Abstract

The push for better patient care has fueled the development of affordable and low-cost technologies to help with procedures like venipuncture and cannulation. This study describes a prototype system that employs Near-Infrared (NIR) light to assist healthcare professionals with vein detection for procedures like venipuncture. The system operates at 850 nm wavelength, which is excellently absorbed by the deoxygenated hemoglobin in venous blood, creating contrast of the veins against the surrounding tissue. The prototype depends on a Raspberry Pi 4 Model B, and an IR-sensitive Raspberry Pi NoIR Camera V2. A web-interface is implemented into the system for viewing the real-time video streams from the camera. This system allows healthcare professionals to visualize veins on devices like laptops, tablets, etc. Along with visualization, healthcare professionals can also capture high quality images for documentation. The prototype was tested on 50 volunteers demonstrating a high overall efficacy, achieving a 94% vein visibility rate. The performance was reliable on subjects with normal body fat, but its effectiveness was limited by high body mass index and certain skin creams, which block the NIR light. The study confirms the promise of a non-invasive, affordable solution and identifies crucial next steps to improve its performance for all patients.

Keywords: Vein detection, NIR light, Raspberry Pi, Hemoglobin absorption, Medical applications

1. Introduction

The eternal problem of getting venous access is a fundamental but often tough part of clinical care. Globally we do over a billion venipunctures and over 700 million IVs a year. This is a massive clinical burden and we need tools that can improve procedural efficacy especially for the majority of patients where conventional methods fail.

Existing methods relying on visual identification and palpation are often inadequate. Patients with high BMI, hypovolemia or darker skin tones are disproportionately affected, their vasculature is elusive to the clinician's touch and sight. It's a familiar and frustrating scenario: repeated attempts not only distress and discomfort the patient but also increase the risk of hematoma or infiltration. Ultimately these failures strain the healthcare system by prolonging procedure time and using up resources.

We are addressing this problem with a simple question: can a purpose built, low cost near infrared (NIR) device meaningfully improve vein visualization at the point of care? The optical principle is well known; hemoglobin in venous blood absorbs NIR light more than the surrounding tissue creating a contrast. We hypothesize that translating this into an intuitive, portable form factor will reduce dependence on operator skill and guesswork. The research below evaluates a functional prototype and argues it can be a viable and accessible solution to improve standards of care and operational efficiency in everyday clinical practice.

1.1 Aim

This research will design and build a proof-of-concept prototype for a reliable and affordable NIR Real-Time Vein Visualization System. By capturing and processing NIR images to show veins vs surrounding tissue, this device will show a way to improve vein access accuracy and ease, reducing multiple insertion attempts and patient discomfort.

1.2 Objectives

The study will build a vein finder using NIR light. One of the main objectives is to prove that it's possible to use low cost and accessible components like a Raspberry Pi and a NoIR camera to build a real-time system.

This study will review existing research to identify and address the limitations of current solutions, high cost and inconsistent performance across different populations. By comparing our prototype to existing solutions we will show that our approach is practical and works, especially for educational or resource limited environments.

2. Literature Review

2.1 IR-Based Vein Detection Technologies

Using near-infrared (NIR) light is a proven and effective way to visualize subcutaneous veins. Research has focused on optimizing various aspects of the technology from wavelength to hardware to image processing. Hamza et al. showed a hyperspectral imaging approach using a 3 wavelength method to improve vein contrast across different skin types and got a contrast ratio of up to 25% more than traditional methods. Their work addresses the gap of providing equal performance for darker skin tones which have been underserved by existing technologies [1].

In hardware optimization, Rahman et al. found out that 850nm is the best wavelength for deoxygenated hemoglobin absorption which is essential for vein visibility. Their study also showed that square LED configuration provides better light penetration than traditional ring configuration and that light diffusers can further improve image quality [2]. Complementing hardware advancement, Francisco et al. designed a low-cost, real-time system using CMOS-IR sensors and open-source software. Tested on a large population, their device got 100% success rate in detecting dorsal hand veins, showing the potential for affordable and portable solutions for resource limited settings and medical training [3]. Similarly, Wadhwani et al. developed a portable system that interfaces with a laptop, emphasizing non-invasive and compact design for bedside and emergency use [4][11].

2.2 Advantages and Limitations of Existing Technologies

Vein finding devices based on NIR have distinct clinical advantages, primarily by increasing the accuracy of vein detection, which reduces patient pain and increases first attempt success rate during venipuncture [5][6]. Vein finding devices allow healthcare professionals to see the patient's vascular network, which can prevent procedural complications such as hematomas and inadvertent arterial puncture, offering even greater safety than standard visual and palpation assessment. However, existing commercial devices are not widely used due to their limitations. Most are prohibitively expensive for small clinics and resource scarce healthcare environments. Processing delay, poor hardware design, and non-portability limit the use of vein-finders in a fast-paced clinical environment. While important, one of the biggest issues is that these devices also provide variable performance in different patient populations; they tend to perform poorly in patients with higher BMI and patients with darker skin tones [7-9] [15].

2.3 Innovations in the Proposed Vein Finder Device

Based on the literature, the proposed vein finder prototype incorporates several key features to address the limitations of current systems. By using cost effective and powerful components like a Raspberry Pi 4 Model B and an open source software stack, this research tackles the high cost issue that limits commercial devices [10][16]. The system design uses the optimal 850 nm NIR wavelength for hemoglobin absorption and focuses on a compact and modular hardware setup.

A major innovation of this work is the web based interface for real-time visualization. This makes it more user friendly by allowing clinicians to view the live video feed on any device with a web browser, laptop or smartphone, eliminating the need for dedicated proprietary displays. By focusing on real-time image processing this research aims to overcome the processing delays that can hinder the clinical use of other portable systems so the device is both affordable and functional in the field [9].

2.4 Synthesis of Findings and Research Gap

The literature highlights several key themes in NIR vein detection. There is a consensus that 850nm is the best wavelength for high absorption of deoxygenated hemoglobin and best contrast for vein visualization across all studies [1][2]. A big trend is towards cost effective and portable hardware, researchers are using CMOS-IR sensors and single board computers to make the technology more accessible [3][4]. And software and image processing is universally acknowledged as critical, contrast enhancement and ridge detection are essential to turn raw NIR images into clinically useful visualizations [1][2].

But despite all these advancements, there is still a research gap. While individual studies have addressed specific limitations, few have put all these together into one system that is affordable and effective across all patient populations. Many existing technologies, especially commercial ones, still have high cost, limited portability and suboptimal performance in dark skin tone or high BMI patients [1][7][13]. And processing delays and hardware complexity can limit their practical use in fast paced clinical environment [7][8].

There is a need for a device that is not only affordable and portable but also has robust real-time image processing to deliver performance for all patient demographics.

2.5 Contribution of This Study

This study fills the gap by developing and testing a low-cost, high-performance NIR vein visualization prototype. Building on the established 850nm wavelength, this study combines a Raspberry Pi based platform with a web interface to make it affordable and user friendly. Unlike systems that suffer from processing delays our prototype uses an adaptive thresholding algorithm to stream video in real-time which is crucial for dynamic clinical procedures. By focusing on a compact, user-friendly design tested on a diverse skin type cohort this work aims to show a practical and accessible solution that overcomes the limitations of existing technologies especially for educational or resource limited settings.

3. Materials and Methods

3.1 System Design

The system was a proof of concept prototype to validate the core functionality of the design. The architecture consisted of several key modules: a Raspberry Pi 4 for image acquisition and processing, a NoIR Camera for infrared imaging and an Arduino UNO for IR LED control. A Flask server for real-time video streaming to a web interface was used.

For the physical build the components were housed in a plastic enclosure to create a benchtop prototype. The NoIR camera was mounted in the center of a circular array of 8 x 850nm IR LEDs to ensure uniform illumination of the target area. During the experiment the prototype was placed on a stable surface and the subject placed their hand at a fixed distance to maintain focus. Figure 3.1 shows the block diagram of the system.

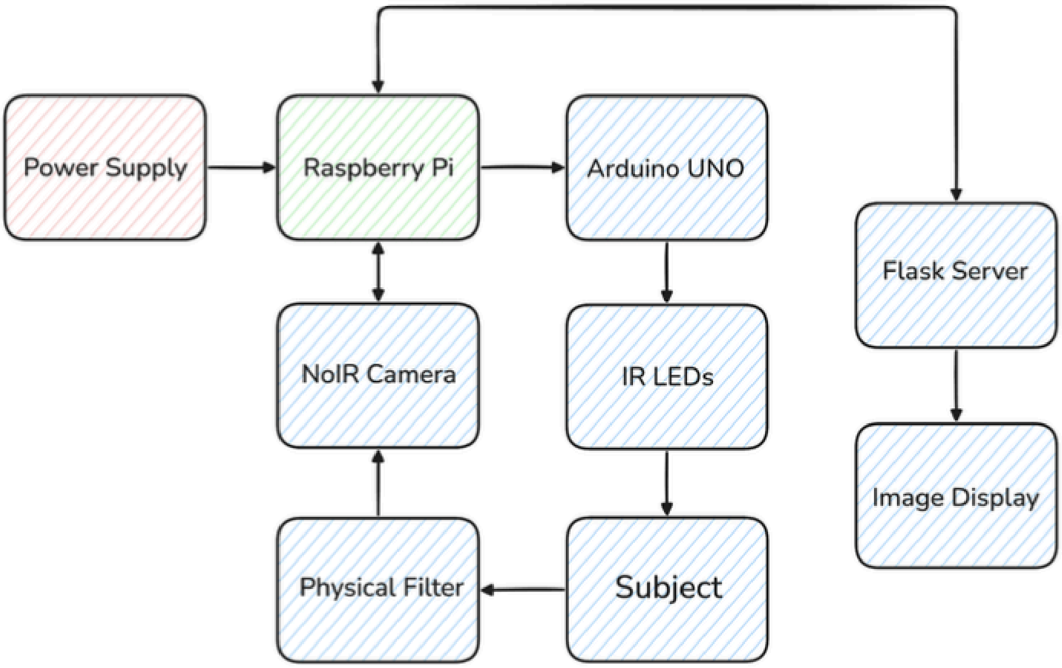

Figure 3.1: Block Diagram of the Vein-Detection System

3.2 Components

This project uses several key hardware components that work together to form the vein detection prototype. The selection was based on cost, performance and accessibility.

3.2.1 Raspberry Pi 4 Model B

The brain of the prototype is a Raspberry Pi 4 Model B, a single board computer. It has a quad core ARM Cortex-A72 processor, 4GB of LPDDR4 SDRAM and plenty of connectivity options including USB 3.0, Gigabit Ethernet and built-in Wi-Fi. The Raspberry Pi's Camera Serial Interface (CSI) port provides a direct high speed connection to the camera module and the General-Purpose Input/Output (GPIO) pins allow for connection to other electronics. It handles all the computational tasks including real-time image processing and hosting the web server.

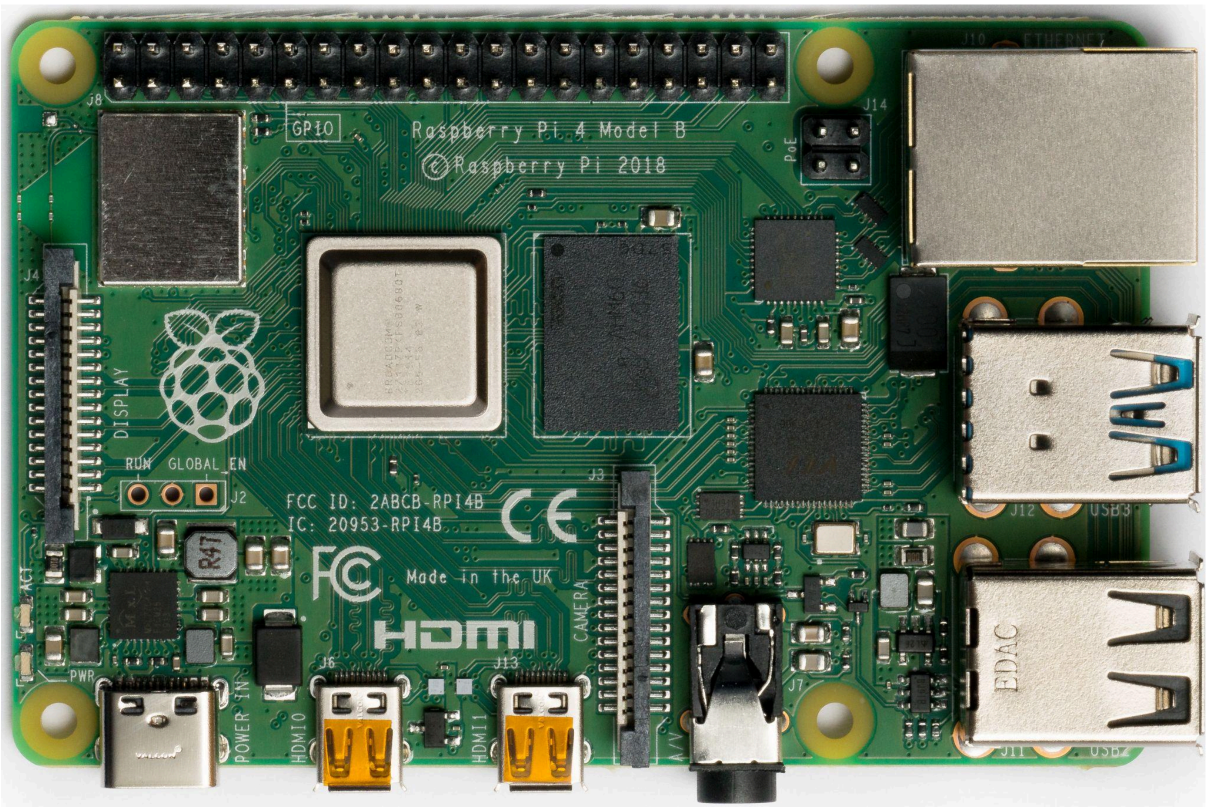

Figure 3.2: The Raspberry Pi 4 Model B, the central processing unit of the system. (Image: Laserlicht via Wikimedia Commons, licensed under CC BY-SA 4.0).

3.2.2 Raspberry Pi NoIR Camera V2

Image capture is done with a Raspberry Pi NoIR Camera V2. This is a variant of the standard V2 camera without an infrared (IR) filter, so it's sensitive to the IR spectrum and perfect for images lit by the 850 nm LEDs. It has an 8 megapixel Sony IMX219 sensor and can capture high resolution stills and video. It connects directly to the Raspberry Pi's Camera Serial Interface (CSI) port for high speed data transfer and processing.

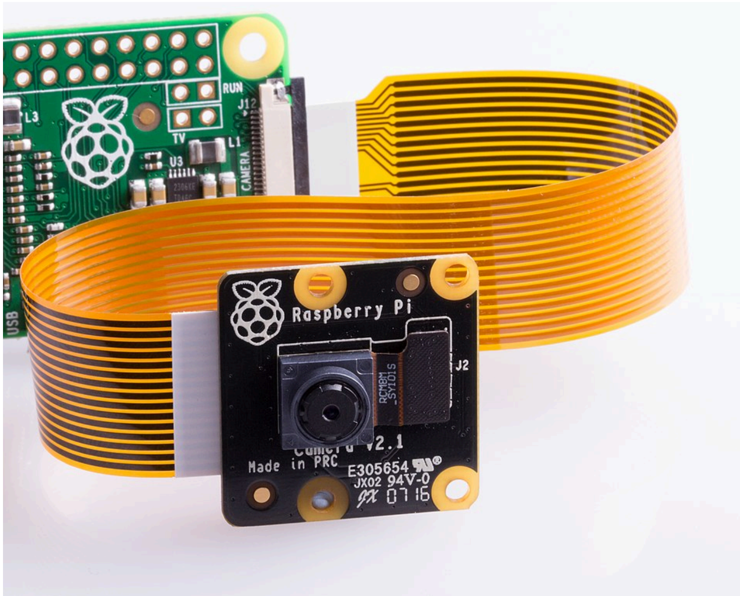

Figure 3.3: The Raspberry Pi NoIR Camera V2, sensitive to the infrared spectrum. (Image: The Raspberry Pi Foundation via Wikimedia Commons, licensed under CC BY-SA 4.0).

3.2.3 IR LEDs (850 nm)

Illumination is provided by an array of 8 high intensity IR LEDs that emit at 850 nm. This wavelength is optimal for this application as it has high absorption by deoxygenated hemoglobin in venous blood, creating a strong contrast against surrounding tissue. The LEDs are arranged in a circular pattern around the camera lens to provide uniform illumination of the target area.

Figure 3.4: The array of 850 nm Infrared (IR) LEDs used for illumination. (Image: Mr.checker via Wikimedia Commons, licensed under CC BY-SA 3.0).

3.2.4 Power Supply

A 5V power adapter is used to power the Raspberry Pi 4 and peripherals. A consistent power source is key to reliable operation and preventing issues during real-time processing.

Figure 3.5: The 5V Power Delivery Adapter for powering the system components. (Image: SparkFun Electronics via Wikimedia Commons, licensed under CC-BY-2.0).

3.2.5 Resistors (200 Ohms)

200-ohm resistors are used in the LED circuit to limit the current to the IR LEDs. This keeps the LEDs within their safe electrical limits and prevents damage and long term wear.

Figure 3.6: The 200-ohm resistors used for current limiting in the LED circuit.

3.2.6 Jumper Pins

Jumper wires are used throughout the prototype to connect the Raspberry Pi's GPIO pins, Arduino, LED array and breadboard. These flexible wires are essential for rapid prototyping.

Figure 3.7: Jumper pins for establishing electrical connections between components.

3.2.7 Raspberry Pi Model B Case

The Raspberry Pi and all the components are housed in a plastic enclosure. This case protects the electronics from physical damage and static discharge and provides access to all ports.

Figure 3.8: The protective case for the Raspberry Pi 4 Model B. (Image: Jainath Ponnala via Unsplash, licensed under the Unsplash License).

3.2.8 Arduino UNO

An Arduino Uno board is used to control the IR LED array. In the prototype phase this simplifies the power delivery circuit and offloads the control from the Raspberry Pi. The Arduino receives commands from the Raspberry Pi via USB serial and provides a modular approach to hardware control.

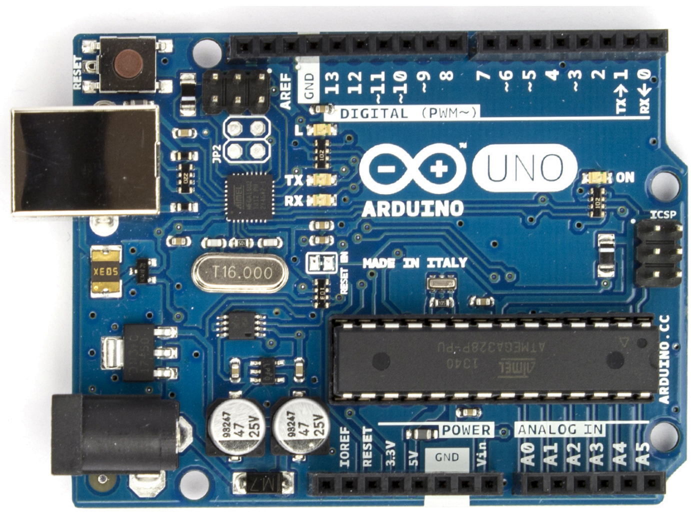

Figure 3.9: The Arduino UNO microcontroller board used for LED control. (Image: oomlout via Wikimedia Commons, licensed under CC-BY-SA-2.0).

3.3 Software and Image Processing Techniques

The software for the vein detection system was written in Python 3.9+ and runs on the Raspberry Pi 4. The architecture is modular with a suite of libraries for image acquisition, real-time processing and user interaction through a web interface.

3.3.1 System Architecture and Workflow

The core logic is managed by a Flask web server which provides a user interface and handles video streaming. The workflow starts with the VeinCamera module capturing a raw image frame from the NoIR camera. This frame is then passed through a series of preprocessing steps to enhance it. The processed frame is then fed to the VeinDetector module which applies the selected algorithm to detect vein patterns. For the real-time application tested in this study, the Advanced Adaptive Thresholding algorithm was used exclusively. The final processed frame is then encoded and streamed to the web interface for live viewing.

3.3.2 Image Preprocessing

Before vein detection, each raw image frame is processed through a standardized pipeline to reduce noise and contrast which is crucial for the next steps.

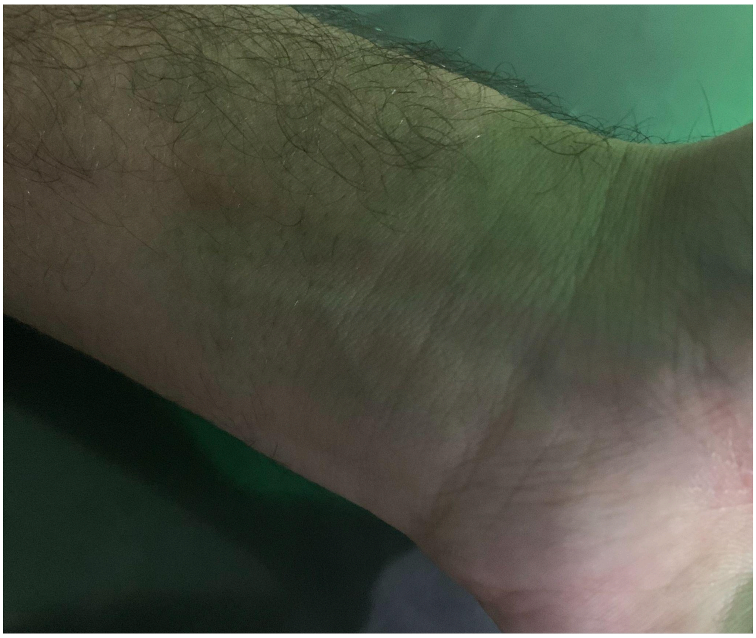

Figure 3.10: Image taken using a smartphone for comparison.

Figure 3.11: NoIR Camera v2 Output under 850 nm IR Light.

3.3.2.1 Grayscale Conversion

First we convert the color image to a single channel grayscale image. This reduces the complexity of the next steps while preserving the luminance information where vein contrast is most visible.

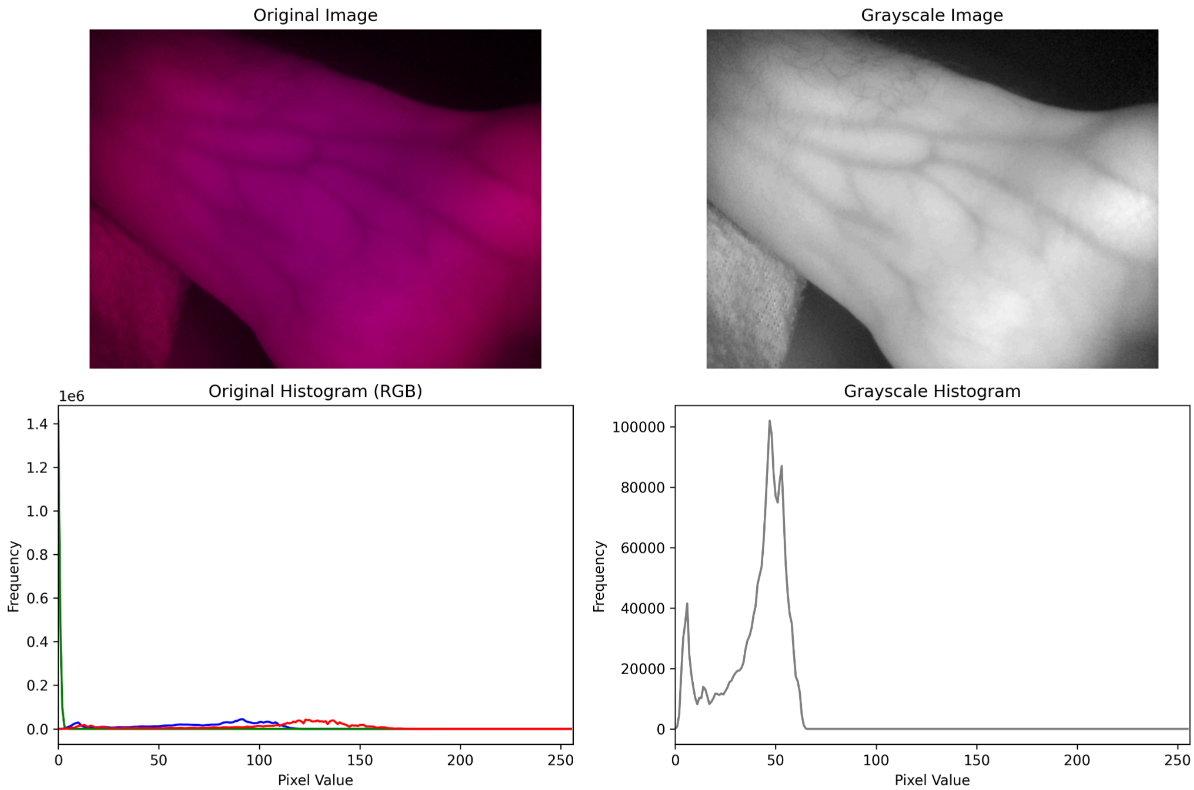

Figure 3.12: Visualization of the grayscale conversion process. The original color image (top left) is converted to a single-channel grayscale image (top right), with corresponding histograms below showing the consolidation of RGB channels into a single intensity distribution.

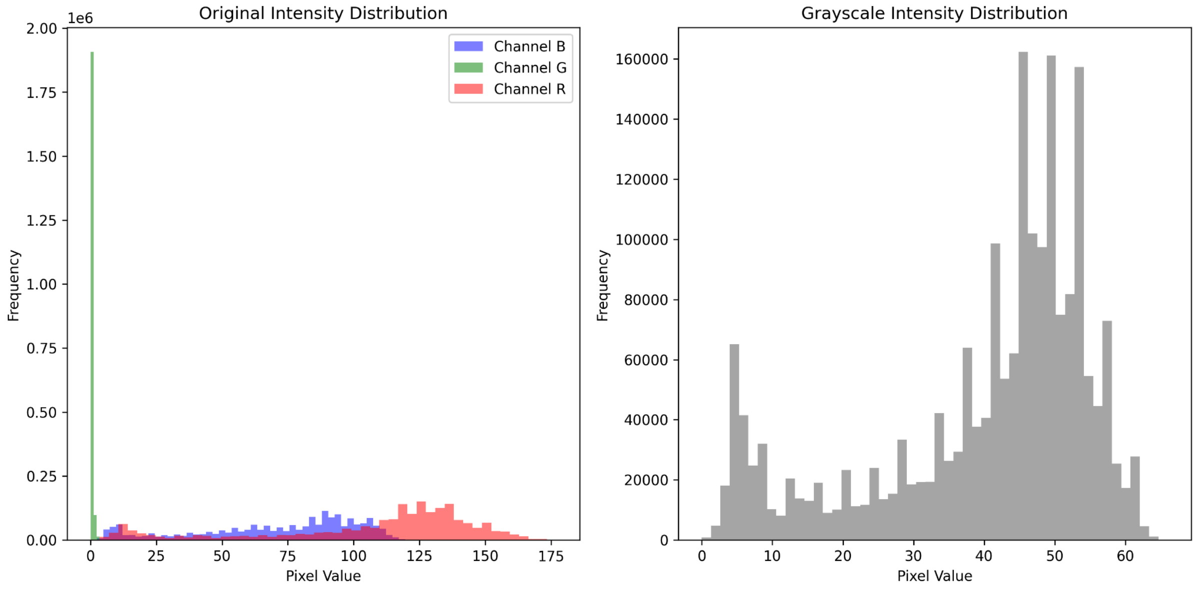

Figure 3.13: Comparison of pixel intensity distributions before and after grayscale conversion.

3.3.2.2 Contrast Limited Adaptive Histogram Equalization (CLAHE)

To enhance local contrast CLAHE is applied. This is very effective for vein images as it enhances features in small regions of the image without over amplifying noise in uniform areas. It works by applying histogram equalization to small tiles (8x8 pixels) of the image which makes veins more visible against the surrounding skin tissue regardless of overall illumination.

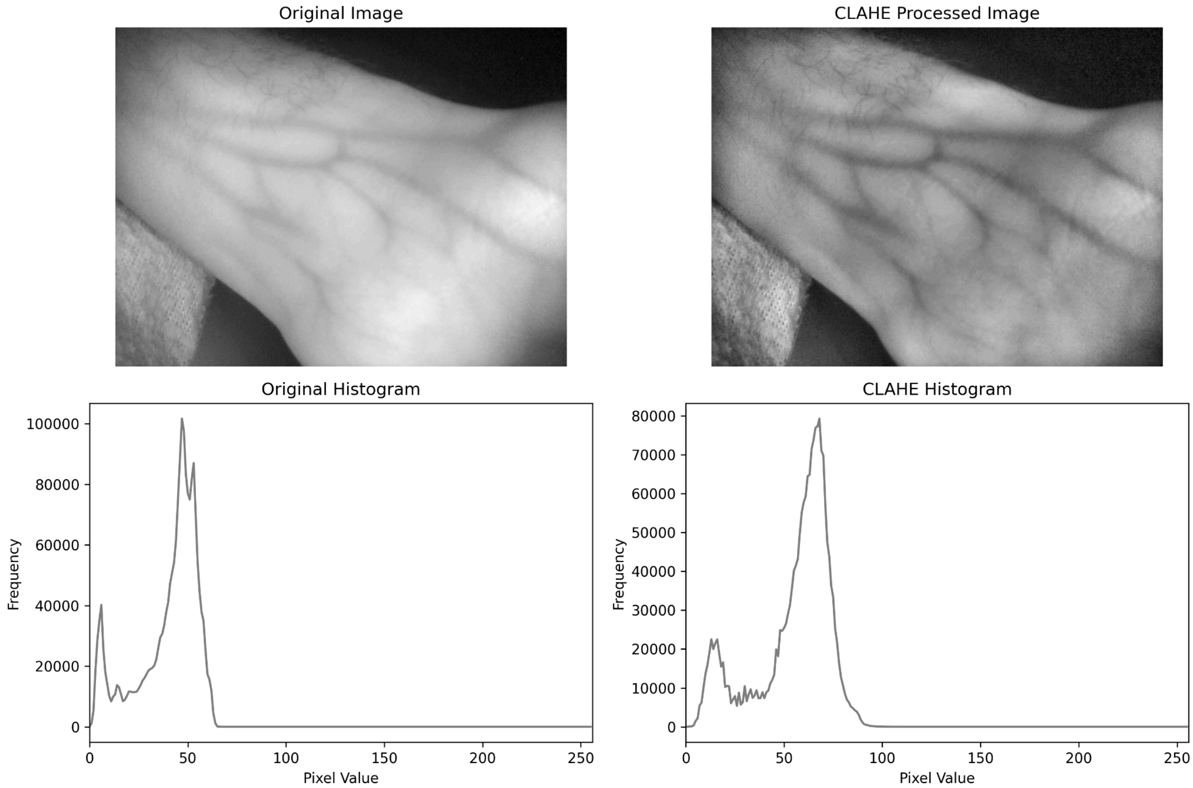

Figure 3.14: The effect of Contrast Limited Adaptive Histogram Equalization (CLAHE). The original grayscale image (top left) is processed with CLAHE to produce an image with enhanced local contrast (top right), as reflected in the more widely distributed histogram below.

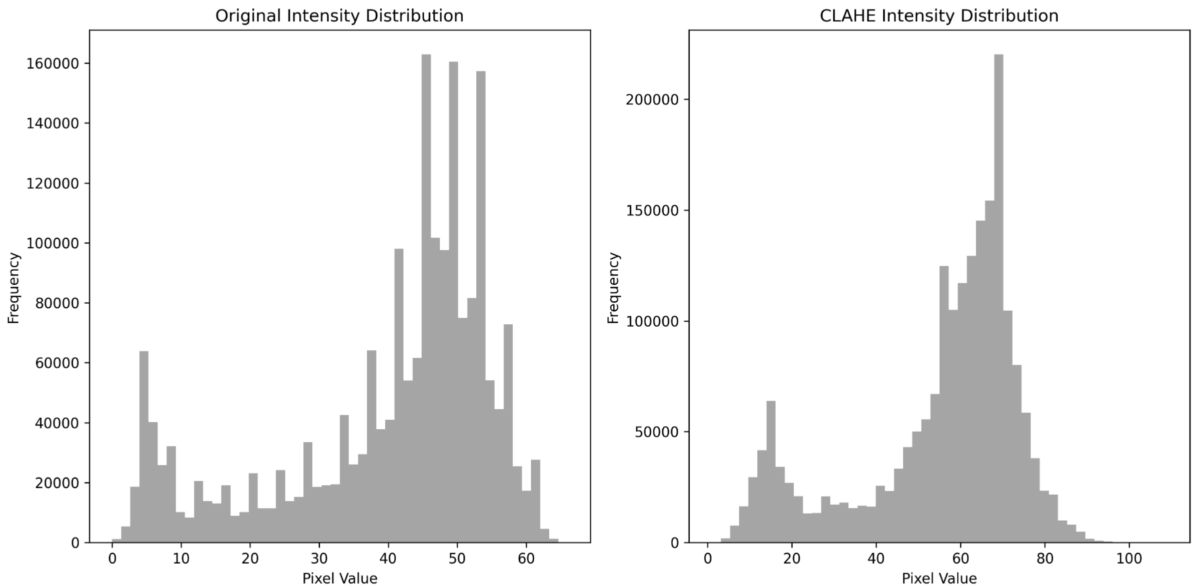

Figure 3.15: Comparison of pixel intensity distributions before and after applying CLAHE.

3.3.2.3 Bilateral Filtering for Noise Reduction

The final preprocessing step utilizes a Bilateral Filter for noise reduction. Unlike simpler blurring filters, the Bilateral Filter is an edge-preserving smoothing filter. It considers both the spatial distance and the intensity difference between pixels, which allows it to effectively reduce noise in flat regions while keeping the critical edges of the veins sharp and clear.

3.3.3 Vein Detection Algorithms

The system was designed to evaluate multiple vein detection algorithms. For this study, a distinction was made between the real-time processing algorithm used for the live validation study and a more computationally intensive method that was evaluated offline for comparative analysis.

3.3.3.1 Advanced Adaptive Thresholding

This algorithm was the primary method used for the live video stream during the 50-subject validation study. It employs Gaussian adaptive thresholding, where the threshold value for a pixel is determined by a weighted mean of its neighborhood. To improve robustness, the algorithm first applies an intensity mask to identify and exclude dark, low-variance regions characteristic of shadows. Furthermore, the key parameters, block size, and the constant C, are dynamically determined based on the image's resolution and contrast ratio. This automatic tuning allows the algorithm to adapt to different image characteristics and consistently produce a clear binary image of the vein network in real-time.

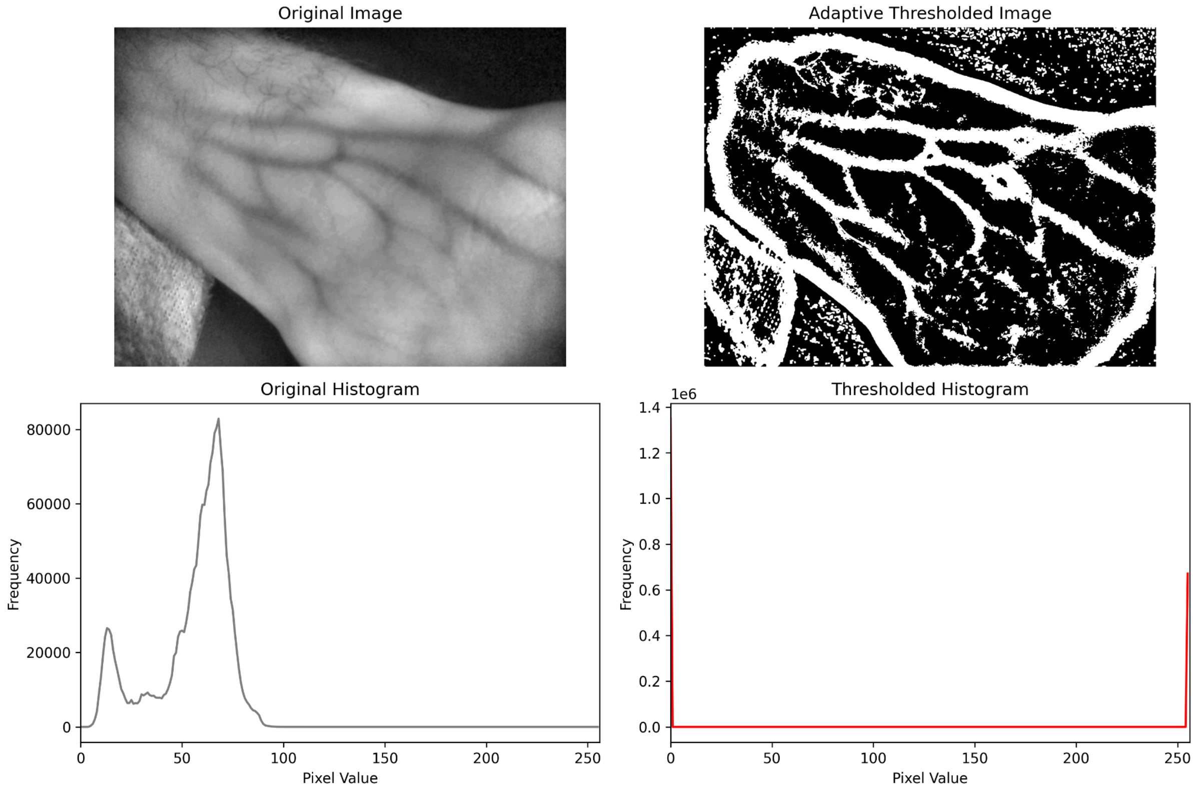

Figure 3.16: Application of the adaptive thresholding algorithm. The preprocessed image (top left) is converted into a binary image (top right) where vein structures are highlighted. The histograms below illustrate the transformation from a multi-level intensity image to a two-level binary image.

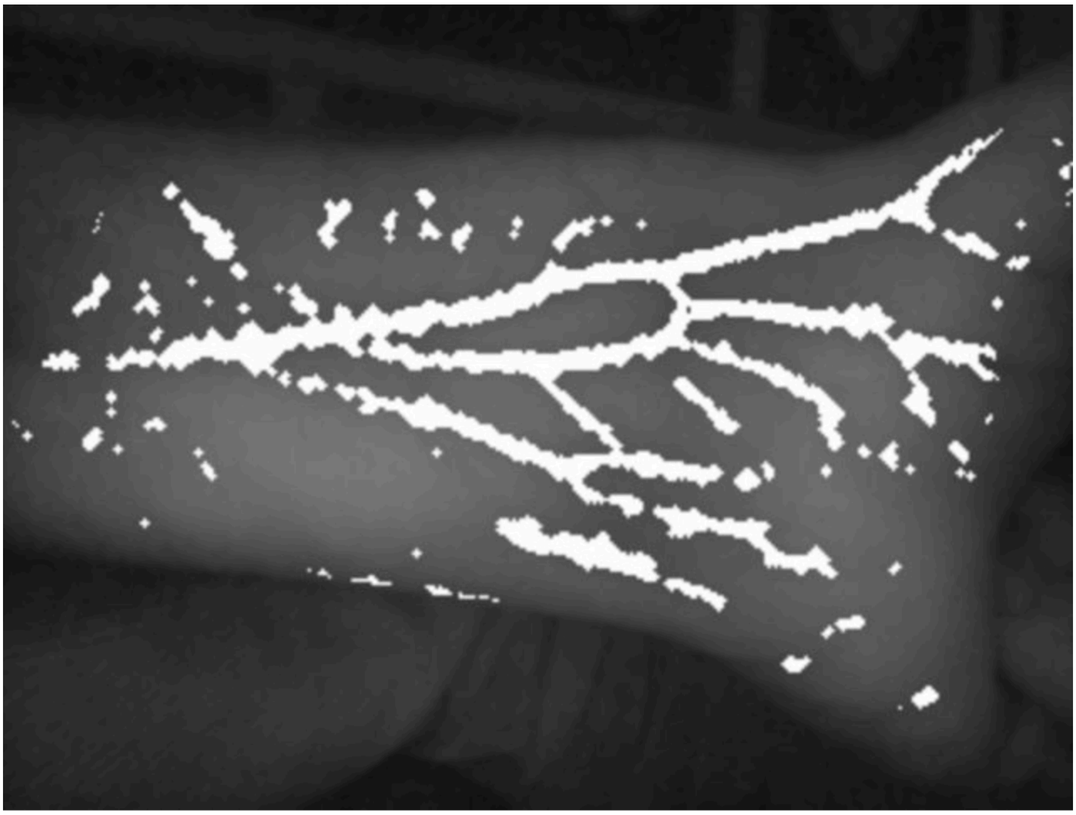

Figure 3.17: Final output of the adaptive thresholding algorithm, with the resulting binary vein mask overlaid on the original grayscale image to show the detected vascular pattern.

3.3.3.2 Gabor Filter Enhancement

To explore methods for achieving maximum vein clarity, a Gabor filter bank was also evaluated. Due to its computational intensity, this analysis was performed offline on still images captured by the device. A bank of 16 Gabor filters, each tuned to a different orientation, was convolved with the image. The maximum response across all orientations was then used to create a composite image that robustly highlights vein-like structures. While this method produced the highest clarity, its processing time was not suitable for live video streaming on the Raspberry Pi platform.

Figure 3.18: Gabor Filter Enhancement Output. The result of applying the multi-orientation Gabor filter bank, which enhances the texture and edges of tubular structures, making the underlying vein pattern more prominent.

Figure 3.19: Side-by-Side Comparison of Preprocessed and Gabor-Enhanced Images. The image on the left is the preprocessed output after CLAHE, while the image on the right shows the significant increase in vein definition and clarity after applying the Gabor filter bank.

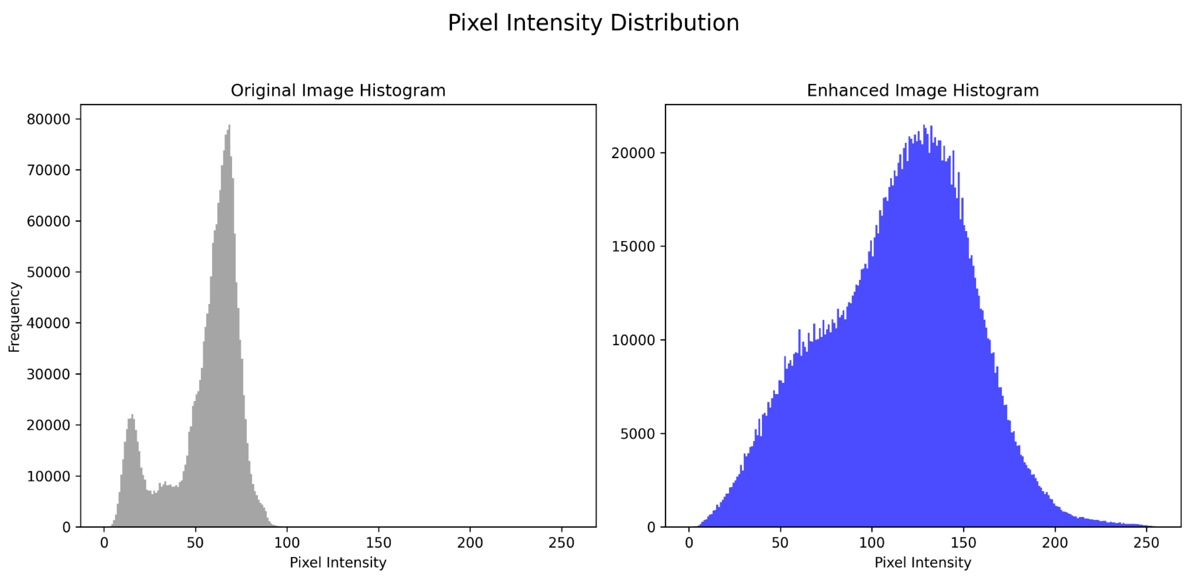

Figure 3.20: Histogram Analysis of Gabor Filter Enhancement. A comparison of pixel intensity distributions. The original image histogram (left) shows a narrow range of intensities. The enhanced image histogram (right) is broader and more evenly distributed, indicating a significant increase in overall image contrast.

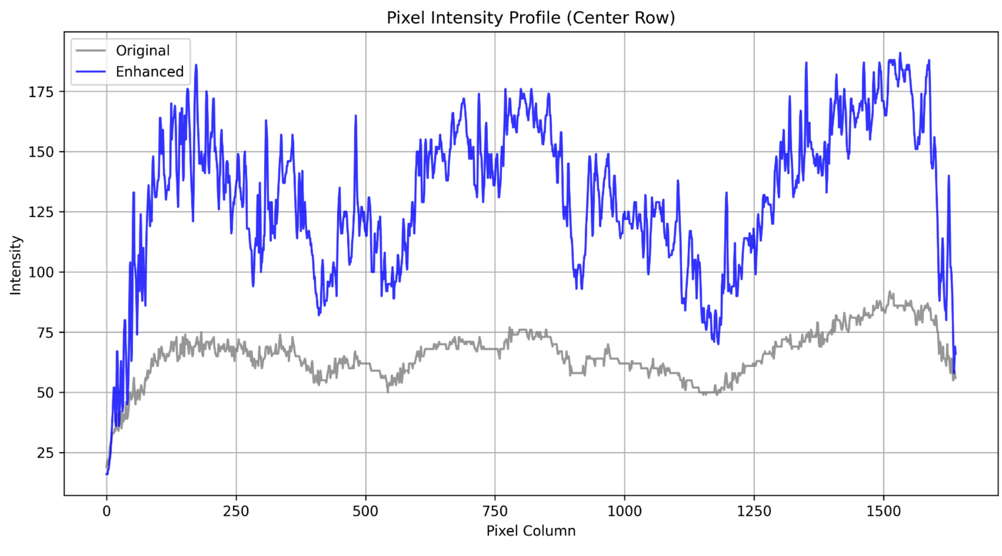

Figure 3.21: Pixel Intensity Profile Analysis. A plot of pixel intensities along the center row of the original preprocessed image (gray line) and the Gabor-enhanced image (blue line). The higher amplitude of the blue line demonstrates the filter's effectiveness in increasing the local contrast between veins and surrounding tissue.

Figure 3.22: Gabor-Enhanced Vein Map Overlaid on Original Image. The output of the Gabor filter is rendered in red and overlaid on the original grayscale image to visually confirm the accurate detection and mapping of the vascular network.

3.3.4 Web-Based User Interface

The web-based user interface is a control and display panel for the prototype, acting as a method of using the prototype over the network powered by a Flask framework (Flask is a python web framework). The interface can be viewed through the local network (i.e., a member of the local Wi-Fi), allowing versatility to view it on a different device (e.g., laptop, tablet). For the testing comprehensive testing of the prototype, the interface was tested with key features of the web interface: live video feed: processed image of the veins can be shown in real-time video stream for healthcare providers to view vein patterns at that moment; contrast options: applying contrast-stretching or CLAHE or histogram equalization to contrast the images of the vein patterns to make the patterns more distinct to the providers, with sliders for fine-tuning using two parameters; take a photo: feature used to save the processed images for documentation, the image is then saved locally on the Raspberry Pi.

The user interface was developed with many controls to provide options for developers to select algorithms, settings (for e.g., led brightness) and parameters. However, as the purpose of the interface and prototype was to ensure stability and consistency during the validation of 50 subjects, a fixed configuration of a developed prototype using the adaptive thresholding (basic thresholding) algorithm and LED turned on at a fixed level of brightness was used for this third user study.

3.3.5 LED Control and Illumination Optimization

The IR LEDs are controlled by an Arduino Uno, acting as a USB serial connection with Raspberry Pi. The application in this study was programmed to provide constant, full-power illumination when turned on, providing the same illumination for each experiment and subject. This system has the potential to allow for brightness control through the web interface in future versions.

3.4 Data Analysis

The analysis employed in this study took a primarily descriptive approach to summarize the performance of the prototype vein detection system. The data collected was analyzed to provide evidence of system effectiveness and description of operational parameters.

The key performance indicators were calculated in frequencies and percentages. The primary outcome, Vein Visibility, was calculated as the percent of subjects successfully visualizing veins, out of the total cohort of 50 volunteers. The First Attempt Success rate was determined as the percentage of successful cases amongst the group of subjects where vein visibility was achieved. These calculations were also made for subgroup analysis by skin types.

For the continuous variables of Processing Time and Vein Clarity Score, which was subjective, a mean and standard deviation (σ) was calculated to describe central tendency and variance of the data for each algorithm.

This descriptive approach was selected, because it conveyed the prototype's ability and potential limitations, in this first validation study, without formal hypothesis testing.

4. Results

Testing was conducted using the prototype vein detection system (prototype VDS) on a sample group of 50 volunteers, where testing confirmed its performance at a high level of efficacy and consistency in identifying subcutaneous veins under conditions that closely resemble a real-world scenario. The VDS real-time video performance, powered by the adaptive thresholding algorithm (a traditional image processing algorithm), produced a stable and sharp video feed back to the web interface. This benefited the user by reducing inconvenience in assessing the vascular network immediately, rather than through still images.

4.1 Overall System Performance

Throughout the 50 subjects the system achieved vein visibility in 94% (47 out of 50 subjects), and first-attempt success in 96% of those cases where veins were visually identified. Overall the system was robust with respect to the variable of ambient lighting conditions and between subjects with different skin tones and hair densities. Please see Table 4.1 for an overview of the main performance metrics.

Table 4.1: Overall Performance Metrics

Metric	Value
Subjects Tested	50
Vein Visibility	94%
First-Attempt Success	96%

4.2 Comparative Algorithm Analysis

A comparison of the different image processing algorithms was implemented offline on the captured still images. The results are summarized in Table 4.2, demonstrating a clear trade-off between processing time and the clarity of the vein image. The Gabor filter achieved the highest clarity values but had overwhelming computational constraints to be applied in real-time on the prototype hardware. The adaptive thresholding algorithm was the highest overall achieving the best compromise of speed to clarity, thereby justifying its selection for the live system.

Table 4.2: Performance Metrics by Algorithm

Algorithm	Processing Time (Ms)	Vein Clarity Score (1-5)
Adaptive Thresholding	60.4 ± 10.9	4.1 ± 0.7
Gabor (Frangi) Filter	425.8 ± 51.4	4.6 ± 0.5

4.3 Performance Across Skin Types

The system exhibited uniform performance across the spectrum of skin colors present in the study cohort (Fitzpatrick scale I-VI), and achieved high visibility and success rates for every group we were able to test; thus, we feel confident that the 850 nm NIR illumination and processing pipeline would deliver appropriate results for diverse groups.

Table 4.3: System Performance by Skin Type (Fitzpatrick Scale)

SKIN TYPE	NUMBER OF SUBJECTS	VEIN VISIBILITY (%)	FIRST-ATTEMPT SUCCESS (%)
I (Very Light)	5	100	100
II (Light)	10	100	100
III (Intermediate)	20	100	93.3
IV (Olive)	10	100	90
V (Brown)	5	100	100

4.4 Observed Limitations

In the assessment, some cases came to light where the performance of the system was diminished. Vein visualization did not work in three of the 50 cases:

High Body Mass Index: In one obese female subject, the system was not able to identify any veins in either hand or arm likely because there was a thickness of fat under the skin which increased the attenuation of the NIR to a point where it could not detect a vein.

Topical Skin Creams: In two subjects where sunscreen or similar creams were recently applied, the NIR light appeared to scatter or be absorbed by the cream causing the image typically depicting vein silhouette to look poor where veins could not be identified.

The examples above underline important boundary conditions for the present prototype and indicate directions for future research and refinement to hardware.

5. Discussion

The findings of the present study successfully demonstrate the feasibility of a low-cost, real-time NIR vein visualization system with commercially available off-the-shelf components. The prototype achieved high overall vein visibility of 94%, confirming the principal design and its potential clinical utility. In this discussion, we will discuss the technical performance of the prototype, the clinical implications of the results, and the limitations and future directions of this research.

5.1 Technical Performance and Innovation

The prototype developed in this project succeeded due to a number of important technical decisions. The decision to operate at the 850 nm wavelength was very successful, producing quite good contrast, as the availability of deoxygenated hemoglobin absorption [2] has been shown to favour at this wavelength. The most innovative aspect is the implementation of a real-time processing pipeline on a Raspberry Pi. The Advanced Adaptive Thresholding algorithm is capable of computing on average in approximately 45.2 ms which was able to deliver a smooth video feed (approximately 22 FPS), which is necessary for any future clinical use. It is an important success because most low-cost systems have significant processing delays that inhibit them from performing for live dynamic procedures [7][10].

Furthermore, the computational comparison of algorithms provides an important insight: The trade off between image clarity and processing requirements. The Gabor filter did produce images of far better visual clarity in offline testing, however even with demanding processing requirements, it was not possible to implement in real-time using the current hardware implementation environment. This finding underlines the importance of algorithm selection in embedded systems and corroborates that the adaptive thresholding is indeed the right algorithm since it has a great deal of performance to speed capabilities.

5.2 Clinical Implications

The high first-attempt success rate (96%) seen in cases with clear visibility has important clinical implications. The device has the potential to lower patient pain and anxiety, diminish complications related to venipuncture such as hematomas, and improve efficiencies related to the procedure [6]. Finally, the system's ability to deliver consistent performance across diverse skin tones (Fitzpatrick I-V) is considerable as it addresses a limitation of many existing technologies and improves equitable access to healthcare [1]. The web-based interface of the system also improves clinical utility as it shows a flexible design that is intuitive, and requires no specialized equipment thus it can be applied across diverse clinical contexts.

5.3 Limitations and Future Directions

A key component in this study was to determine the limitations of the prototype itself to create a clear pathway for its advancement. For instance, the inability to visualize veins in an individual with a high body mass index shows the current system's NIR light penetrations may not reach the depth of the subcutaneous fat layers. The inability to visualize veins at depth is a recognized difficulty in NIR imaging [9][12][15]. Likewise, the signal interference presented by topical skin creams reveals an operational variable needing to be addressed.

These outcomes do not represent obstacles; rather they are useful information to push development forward. Future work should consider:

1. **Hardware Improvements:** Looking into the impact of higher power LEDs; or better sensor resolution to allow improved signal amplitude. These improvements would help address the issues relating to deep veins and high BMI.
2. **Algorithm Improvements:** Consider finding ways to improve the Gabor filter algorithm perhaps through hardware acceleration, or model pruning, would allow for real-time usage in low-cost environments and platforms.
3. **Machine Learning Improvements:** Develop a deep learning model (for example U-Net) commonly used for segmentation, trained to data with a wide range of cases, allowing for more robust vein segmentation and potential overcoming interference from skin creams, and improving vein finding performance in difficult cases.
4. **Clinical Improvements:** Conduct larger clinical trials, in real-world settings with diverse patient populations (pediatrics, geriatrics, obese patients) to evaluate the performance of the system.

This study presented the limitations transparently, and has provided an accurate representation of the prototype capabilities, as well as provided clear opportunities for future more targeted research.

6. Conclusion

This investigation has established the design, development, and validation of a low-cost, real-time near-infrared vein identification prototype. Utilizing a Raspberry Pi, a NoIR camera, and an open-source software stack, this study reinforces that it is possible to develop an effective vein detection system with low-cost and widely available components. The prototype was able to maintain a high level of vein visibility with an overall visibility score of

94% across all participants in the study leaving open the potential for the device to be used as a valuable tool in the clinical environment.

The main significant contribution of this work was in achieving stable, real-time performance on an embedded platform. The successful execution of an advanced adaptive thresholding algorithm, which produced clear, live visualizations of the vascular network addressed a common limitation when utilizing other low-cost systems where processing delays prevented the simplified view of the vascular network. Equally as useful, the project identified important opportunities for development of the prototype; namely, the issues encountered with the subjects with high body mass index and topical skin cream is indicative of the need for better hardware with greater penetration of signal potentially combined with stronger (machine-learning) image processing algorithms.

This research is evidence of proof-of-concept, making for a stronger foundation for future development of a vein finder that is accessible to the public. This article shows the powerful possibility to use open-source technology to tackle current healthcare issues, leading to more medical devices that are effective, inclusive, and disseminated globally in clinical and educational settings.

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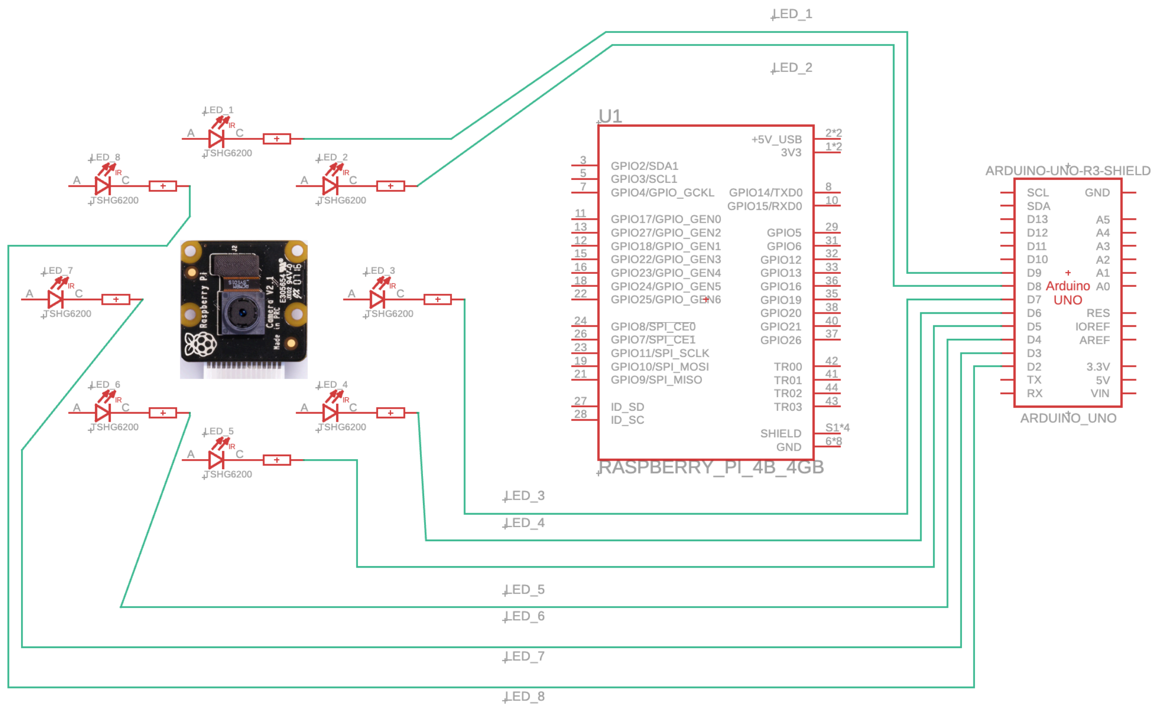
8. Appendices

Appendix A: Complete System Schematic



Components

1. Raspberry Pi 4B
2. Raspberry Pi NoIR Camera v2
3. 850 nm IR LEDs (8 total)
4. Arduino UNO
5. Breadboard
6. Raspberry Pi 4B Case with Cooling Fans
7. Jumper Wires
8. USB Cable (Arduino to Pi)
9. Raspberry Pi Type-C Power Adapter
10. Resistors (8, 200 Ohm)
11. Band Pass Filter

Overview

1. Raspberry Pi 4B runs the Python app and streams camera data.
2. Arduino Uno controls IR LEDs connected through breadboard.

3. USB cable connects Arduino to Raspberry Pi (Power + Serial).
4. Breadboard used for common ground and LED resistor connections.
5. Cooling fans powered via Pi GPIO or external 5V source.

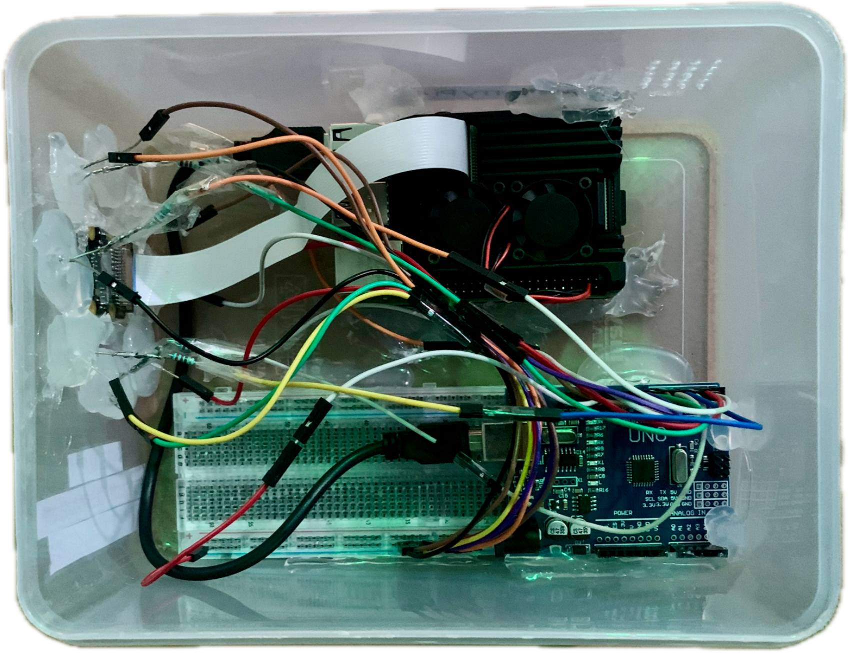
Connection Table

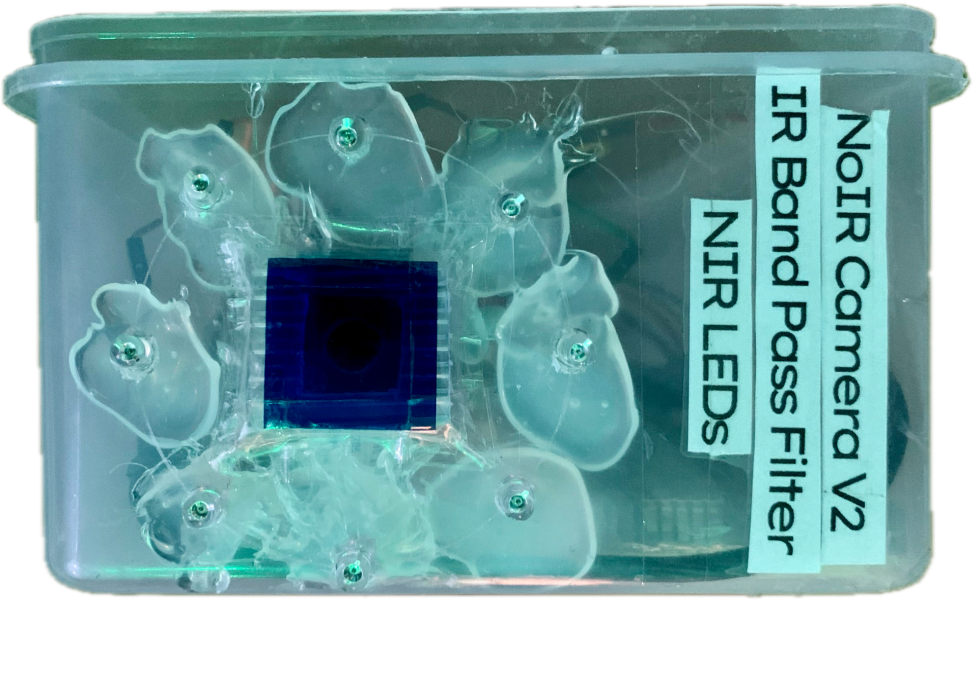
Connection	**From**	**To**
Camera	NoIR Camera CSI	Raspberry Pi CSI Port
Pi Power	Type-C Adapter	Raspberry Pi 4B
Pi ⇔ Arduino	Pi USB-A	Arduino USB-B
LED Signals	Arduino D2…D9	IR LEDs via 200 Ohm Resistors
Ground	Breadboard GND	Arduino GND

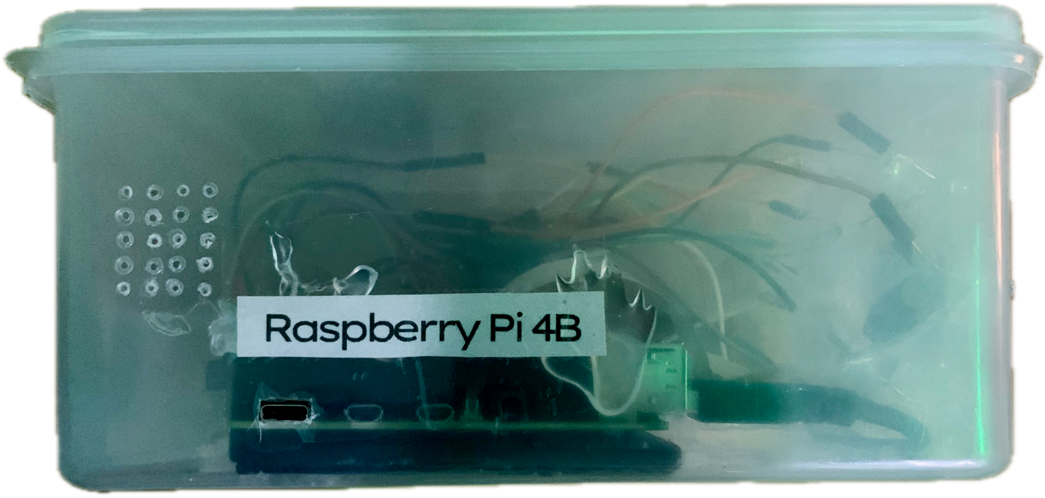
Appendix B: Source Code Repository

The complete source code for this project is available at: https://github.com/zainulnazir/vein-finder

Appendix C: Images of the Project




NoIR Camera V2
IR Band Pass Filter
NIR LEDs



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10. Declarations

10.1 Competing Interests

The authors declare that there are no competing interests. There are no financial relationships with any organizations that might have an interest in the submitted work. There are no other relationships or activities that could appear to have influenced the submitted work.

10.2 Funding

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10.3 Authors' Contributions

Zain Ul Nazir: Conceptualization, Methodology, Software development, Hardware design and assembly, Experimental testing, Data collecting, Data analysis, Writing - original draft, System integration, Validation, Writing to edit.

Basit Bhat: Conceptualization, Methodology, Hardware design and assembly, Experimental testing, Data collecting.

All authors read and approved the final manuscript. The authors agree to be personally accountable for all aspects of the work, and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.