2021, July 07). *Dental Implants Market Size to Reach USD 8.61 Billion in 2028 – Reports and Data.* https://www.biospace.com/article/dental-implants-market-size-to-reach-usd-8-61-billion-in-2028-reports-and-data/#:~:text=The%20global%20dental%20implants%20market,analysis%20by%20Reports%20and%20Data.

Chatcha iKunavisarut (Assistant Professor), Worapat Jarangku l(Graduate Student), Suchaya Pornprasertsuk-Damrongsri (Associate Professor), Tim Joda (Professor) (2021). Patient-reported outcome measures (PROMs) comparing digital and conventional workflows for treatment with posterior single-unit implant restorations: A randomized controlled trial: PROMs comparing digital & conventional workflows. *Journal of Dentistry*. https://doi.org/10.1016/j.jdent.2021.103875

Guihua Wang, Xiaoli Gao, Edward C.M. Lo (2015). Public perceptions of dental implants: a qualitative study. *Journal of Dentistry*, *43*(7), 798-805. https://doi.org/10.1016/j.jdent.2015.04.012

James Delaney Jr., D.D.S. & Melanie Burke, D.M.D. (2016, October 03). *The Different Parts Of A Dental Implant*. https://www.delaneydental.com/blog/post/the-different-parts-of-a-dental-implant.html

Jessica E. Canallatos, DDS, MS, Gerald R. Hobbs, PhD, Matthew S. Bryington, DMD, MS, and Bryan D. Dye, DDS, MS (2019). The effect of implant prosthesis complications on patient satisfaction. *The Journal of Prosthetic Dentistry. 123*(2), 269-276. https://doi.org/10.1016/j.prosdent.2018.11.015

Jones (2020). *Picamera.* https://picamera.readthedocs.io/en/release-1.13/index.html

Kargwal (2020,Jun 22). *Color Segmentation using OpenCV.* https://medium.com/srm-mic/color-segmentation-using-opencv-93efa7ac93e2
Meral Kurt, DDS, PhD, Seçil Karakoca Nemli, DDS, PhD, Merve Bankoglu Güngör, DDS, PhD, Bilge Turhan Bal, DDS, PhDd (2021). Visual and instrumental color evaluation of computerized color matching system for color reproduction of maxillofacial prostheses. *The Journal of Prosthetic Dentistry.* https://doi.org/10.1016/j.prosdent.2021.01.009

Ra'fat I. Farah, BDS, MSc, Abdulrahman S. Almershed, BDS, Bariah F. Albahli, BDS, Sanaa N. Al-Haj Ali, BDS, MSc (2021). Effect of ambient light conditions on tooth color quantification in cross-polarized dental photography: A clinical study. *The Journal of Prosthetic Dentistry*. https://doi.org/10.1016/j.prosdent.2021.01.015

Stephen J.Chu, Richard D.Trushkowsky, Rade D.Paravina (2010). Dental color matching instruments and systems. Review of clinical and research aspects. *Journal of Dentistry*, *38*(2), e2-e16. https://doi.org/10.1016/j.jdent.2010.07.001

TensorFlow. (n.d.) (2021, November 10). *Image Segmentation:Tensorflow Core*. https://www.tensorflow.org/tutorials/images/segmentation#define_the_model.

The NumPy Community (2021, Jun 22). *NumPy v1.21 Manual.* https://numpy.org/doc/stable/index.html

Uddin (2020, June 6). *Cognitive services: Creating Image dataset using Azure's Bing Image Search API*. https://medium.com/@syed.sohaib/cognitive-services-creating-image-dataset-using-azures-bing-image-search-api-39802ae99644

Vygandas Rutkūnas, DDS, PhD, Julius Dirsė, Vytautas Bilius (2019). Accuracy of an intraoral digital scanner in tooth color determination. *The Journal of Prosthetic Dentistry*, *123*(2), 322-329. https://doi.org/10.1016/j.prosdent.2018.12.020