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1. Abstract

Anemia is a major disease that affects billions of people. It is caused by not having enough healthy red blood cells or hemoglobin to carry oxygen to the body's tissues. Having anemia can cause tiredness, weakness and shortness of breath. The tests used for detection of this disease are invasive and their results can take around 24 hours to be processed, leading to delays in diagnosis and treatment.

That's why we developed a mobile application, SnapAnemia, capable of diagnosing anemia in seconds. Our app enables detection through a simple picture of the patient's hand. It also allows an interactive test that analyzes a specific part of the hand selected by the user. Additionally, SnapAnemia enhances ongoing care by allowing doctors to monitor their patients' conditions through analysis of their past test results stored in the cloud. Patients also have access to their previous test results, ensuring they stay informed about their health.

2. Introduction

Anemia is a significant public health issue, mostly caused by nutritional iron deficiency, genetic traits, and infections [1]. In 2019, approximately 1.76 billion individuals were documented as affected by this condition [2]. The disease is characterized by a deficiency in

the number of red blood cells or the amount of hemoglobin in the blood, leading to reduced oxygen-carrying capacity.

The Complete Blood Count (CBC) test is one of the most used tests to detect anemia. This method requires medical personnel and laboratory/testing equipment. Typically, results from this method are available within 24 hours. In underdeveloped regions where the risk of anemia is higher due to malnutrition and poor sanitary conditions, conducting such tests can be challenging due to limited resources, infrastructure, and medical personnel. That is why we created an app that can detect anemia by just taking a picture of the patient's hand.

Our app, SnapAnemia, serves both doctors and patients. Patients can use the app to conduct new tests on themselves or monitor their disease's progression by analyzing their previous test results. Doctors can also access these features and track their patients' data seamlessly. SnapAnemia offers an affordable and fast alternative to conventional tests, potentially increasing early detection rates and saving more lives.

There have been some studies on anemia detection from palm and fingernails using machine learning methods [3][4]. There is also an application called AnemoCheck available on both the AppStore and Google Play that diagnoses anemia from fingernail beds. Our approach differs in anemia detection strategy and app design. We used an analytical approach when detecting anemia (this will be further explained in the System Design section). Our app, contrary to AnemoCheck and Appiahene et al.'s app, can also be used by doctors to track the progression of their patient's disease [4]. The storage of past tests and the ease of conducting new tests create a comprehensive environment for both doctors and patients dealing with anemia.

3. System Design

3.1. Feature Extraction

3.1.1. Automatic Feature Extraction

For extracting the palm image, we are using MediaPipe. This tool allows us to detect the hand in the image and find its landmarks. Based on its result we can either display a warning if there isn't any hand present in the image, or only a portion of it is present, and return back to the camera page to let the user take another picture of their hand. If the hand is present then we extract the palm image based on the MediaPipe landmarks (Fig. 1).

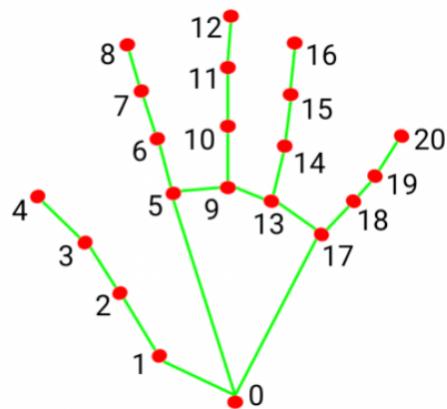


Fig 1. The MediaPipe Landmarks [1]

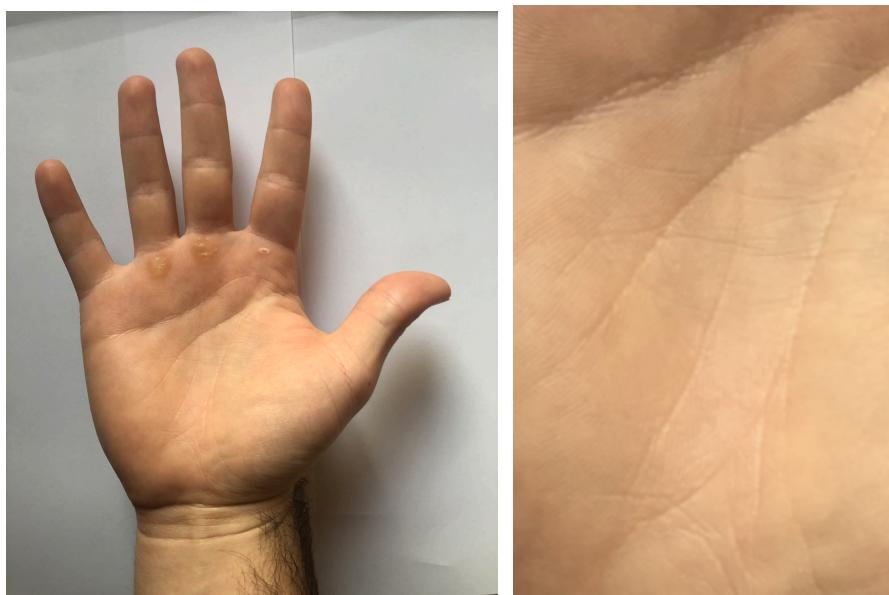


Fig 2. The left image is the input to the palm extraction module and the one on the right is the output.

Using the landmarks numbered 5, 9, 13, 17, and 0, we crop the image to extract only the palm. This extraction is done by first deciding the width of the rectangle to crop. Since people can have different hand shapes, when deciding the width, we take the weighted average of the landmarks. We give higher weight to the inner knuckles so we extract only the palm and not the background. Then using all four landmarks we find a vertical line that is at the center of these knuckles. When deciding on the height of the rectangle, we use the lowest knuckle landmark and the wrist landmark. We take their difference and find a horizontal line that is in the middle of the two landmarks. To not get any background pixel we multiply the difference with 0.7 to get the height of the rectangle to crop. After we get the width and the height, we center the rectangle to the intersection of the vertical and the horizontal lines, so that it is centered. The input and output of this process can be seen at Fig 2.

In this module we can also extract the cropped nail image, however, since it is currently not used during the anemia detection it is unused. Drawing the landmarks to the image also is done in this module with a custom function.

3.1.2. Interactive Feature Extraction

In addition to automatic feature extraction using MediaPipe, we offer an interactive method that allows users to specify a region in the image for analysis. This approach enables more fine-grained and customized analysis. This process can be seen in Fig 3.

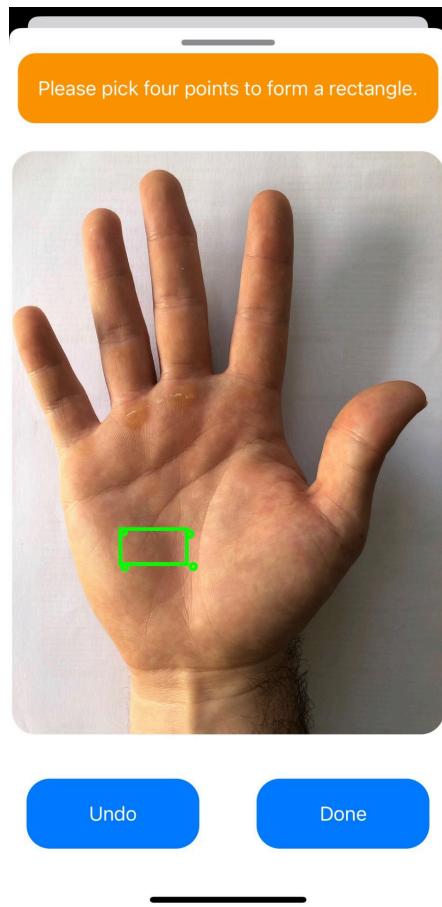


Fig 3. Interactive feature extraction process.

3.2 Data Storage

3.2.1 Database

SnapAnemia uses Firebase Authentication, Cloud Firestore Database and Storage.

Authentication allows a fast sign-in and sign-up method for doctors. Sign-in provider is email and password. For safer and more advanced sign-in methods, two factor authentication with SMS can be applied. Cloud Firestore Database stores multiple collections. These collections can store basic patient information for doctors or more detailed information of patients.

Finally storage is used to keep hand photos of patients.

3.2.2 Storing Users

SnapAnemia app uses two kinds of users;

1- Doctors:

Doctors can register to the app by using an email address and a password. This action creates a new collection in the Cloud Firestore Database for doctors. When doctors enter their account, all patients registered to them are listed on their page by fetching related collections. New patients can be registered by entering their name and id. This action creates a new collection on Cloud Firebase Database for the patient. This patient is only bonded with that doctor, and other doctors cannot interact with the patient.

2-Patients:

Patients do not need authentication to use the app. Patients can enter their id's in the patient view. This action will fetch the collection named with id entered into the text field. This collection contains detailed information of patient tests.

3.2.3 Storing Test Results

Test results are separated into two parts. First part is the collection named after the patient's id. This collection contains multiple files, each file corresponds to a test. Files are named with date and contain multiple variables such as name, id, date, anemia and image url. Image url is used to reach the hand photo used to make the anemia test. These images are stored on Firebase Storage. When a request to view the test is sent, both the file and image associated with the image url is fetched and displayed.

3.3 Anemia Detection

We tried both deep learning and an analytical approach to estimate the chance of anemia.

3.3.1 Deep Learning

We have trained a binary classification model with various architectures on online datasets. Even though we have achieved high accuracy like 87% on online dataset deep learning based approach failed to work on real world datasets that we have collected.

Lack of white skin toned palm images resulted in low accuracy deep learning model.

3.3.2 Image Processing

Based on various trials on real world data that we have collected throughout the semester we have concluded an analytical approach. This approach uses erythema index that compares R and G values in the RGB image. As this method is also suggested by our supervisor we have achieved some amount of heuristic accuracy. Even though we can not say we have quantitative measurements this method performed well when inspected qualitatively.

4. Analysis and Results

Our final product is a functional iOS application designed for use by both doctors and patients. We successfully implemented all the features outlined in our proposal. The application provides an environment for doctors to manage their patients and conduct anemia tests using an image of the patient's hand. Additionally, we added a feature that allows users to conduct custom tests based on their specific choice of location in the hand. Although we initially planned to use deep learning methods for anemia detection, the limited amount of data available prevented this. Instead, we implemented a rule-based detection algorithm utilizing the erythema index.

5. Conclusion

In conclusion, our project has successfully resulted in the development of SnapAnemia, a mobile application that can diagnose anemia quickly and non-invasively. SnapAnemia allows for the detection of anemia using a simple picture of the patient's hand, providing immediate results. Additionally, it offers an interactive test feature where users can select specific parts of the hand for analysis, enhancing the precision and flexibility of the diagnostic process. The app's ability to store historical test data in the cloud enables both doctors and patients to monitor the progression of anemia over time, ensuring continuous and comprehensive care. Despite initial challenges with deep learning methods due to limited data, our rule-based detection algorithm utilizing the erythema index has proven effective.

For future improvements, increasing the diversity and volume of training data, could enhance accuracy and enable the successful implementation of deep learning methods.

Additionally, refining the user interface for greater intuitiveness and enhancing security measures to protect patient data are areas that can be further explored.

6. References

[1] World Health Organization, “Anaemia,” www.who.int, 2023.

<https://www.who.int/news-room/fact-sheets/detail/anaemia>

[2] “Anemia - Level 1 impairment | Institute for Health Metrics and Evaluation,” www.healthdata.org.

<https://www.healthdata.org/research-analysis/diseases-injuries-risks/factsheets/2021-anemia-level-1-impairment>

[3] “Hand landmarks detection guide | Edge,” *Google for Developers*.

https://ai.google.dev/edge/mediapipe/solutions/vision/hand_landmarker

7. Appendix

Github link: [ZenginU/Comp491Project: Senior design project for COMP 491 course in Koc University. \(github.com\)](https://ZenginU/Comp491Project)