Software Engineering Department

ORT Braude College

Capstone Project Phase B – 61999

PulseVision: Video Based Heart Rate Measurement Using Variable Lighting

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PulseVision

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Abstract

Heart rate measurement is a fundamental parameter for assessing health and is widely applied in medical diagnostics, sports science, and remote healthcare. Non-contact methods, particularly remote photoplethysmography (rPPG), offer the advantage of eliminating physical sensors, thereby improving comfort and reducing contamination risks.

Building upon the research conducted in Phase A, this project presents the full implementation of *PulseVision*, a video-based rPPG system designed to operate reliably under challenging real-world conditions, including artificial flickering light. The system leverages multiple regions of interest (forehead and cheeks), robust face detection and tracking, and the extraction of the green channel for optimal physiological signal clarity. Signal preprocessing incorporates temporal smoothing and adaptive notch filtering to suppress noise, while signal enhancement employs bandpass filtering, normalization, and multi-ROI signal fusion to increase robustness. Heart rate estimation is performed in the frequency domain using Welch's Power Spectral Density, followed by peak scoring and outlier rejection with z-score analysis to ensure stability.

The implemented system was tested on ~20 subjects aged 20–65, across diverse indoor and outdoor environments and under varying lighting conditions. Results demonstrated that the system consistently achieved heart rate accuracy within ±5 BPM of reference measurements, with occasional deviations up to ±10 BPM during sudden movements or extreme light changes. These outcomes validate the feasibility of non-contact heart rate monitoring using consumer-grade webcams, advancing the applicability of rPPG for practical healthcare and fitness applications.

Keywords: Heart rate measurement, Remote photoplethysmography (rPPG), Non-contact monitoring, Signal preprocessing, Frequency domain analysis, Multi-ROI fusion, Real-time implementation.

1 Introduction

In the modern era, advancements in healthcare technology have significantly improved patient monitoring and diagnostics. Non-contact heart rate measurement has emerged as a promising alternative to traditional contact-based methods, offering enhanced patient comfort and usability in various healthcare and fitness applications. This technology is particularly valuable in environments where continuous monitoring is required, such as hospitals, remote healthcare facilities, and sports science laboratories. However, the accuracy and reliability of non-contact methods remain a challenge, especially under varying lighting conditions.

Traditional heart rate monitoring methods, such as pulse oximeters and electrocardiograms (ECGs), require direct physical contact with the patient. While these methods provide accurate readings, they can be intrusive, uncomfortable, and impractical for continuous, long-term monitoring. In contrast, video-based heart rate measurement leverages image processing techniques to extract cardiovascular signals without physical sensors. This approach utilizes subtle color variations in the skin, particularly in the green light channel, to detect pulsatile blood flow and estimate heart rate.

Building upon previous research, this project aims to extend the capabilities of non-contact heart rate measurement by addressing the challenges posed by non-continuous lighting conditions. A prior study successfully demonstrated heart rate extraction using video processing under natural and continuous artificial lighting. However, the presence of flickering in non-continuous light sources, such as LEDs and fluorescent lamps, introduced significant signal distortions, reducing measurement accuracy.

To overcome these limitations, this project focuses on developing a robust signal processing framework that compensates for the effects of flickering light. The system will analyze the wave properties of the light source and their interaction with physiological signals, implementing advanced filtering and frequency-domain techniques to enhance signal clarity. By improving the stability of heart rate measurements under varying lighting environments, this research aims to contribute to the broader field of biomedical imaging and remote health monitoring.

The following sections of this paper will provide a comprehensive overview of related work in non-contact physiological measurement, present the theoretical background on light-wave interactions and signal extraction, and describe the proposed system architecture. Furthermore, the research methodology, data processing techniques, and evaluation framework will be outlined. Finally, the study will discuss the anticipated impact of this research on real-world healthcare applications and future improvements in video-based biometric monitoring.

2 Background and related work

Non-contact heart rate measurement has gained considerable attention in recent years due to its potential to provide non-invasive, real-time monitoring of vital signs across a range of applications in healthcare, sports science, and remote patient monitoring. Accurate and timely heart rate measurement is essential in diagnosing and managing cardiovascular conditions, particularly in medical environments. Traditional methods, such as pulse oximeters and electrocardiograms (ECGs), require direct physical contact with the patient, which can be uncomfortable, especially for elderly individuals or long-term monitoring. In contrast, non-contact methods offer an alternative by leveraging photoplethysmographic techniques using video data to estimate heart rate without requiring sensors attached to the skin.

The primary mechanism underlying this approach is photoplethysmography (PPG), which measures blood volume changes by analyzing variations in light absorption. The remote variation of this technique, known as Remote Photoplethysmography (RPPG), uses cameras instead of direct light sensors to capture changes in skin reflectance that occur with each heartbeat. Among the three primary color channels (red, green, and blue), the green channel is preferred due to its sensitivity to hemoglobin absorption, providing a strong signal-to-noise ratio for detecting cardiovascular activity.

While significant progress has been made in video-based heart rate monitoring, several challenges remain, particularly when ambient lighting conditions vary. Non-continuous lighting sources, such as LED and fluorescent lights, produce periodic flickering due to alternating current (AC) power supplies. This flickering introduces noise that can interfere with accurate signal extraction. Addressing this challenge is the primary goal of this project.

2.1 Medical background – Cardiovascular system

The cardiovascular system is responsible for transporting oxygenated blood throughout the body, ensuring that tissues receive the necessary nutrients for cellular function. It consists of the heart, blood vessels, and blood, which work together in a continuous cycle of oxygenation and circulation. The heart beats rhythmically, contracting (systole) to pump oxygen-rich blood into arteries and relaxing (diastole) to allow blood to return via veins.

Hemoglobin, a key component of red blood cells, plays a vital role in oxygen transport. It binds with oxygen in the lungs to form oxyhemoglobin, which gives blood its bright red color. This process directly affects skin reflectance properties, making it possible to extract cardiovascular signals using optical methods such as Photoplethysmography (PPG). The forehead, which receives blood primarily from the internal carotid artery, is particularly suitable for non-contact heart rate monitoring as it exhibits stable blood flow with minimal motion artifacts.

2.2 Photoplethysmography (PPG) and Remote PPG (RPPG)

2.2.1 PPG

Photoplethysmography (PPG) is a non-invasive optical technique that measures changes in blood volume using light absorption. A light source, typically infrared or green light, illuminates the skin, and the reflected light is captured to detect periodic variations caused by the cardiac cycle. The resulting PPG waveform provides insight into heart rate and cardiovascular activity. PPG is commonly used in medical devices such as pulse oximeters, where it is applied at fingertips or earlobes for continuous monitoring.

2.2.2 RPPG

Remote Photoplethysmography (RPPG) extends PPG principles to video-based heart rate monitoring. Instead of using direct-contact light sensors, RPPG analyzes subtle color variations in the skin using standard cameras. These variations, particularly in the green channel of the RGB model, correspond to blood volume fluctuations, allowing heart rate to be extracted. Facial regions such as the forehead and cheeks are commonly used as regions of interest (ROI) for signal extraction. However, RPPG is highly sensitive to motion artifacts, skin tone variations, and ambient lighting conditions, requiring robust signal processing techniques for accurate measurement.

2.3 Impact of Lighting Conditions on PPG Signals

Photoplethysmography (PPG) relies on the interaction between light and biological tissues to extract cardiovascular signals. However, ambient lighting conditions, particularly those involving non-continuous light sources such as LEDs and fluorescent lights, can significantly impact the accuracy and stability of PPG signals. Flickering, variations in intensity, and spectral distortions can introduce undesired artifacts, making it challenging to extract precise heart rate information.

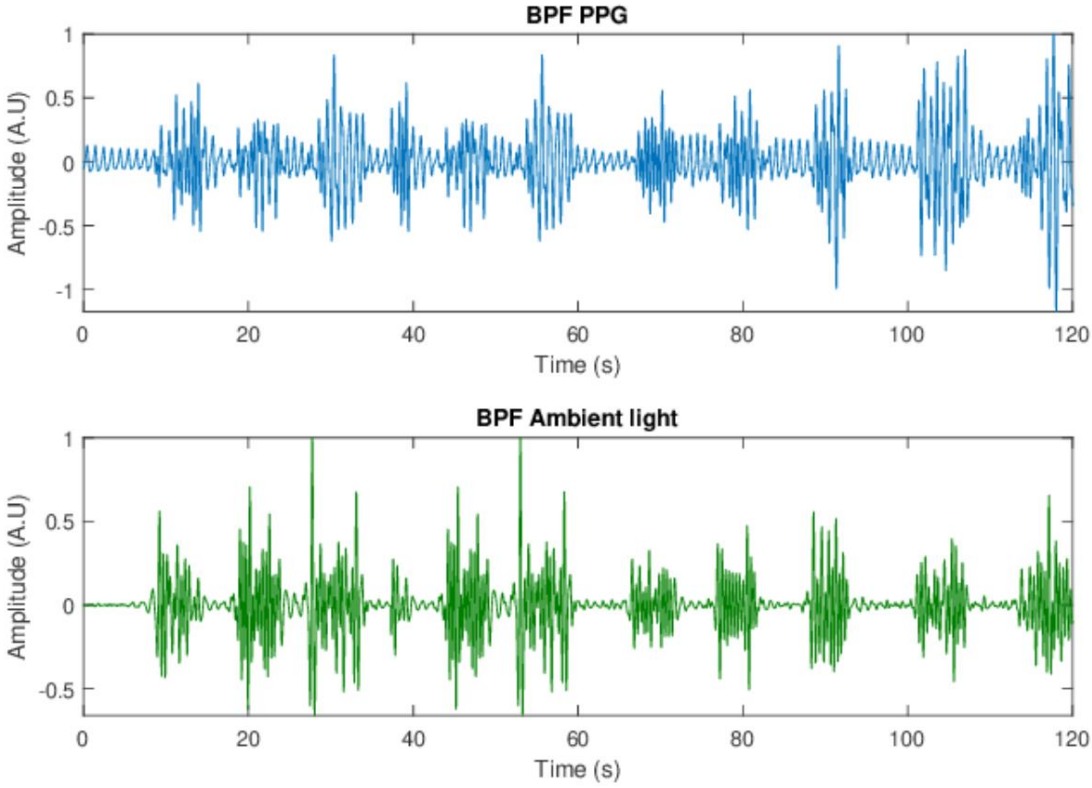


Figure 1: Bandpass-filtered PPG and ambient light signals

Figure 1 illustrates the impact of ambient light variations on the PPG signal. The top graph represents the bandpass-filtered PPG signal, showing periodic oscillations corresponding to blood volume changes. The bottom graph displays the bandpass-filtered ambient light fluctuations, which introduce noise into the PPG signal.

This section explores the keyways in which non-continuous lighting conditions influence PPG signal quality and discusses theoretical explanations related to light wave behavior, interference patterns, and frequency-domain distortions caused by flickering light sources.

2.3.1 Influence of Light Spectra and Intensity on PPG Signals

Light sources emit radiation across different wavelengths and intensities, which can significantly affect how PPG signals are absorbed and reflected by skin tissue. Different light spectra interact with oxygenated and deoxygenated hemoglobin in unique ways, influencing the signal amplitude and the signal-to-noise ratio (SNR) of the extracted heart rate waveform.

- Green light (~530 nm) is most commonly used for PPG because it exhibits the highest contrast between blood volume changes and background noise.
- Infrared light (~850-950 nm) penetrates deeper into tissues but is more susceptible to motion artifacts and external light interference.
- Red light (~660 nm) is often used in pulse oximetry but may be affected by surface-level reflections in ambient environments.

Variations in light intensity especially in artificial environments can lead to inconsistent PPG signal amplitudes, making it difficult to distinguish physiological changes from background fluctuations. This issue becomes more pronounced in dynamic lighting conditions where intensity fluctuates over time.

2.3.2 Effects of Ambient Light Flicker on PPG Signals

One of the most significant challenges in non-contact PPG is the presence of light flicker, particularly from LED and fluorescent sources. Unlike natural light, which is continuous and uniform, artificial lighting in many environments operates at alternating current (AC) frequencies, introducing periodic brightness fluctuations.

How Light Flickering Affects PPG Signals:

1. Flicker Frequency Interference
    - Most LED and fluorescent lights flicker at a frequency matching the power supply frequency (50 Hz in Europe, 60 Hz in North America).
    - These flickers introduce modulations in the intensity of light captured by the camera, causing periodic distortions in the extracted PPG waveform.
    - If the flicker frequency overlaps with the physiological frequency range of heartbeats (~1–1.67 Hz at 60-100 BPM), it can corrupt the true heart rate signal.
2. Aliasing and Beat Frequency Effects
    - When the sampling rate of the camera does not match the flicker frequency, an aliasing effect can occur, leading to the appearance of false frequency components in the extracted signal.

- This effect is particularly problematic in low-frame-rate video recordings, where periodic lighting variations mimic physiological fluctuations, leading to false pulse detections.

3. Waveform Distortion
    - Flickering light sources can alter the shape and amplitude of the PPG waveform, causing erroneous heart rate estimations.
    - This distortion can manifest as artificial peaks in the frequency-domain analysis (Fast Fourier Transform, FFT), leading to inaccurate pulse rate measurements.

2.3.3 Challenges in Low-Light Environments

In environments with insufficient illumination, PPG signal quality degrades due to:

- Reduced signal amplitude, making it harder to distinguish heart rate variations from background noise.
- Lower contrast between tissue absorption and ambient reflection, leading to unreliable data.
- Increased noise sensitivity, as minor fluctuations in light intensity become more prominent when the overall signal strength is weak.

Potential solutions for low-light conditions include:

- Increasing camera exposure settings to capture more reflected light.
- Using narrow-bandpass optical filters to selectively enhance relevant wavelengths while suppressing ambient noise.
- Applying software-based noise reduction techniques, such as adaptive filtering, to compensate for reduced signal strength.

2.3.4 Theoretical Basis of Light Wave Interaction in PPG Under Flickering Conditions

To understand the fundamental impact of non-continuous lighting on PPG signals, it is necessary to analyze light wave behavior in terms of frequency-domain interactions and interference effects.

1. Constructive and Destructive Interference

- If the flickering frequency aligns with the PPG signal frequency, it can either amplify (constructive interference) or suppress (destructive interference) certain components of the waveform.
- This interference creates inconsistencies in heart rate estimation, making it difficult to extract a stable signal.

2. Harmonic Distortions and Signal Artifacts
    - Many artificial light sources exhibit higher-order harmonics (multiples of their base flicker frequency), introducing additional noise components into the frequency spectrum.
    - These harmonics can create ghost signals in FFT analysis, leading to incorrect heart rate detection.
3. Power Spectral Density (PSD) Analysis of Flicker Noise
    - By analyzing the PSD of an extracted PPG signal, it is possible to detect dominant flicker-induced frequency components and design filters to suppress them.
    - Adaptive noise cancellation techniques can be employed to separate true cardiac rhythms from environmental flicker artifacts.

2.4 Signal processing techniques

2.4.1 Fast Fourier Transform (FFT)

The Fast Fourier Transform (FFT) is a mathematical algorithm used to convert time-domain signals into the frequency domain, allowing dominant frequency components such as heart rate to be identified. This is particularly useful in RPPG-based systems, where the extracted signal contains noise from ambient light fluctuations and motion artifacts. By applying FFT to the green channel signal, frequency peaks corresponding to heart rate (typically 1-1.67 Hz for resting heart rates of 60-100 bpm) can be isolated.

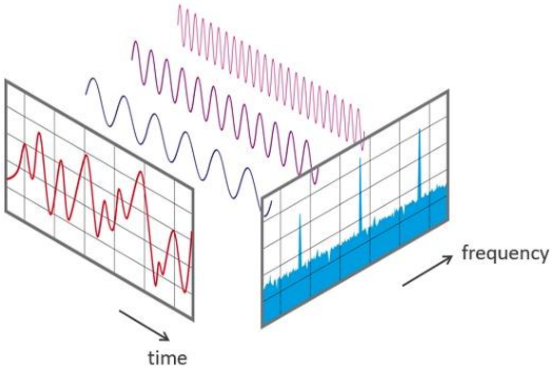


Figure 2: Fast Fourier Transform (FFT) converting a time-domain signal into the frequency domain

2.4.2 Welch's Power Spectral Density

Welch's method is a frequency-domain technique that improves upon the basic Fast Fourier Transform by reducing spectral noise. Instead of analyzing the entire signal with a single FFT, the signal is divided into overlapping segments. Each segment is windowed to minimize edge effects, and the FFT is applied individually. The resulting spectra are then averaged to produce a smoother and more reliable estimate of the power distribution across frequencies.

This approach is particularly advantageous in rPPG applications where signals are often corrupted by noise from motion, ambient light, and camera limitations. By averaging multiple segments, Welch's method suppresses random fluctuations and highlights stable frequency components, such as the periodic peaks corresponding to heart rate. In this way, it provides greater robustness than a single FFT, especially when working with short or noisy recordings.

2.4.3 Adaptive Notch Filtering

Adaptive notch filtering is employed to suppress periodic noise components in the signal that arise from environmental lighting conditions. Artificial light sources such as fluorescent bulbs and LEDs are driven by alternating current and often introduce flicker artifacts at specific frequencies, typically around 1 Hz, 2 Hz, and 3 Hz. These frequency components can overlap with the physiological range of heart rate signals, thereby reducing measurement accuracy.

The notch filter is designed to selectively attenuate narrow frequency bands centered on these flicker frequencies while preserving the surrounding frequency spectrum. By applying an Infinite Impulse Response (IIR) notch filter with a high quality factor (Q=30), the method ensures effective removal of these periodic disturbances with minimal distortion to the underlying physiological signal. The adaptive nature of the filter allows it to adjust dynamically depending on the signal properties and lighting conditions.

This preprocessing step significantly improves robustness by ensuring that subsequent frequency analysis methods, such as Welch's power spectral density estimation, operate on signals less contaminated by ambient flicker.

2.4.4 Robust Normalization

Robust normalization is a preprocessing technique designed to stabilize physiological signals by reducing the influence of outliers and sudden variations. Unlike standard normalization, which uses the mean and standard deviation, robust normalization relies on the median and the median absolute deviation (MAD). This makes it less sensitive to extreme values introduced by noise, motion artifacts, or abrupt illumination changes.

In rPPG systems, robust normalization ensures that the extracted green-channel intensity signal remains consistent and comparable across time, even when local disruptions occur. By centering the signal around the median and scaling it relative to typical variations, this method enhances the stability of subsequent frequency-domain analysis, improving the reliability of heart rate estimation.

2.4.5 Bandpass filtering

A bandpass filter is an electronic filter that removes frequencies outside a specified range while preserving relevant signal components. In heart rate monitoring, a bandpass filter (typically 0.75–4 Hz) is applied to isolate physiological heart rate variations from other noise sources, such as motion artifacts and environmental flickering. This filtering process improves signal clarity and enhances measurement accuracy.

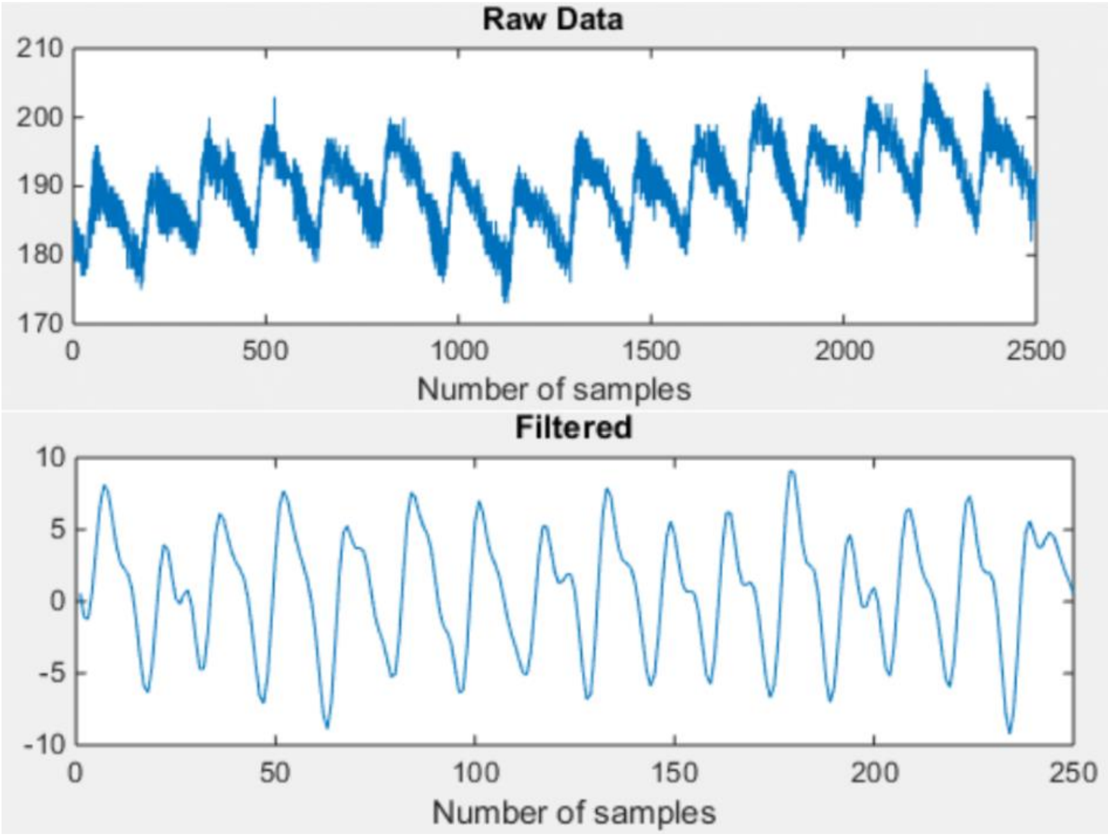


Figure 3: Bandpass filtering of a signal

The images illustrate the effect of bandpass filtering on a raw PPG signal. The first image shows the unprocessed PPG data captured at 200 Hz, which includes both heart rate variations and unwanted noise from motion artifacts and ambient light interference. The second image demonstrates the same signal after applying a Finite Impulse Response (FIR) bandpass filter, which isolates the relevant heart rate frequency range (typically 0.75–4 Hz). By removing low-frequency drift and high-frequency noise, the filtered signal provides a cleaner and more periodic waveform, improving the accuracy of heart rate estimation.

2.4.6 Signal Quality Assessment

Signal quality assessment is an essential step in non-contact heart rate measurement to ensure that the extracted photoplethysmographic signal is reliable before frequency-domain analysis. Since video-based signals are highly susceptible to motion artifacts, illumination changes, and sensor noise, assessing quality allows the system to avoid misinterpretation of corrupted data.

Several metrics are combined to evaluate signal quality. First, the signal-to-noise ratio (SNR) is computed within the physiological heart rate band to quantify the strength of the pulsatile component relative to background noise. Temporal consistency is then examined by measuring the variation in successive signal amplitudes, abrupt changes indicate possible motion disturbances. Finally, frequency-domain evaluation is performed by analyzing the prominence of dominant peaks within the expected heart rate band, ensuring that physiological frequencies are distinguishable from noise.

By integrating these criteria into a composite quality score, the system dynamically adapts its filtering and smoothing strategies. High-quality signals are processed with lighter smoothing to preserve detail, while lower-quality signals undergo stronger filtering. This adaptive mechanism improves overall robustness and maintains accuracy across varying environmental and subject conditions.

2.5 Image processing techniques

2.5.1 RGB model

The RGB color model represents images using red, green, and blue channels, each corresponding to different light absorption properties in human tissue. The green channel is the most effective for heart rate measurement due to its sensitivity to hemoglobin absorption, providing a strong contrast between pulse-induced variations and background noise. Unlike red and near-infrared wavelengths, which penetrate deeper into tissue and are more susceptible to motion artifacts, the green channel captures superficial blood flow changes with higher accuracy.

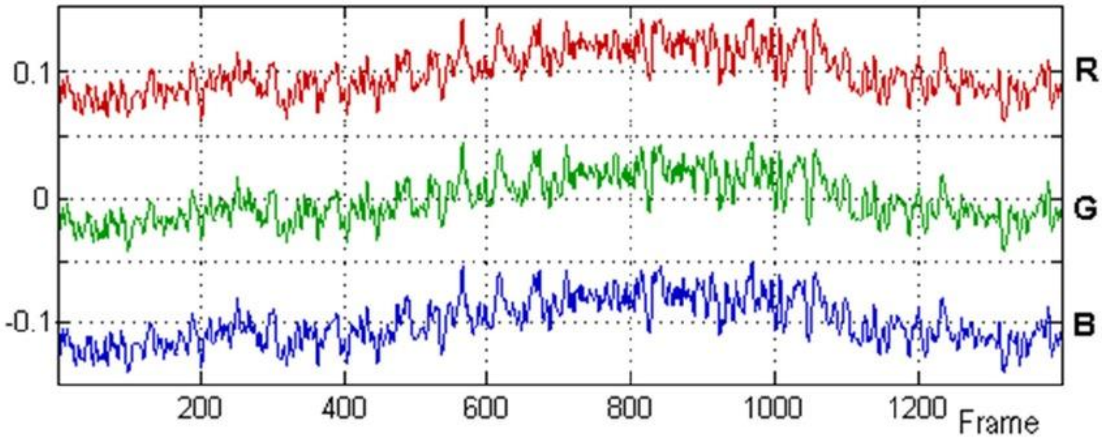


Figure 4: RGB channel signals

2.5.2 MediaPipe FaceMesh

MediaPipe FaceMesh is a machine learning–based framework that detects 468 facial landmarks in real time. Unlike traditional methods such as Haar cascades, it provides robust and precise landmark localization under varying lighting conditions and head poses. This allows accurate extraction of regions of interest (ROIs), including the forehead and cheeks, which are critical for rPPG signal acquisition.

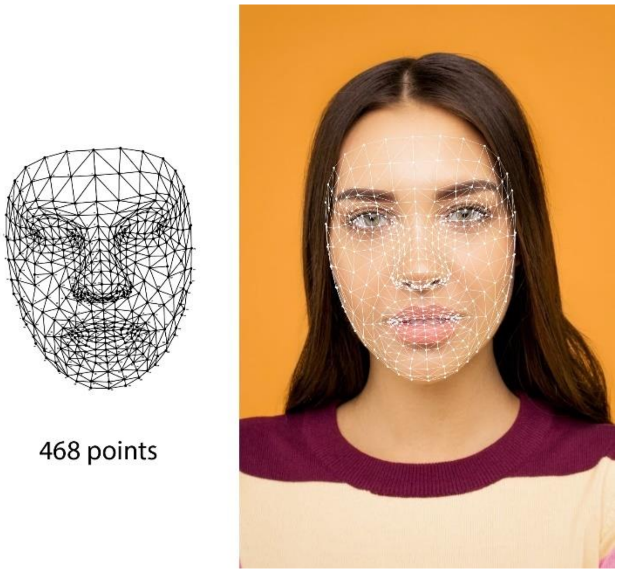


Figure 5: MediaPipe FaceMesh landmark detection with 468 facial points

2.5.3 ROI Extraction and Smoothing

After landmark detection, specific facial regions are selected as ROIs to capture skin areas with strong pulsatile signals. The forehead is typically prioritized due to minimal motion, while the cheeks provide additional redundancy. To reduce jitters in ROI positioning across frames, an exponential moving average (EMA) smoothing method is applied. This ensures temporal stability and prevents noise being introduced by small detection fluctuations.

3 Expected achievements

3.1 Outcome

The project successfully implemented a complete non-contact heart rate measurement system, named PulseVision, which demonstrated robust performance under real-world conditions. The system integrates advanced image processing and signal processing techniques into a unified pipeline that operates in real time.

The main outcomes include:

- Accurate Heart Rate Measurement: Achieved up to ±5 BPM accuracy compared to ground truth measurements across approximately 20 subjects, with ages ranging from 20 to 65. In some cases, involving sudden movement or abrupt lighting changes, deviations of up to ±10 BPM were observed.
- Robustness to Lighting Conditions: Adaptive notch filtering effectively suppressed flicker artifacts introduced by artificial lighting sources such as LEDs and fluorescent lamps, allowing reliable operation in both indoor and outdoor environments.
- Multi-ROI Signal Extraction: By leveraging MediaPipe FaceMesh for face detection, the system was able to extract signals from multiple regions of interest (forehead and cheeks), increasing resilience against motion and partial occlusion.
- Signal Quality Control: A signal quality assessment mechanism, based on SNR, temporal consistency, and frequency-domain peak prominence, allowed dynamic adjustment of filtering strategies to maintain measurement stability.

- User Interface and Data Management: A PyQt-based GUI was developed to provide real-time visualization of video, extracted signals, and heart rate values. Measurements were stored in a local SQLite database, linked to patient profiles, enabling systematic data collection and retrieval.

Overall, these outcomes demonstrate that PulseVision can provide reliable, contact-free heart rate monitoring across diverse subjects and environments, making it suitable for healthcare, fitness, and research applications.

3.2 Unique Features

PulseVision introduces several innovations that distinguish it from traditional rPPG-based systems. While many existing approaches focus solely on extracting raw signals from a single facial region, this system integrates multiple advanced techniques to improve robustness, accuracy, and adaptability in real-world scenarios.

3.2.1 Multi-ROI Signal Acquisition

Instead of relying on a single region, PulseVision simultaneously extracts signals from the forehead and both cheeks using MediaPipe FaceMesh landmarks. This redundancy improves resilience against motion artifacts, partial occlusion, and uneven illumination.

3.2.2 Adaptive Notch Filtering

The system applies IIR-based notch filters at 1 Hz, 2 Hz, and 3 Hz with a high quality factor (Q=30) to suppress flicker noise from artificial light sources. This feature ensures reliable performance under challenging indoor lighting conditions.

3.2.3 Robust Normalization

Median and Median Absolute Deviation (MAD) normalization techniques are used to stabilize the extracted signals. This approach reduces the influence of outliers and ensures consistency across subjects with varying skin tones and lighting environments.

3.2.4 Signal Quality Assessment

PulseVision incorporates a multi-metric quality evaluation process that considers signal-to-noise ratio, temporal consistency, and frequency-domain prominence. This enables dynamic adjustment of smoothing and filtering strategies, ensuring stable output even during noisy conditions.

3.2.5 Baseline and Convergence Mechanism

To prevent sudden fluctuations, the system establishes a baseline heart rate after an initial stabilization period. Subsequent measurements are compared against this baseline, with convergence rules limiting physiologically implausible changes. This feature improves measurement continuity during long sessions.

3.2.6 Real-Time Visualization and Storage

The graphical interface provides immediate feedback by displaying the user's video stream, region-of-interest overlays, real-time signal plots, and heart rate values. All measurements are stored in an SQLite database linked to patient profiles, supporting longitudinal monitoring.

3.3 Criteria for success

The success of PulseVision was evaluated against a set of predefined criteria designed to ensure both technical reliability and practical usability. These criteria included:

3.3.1 Accuracy

The system should achieve heart rate measurements within ±5 BPM of ground truth values under normal conditions. Minor deviations of up to ±10 BPM were considered acceptable in cases of sudden motion or abrupt lighting changes.

3.3.2 Robustness to Environmental Conditions

The system should maintain consistent performance across varying indoor and outdoor environments, including scenarios with artificial lighting flicker (e.g., LED and fluorescent sources).

3.3.3 Real-Time Operation

The entire processing pipeline, from video capture to heart rate output, should operate in real time at approximately 30 frames per second. This requirement ensures usability in live monitoring scenarios.

3.3.4 Multi-Subject Generalization

The system should demonstrate reliability across diverse populations, including variations in age, skin tone, and facial characteristics. Testing was performed on approximately 20 participants between the ages of 20 and 65.

3.3.5 User Accessibility

The graphical interface should allow users to clearly view their heart rate measurements, understand signal quality indicators, and easily operate the system without technical expertise.

3.3.6 Data Persistence

Measurement results should be stored securely in the local database, linked to patient profiles, allowing retrieval and longitudinal tracking over multiple sessions.

3.4 Special Components and Engineering/Research Challenges

3.4.1 Non-Invasive Measurement

- Unlike traditional ECGs and pulse oximeters, this system requires no physical contact, enhancing patient comfort and hygiene.
- The system should maintain accuracy without the need for specialized cameras, making it accessible using standard webcams or smartphone cameras.

3.4.2 Noise Reduction

Noise reduction was a central challenge in the development of PulseVision, as the rPPG signal is highly sensitive to both environmental and physiological disturbances.

Several strategies were integrated into the pipeline to ensure robust extraction of the heart rate signal:

- Motion Artifact Mitigation: Head movements and facial expression changes introduce significant variability in pixel intensity values. To address this, temporal smoothing and ROI stabilization with exponential moving averages were implemented, reducing jitter in the extracted signal.
- Adaptive Notch Filtering: Artificial lighting sources, particularly LED and fluorescent lights, produce periodic flicker at 1, 2, and 3 Hz. Narrowband IIR notch filters with high quality factor (Q=30) were applied to selectively remove these artifacts without attenuating physiological frequencies.
- Robust Normalization: Median and Median Absolute Deviation (MAD) based normalization was used to suppress outliers and reduce the influence of sudden illumination changes, providing a stable baseline for heart rate extraction.
- Skin Tone and Illumination Variability: Variations in skin reflectance and ambient lighting were managed through multi-ROI signal extraction (forehead and cheeks), improving resilience across diverse populations and testing conditions.

By combining these techniques, the system achieved a signal quality sufficient for reliable frequency-domain analysis and robust heart rate estimation across a wide range of environments and subjects.

3.4.3 Real-Time Processing and Efficiency

Real-time operation was a key requirement for PulseVision to ensure practical usability in healthcare and wellness applications. The system was designed to process video frames at approximately 30 frames per second while maintaining a balance between computational efficiency and signal accuracy.

- Optimized Signal Processing Pipeline: Lightweight filtering methods such as Savitzky–Golay smoothing and adaptive notch filters were selected for their low computational overhead while preserving physiological detail.

- Efficient Frequency Analysis: Welch's Power Spectral Density estimation was preferred over standard FFT for heart rate calculation, as it provides smoother and more reliable results with fewer samples, reducing the need for long observation windows.
- Scalability for Real-Time Monitoring: The modular pipeline design ensures that each stage from face detection to heart rate estimation can be parallelized or optimized for hardware acceleration, supporting future deployment on mobile or embedded systems.
- Compatibility with Telemedicine Platforms: By maintaining low latency and efficient memory usage, the system can be integrated with remote health monitoring and telemedicine services, enabling real-time feedback to patients and clinicians.

4 Research / Engineering process

4.1 Process

The development of PulseVision followed a structured research and engineering process combining medical, image processing, and signal processing research with iterative experimentation. The main objective was to design a non-contact heart rate monitoring system that remains accurate and robust under real-world conditions such as artificial lighting flicker, motion artifacts, and user diversity.

4.1.1 Signal Processing with Flickering Light Compensation

A central challenge addressed in this project was the effect of artificial light sources on remote photoplethysmography (rPPG) signals. Fluorescent and LED lights often introduce periodic flicker artifacts that overlap with physiological heart rate frequencies (0.67–3 Hz, corresponding to 40–180 BPM). If uncorrected, these artifacts can create false frequency peaks and reduce the reliability of heart rate estimation.

To mitigate these issues, multiple signal processing strategies were implemented:

- Savitzky–Golay Temporal Smoothing: Applied to reduce short-term fluctuations while preserving physiological waveform shape.
- Adaptive Notch Filtering: Narrow-band IIR notch filters (Q=30) at 1, 2, and 3 Hz were applied to suppress flicker-induced components without distorting the cardiac signal.
- Bandpass Filtering: The signal was restricted to the physiological heart rate band (0.67–3.0 Hz) to remove unrelated low- and high-frequency noise.
- Robust Normalization: Median and Median Absolute Deviation (MAD) scaling was used to normalize the signal while remaining resistant to outliers.
- Frequency-Domain Verification: Welch's power spectral density estimation was applied to confirm suppression of spurious peaks and to enhance the stability of the heart rate estimate.

These combined techniques ensured reliable extraction of cardiovascular signals even under challenging illumination.

4.1.2 Medical Research

Developing a remote heart rate monitoring system requires a strong medical foundation to ensure accurate and reliable physiological measurements. The research process involved:

1. Understanding Cardiovascular Physiology:
   - Reviewing the cardiac cycle, heart anatomy, and blood flow mechanics to identify the most suitable facial regions (forehead, cheeks) for PPG-based heart rate detection.
   - Investigating how hemoglobin's optical properties influence light absorption and reflection, particularly in non-contact photoplethysmography (RPPG).
2. Photoplethysmography and Signal Interpretation:
   - Studying how hemoglobin absorbs and reflects green light to extract pulsatile variations in blood volume.

- Analyzing medical research on PPG waveform characteristics, signal distortions, and the effects of motion artifacts and ambient lighting conditions.

3. Challenges in Non-Contact Measurement:
   - Exploring how skin tone, facial structure, and environmental factors affect PPG signal quality.
   - Investigating existing limitations in remote monitoring systems, especially under non-continuous artificial lighting conditions.

This medical research was fundamental in defining system requirements, selecting appropriate signal processing techniques, and determining factors affecting measurement accuracy.

4.1.3 Different Image Processing Techniques

Image processing research centered on stable, real-time detection of facial regions suitable for rPPG signal extraction. Earlier approaches such as Haar cascades and GrabCut segmentation were evaluated but discarded due to limited robustness in diverse lighting and pose conditions. Instead, MediaPipe FaceMesh was adopted for precise and efficient landmark detection.

Key steps included:

- ROI Extraction: Using 468 landmarks, forehead and bilateral cheek regions were defined for signal extraction.
- ROI Stabilization: Exponential Moving Average (EMA) smoothing and temporal buffers were applied to reduce jitter from frame to frame.
- ROI Quality Assessment: Standard deviation of pixel intensities in grayscale was used to verify ROI stability, with adaptive thresholds depending on ROI size.

This pipeline ensured consistent extraction of reliable physiological signals across different environments.

4.1.4 Hardware – Quality and Resolution

The accuracy and reliability of a video-based heart rate monitoring system are highly dependent on camera quality and resolution. Extensive research was conducted to determine the optimal hardware specifications required for accurate remote heart rate detection.

Key Considerations in Camera Selection:

1. Resolution Requirements:
    - Higher resolution cameras (720p and above) provide sharper details, allowing precise color-based signal extraction.
    - Lower-resolution videos introduce pixelation artifacts, making heart rate estimation less reliable.
2. Frame Rate Selection:
    - A frame rate of at least 30 fps ensures smooth temporal analysis for accurate PPG waveform extraction.
    - Lower frame rates (15 fps or below) increase the risk of aliasing artifacts, particularly under flickering light conditions.
3. Sensor Sensitivity & Low-Light Performance:
    - Cameras with high dynamic range (HDR) sensors capture more details in variable lighting environments.
    - Infrared-assisted sensors were considered but discarded due to higher computational costs.
4. Camera Placement:
    - Users were positioned 30–60 cm from the camera to balance ROI size and facial clarity.
5. Mobile vs. Fixed Camera Performance:
    - Research compared mobile phone cameras vs. dedicated webcams for signal clarity, flicker response, and ease of deployment.
    - The final choice balances accessibility, cost, and performance requirements.

By defining these hardware constraints, the system ensures optimal signal capture for accurate pulse detection, even under non-continuous lighting conditions.

4.2 Product

4.2.1 Projects pipeline

The PulseVision system is designed to measure heart rate from normal video input by extracting subtle variations in facial skin color using remote photoplethysmography (rPPG). The pipeline integrates face detection, region-of-interest (ROI) extraction, signal preprocessing, enhancement, and heart rate estimation into a robust workflow that can operate reliably in real-world environments, including those with artificial flickering light.

4.2.1.1 Receiving Video Input

The system supports both live webcam input and pre-recorded video files. Live input enables real-time heart rate monitoring, while recorded video allows offline testing and controlled benchmarking. To ensure reliability, video is captured at a minimum of 30 frames per second and a resolution of at least 720p. Users are positioned 30–60 cm from the camera, ensuring consistent ROI size and stable illumination for accurate signal extraction.

4.2.1.2 Locating the Face and Regions of Interest (ROI)

Face detection and ROI extraction are performed using the MediaPipe FaceMesh framework, which provides 468 facial landmarks. From these landmarks, three stable ROIs are defined: the forehead and both cheeks. The forehead is the primary ROI due to its minimal motion interference, while the cheeks provide supplementary signals that can improve robustness. Exponential moving average (EMA) smoothing and short temporal buffers are applied to stabilize ROI boundaries and reduce jitter.

4.2.1.3 ROI Quality Assessment

Each ROI undergoes stability verification before being used in signal processing. A grayscale standard deviation measure is calculated, with adaptive thresholds depending on ROI size. This prevents unstable or noisy ROIs (e.g., caused by sudden shadows, strong motion, or low lighting) from contaminating the heart rate estimation pipeline.

4.2.1.4 Signal Extraction (Green Channel)

From each valid ROI, the mean pixel intensity of the green channel is extracted. Green light provides the highest sensitivity to hemoglobin absorption and is widely recognized as the optimal channel for non-contact PPG. The extracted values are stored in circular buffers of ~10 seconds for temporal analysis.

4.2.1.5 Signal Preprocessing

The raw green channel signal is refined to improve signal-to-noise ratio and robustness:

- Savitzky-Golay temporal smoothing reduces high-frequency noise while preserving waveform shape.
- Adaptive notch filtering at 1, 2, and 3 Hz suppresses flicker noise from artificial lights.
- Robust normalization using the median and Median Absolute Deviation (MAD) scales the signal and minimizes outlier impact.
- Bandpass filtering isolates the physiological frequency range (0.67–3.0 Hz), corresponding to 40–180 BPM.

4.2.1.6 Signal Enhancement and Frequency Analysis

To estimate heart rate, the system enhances the preprocessed signal by evaluating its spectral composition. Welch's power spectral density estimation is applied, offering higher frequency resolution and improved stability compared to direct FFT. The power spectrum is restricted to the physiological heart rate band, ensuring that non-relevant frequencies are excluded.

4.2.1.7 Heart Rate Estimation

Heart rate is determined by identifying the dominant frequency peak within the power spectrum. Peaks are scored based on prominence and separation from nearby peaks, and the best candidate is selected as the heart rate estimate. The detected frequency is converted to beats per minute (BPM) by multiplying by 60.

4.2.1.8 Outlier Filtering and Stabilization

To ensure robustness, recent heart rate values are stored in a short history buffer. Outlier detection is performed using z-scores, rejecting values that deviate significantly (>2.0 standard deviations) from the mean. If an outlier is detected, the system falls back to the median of the history buffer, preventing sudden unrealistic jumps caused by noise or motion artifacts.

4.2.1.9 Displaying the Results

The final heart rate is presented to the user via a graphical interface, updating in real time. The display is designed for clarity, allowing users to easily interpret results. Confidence levels and trend stability can be visualized to indicate measurement reliability.

4.2.1.10 Summary of the Processing Pipeline

This pipeline integrates computer vision, signal preprocessing, and spectral analysis into a real-time framework. By combining robust ROI extraction (MediaPipe), adaptive noise filtering, frequency-domain analysis (Welch), and outlier rejection, the system achieves stable heart rate estimation within ±5 BPM accuracy across varied subjects and lighting conditions.

4.2.2 Requirements

The system's requirements are divided into functional and non-functional categories to ensure both the correct operation and usability of the heart rate monitoring system. Functional requirements define the core capabilities and expected performance, while non-functional requirements establish quality attributes, ensuring the system operates efficiently and effectively across different conditions.

4.2.2.1 Functional Requirements

The system must meet the following functional requirements to ensure accurate heart rate estimation, real-time processing, and robustness under diverse conditions:

No.	Requirement	Status
1)	Process Video Input: The system must accept live camera feeds and recorded video files as input for heart rate extraction.	Implemented
2)	Detect and Track Faces: The system must detect the subject's face and continuously track the region of interest (ROI) throughout the video.	Implemented
3)	Enhance Image Quality: The system must apply pre-processing techniques such as contrast enhancement and noise reduction to improve signal clarity.	Implemented
4)	Extract Pulse-Related Signals: The system must isolate blood volume fluctuations from the subject's forehead using photoplethysmography (PPG) principles.	Implemented The system isolate blood volume fluctuations from the subject's forehead and cheeks
5)	Compensate for Motion Artifacts: The system must stabilize the ROI and correct distortions caused by head movement using optical flow tracking.	Implemented Instead of optical flow tracking, the system applies exponential moving average smoothing and ROI stability validation to reduce jitter and motion artifacts in the extracted regions.
6)	Analyze Frequency Components: The system must perform Fast Fourier Transform (FFT) and bandpass filtering to identify dominant heart rate frequencies.	Implemented
7)	Provide Real-Time Heart Rate Readings: The system must compute continuous heart rate values and display them in real-time.	Implemented
8)	Monitor Heart Rate Trends Over Time: The system must provide long-term monitoring, tracking heart rate fluctuations throughout the session.	Implemented
9)	Trigger Alerts for Dangerous Heart Rates: The system must issue alerts when detected heart rates exceed predefined safety thresholds.	Implemented
10)	Adapt to Artificial and Dynamic Lighting Conditions: The system must compensate for LED flickering and brightness changes using adaptive filtering techniques.	Implemented

11)	Ensure Compatibility with Multiple Camera Devices: The system must support various resolutions and frame rates, ensuring usability across webcams, mobile cameras, and external sensors.	Implemented

Table 1: Functional Requirements

4.2.2.2 Non-Functional Requirements

To ensure a seamless user experience, system reliability, and real-time performance, the system must meet the following non-functional requirements:

No.	Requirement	Type	Status
1)	The system must have a clear, user-friendly graphical interface that allows users to easily monitor their heart rate. The heart rate should be displayed in real-time with color-coded alerts, ensuring quick interpretation.	Usability	Implemented
2)	The system must provide heart rate readings with a maximum error margin of ±5 BPM, ensuring reliability comparable to medical-grade pulse oximeters.	Accuracy	Implemented Note: In rare cases of sudden movement or abrupt lighting changes, short-term deviations of up to ±10 BPM may occur before stabilization.
3)	Robustness to Environmental Variations: The system must maintain consistent accuracy across different lighting conditions, skin tones, and facial orientations. It should compensate for LED flickers and sudden brightness changes to avoid measurement inaccuracies.	Reliability	Implemented
4)	Processing Efficiency: The system must process video frames efficiently, maintaining a steady frame rate of at least 20 FPS to prevent lag and ensure smooth operation. It must optimize CPU and GPU usage to prevent excessive computational load.	Performance	Implemented
5)	Multi-Device Compatibility: The system must be compatible with various camera devices, including laptops, mobile phones, and external webcams, without requiring specialized hardware.	Portability	Implemented
6)	Visual Alerts for Dangerous Readings: When the heart rate exceeds safe thresholds, the reading must be highlighted in red,	Usability	Implemented

	and an alert must be triggered to warn the user of potential health risks.		
7)	The system should be modular, with separate components for video capture, signal processing, and GUI, allowing future researchers or developers to update or replace modules easily.	Maintainability	Implemented
8)	The system should be able to handle longer recordings and higher-resolution video inputs without significant degradation in accuracy or performance.	Scalability	Implemented
9)	The system should log measurement sessions (time, patient ID, conditions) for future reference and validation.	Observability	Implemented
10)	The system must maintain structured logs for video capture, ROI detection, and heart rate estimation, enabling traceability and troubleshooting during development and testing.	Observability	Implemented

Table 2: Non-Functional Requirements

4.2.3 Architecture overview

Purpose**:** Provide a high-level view of the system's building blocks, responsibilities, and integration points. Detailed signal steps are shown in 4.2.4 (Processing Pipeline).

Components (container-level)

1. GUI & Control (PyQt) – "View/Controller"

   - Windows: Login, Home, Main (measurement), add User, add Patient.
   - Orchestrates start/stop, patient selection, timers (~30 FPS frames, 100 ms plots).
   - Renders video, ROI overlays, signal plots, BPM, alerts.

2. Video I/O

   - VideoCapture wrapper over OpenCV.
   - Sources: webcam or file.
   - Frame pacing and recovery, exposes frames to downstream modules.

3. Face & ROI Service

   - MediaPipe FaceMesh (468 landmarks).
   - ROI selection: forehead + left/right cheeks.

- ROI smoothing (EMA) and stability check (grayscale std with size-adaptive thresholds).

4. Signal Processing Service

   - Preprocessing: Savitzky-Golay smoothing, adaptive IIR notch at 1/2/3 Hz; robust normalization (median/MAD), bandpass 0.67–3.0 Hz.
   - Enhancement & Estimation: Welch PSD, peak scoring (prominence, separation), convergence logic.
   - Post-filtering: z-score outlier rejection with median fallback, baseline HR smoothing.

5. Persistence

   - SQLite DB: users, patients, measurements.
   - Saves BPM + status (Normal/Brady/Tachy) with timestamps and patient linkage.

6. Auth & Access

   - Credential check on login, role-based navigation (admin/doctor).

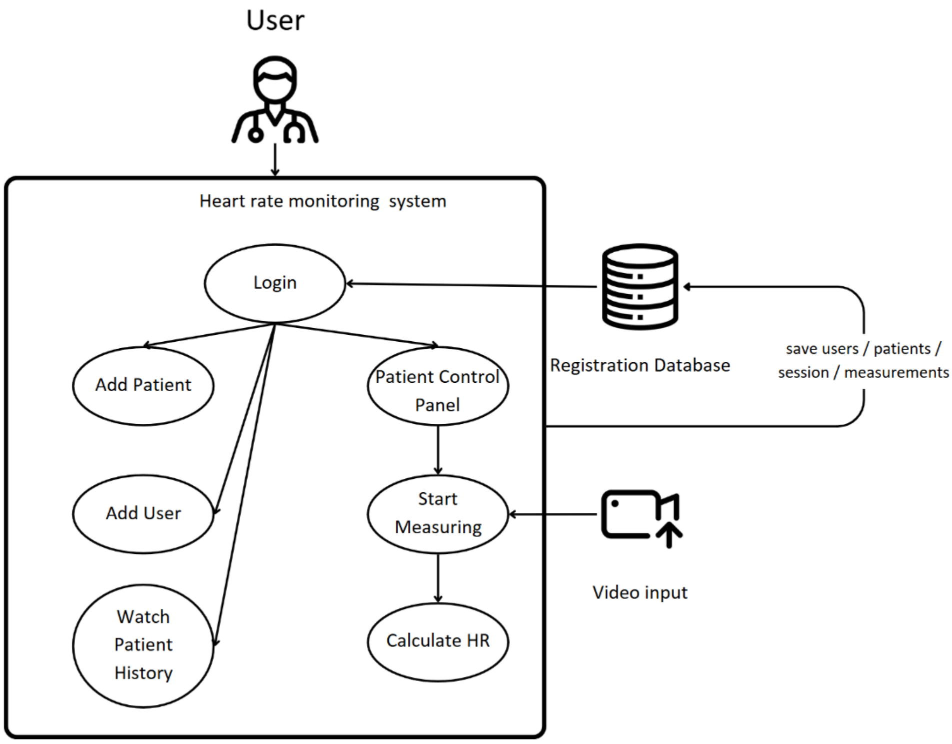


Figure 6: Functional overview of the heart rate monitoring system

4.2.4 Processing Pipeline (Data Flow)

- Input Video
- Face Detection
- ROI Tracking (forehead, cheeks)
- Green-channel mean per ROI
- Preprocessing (SG, notch, robust norm, bandpass)
- Welch PSD, Peak scoring, BPM
- Outlier filtering & baseline smoothing
- GUI display + DB save + alerts

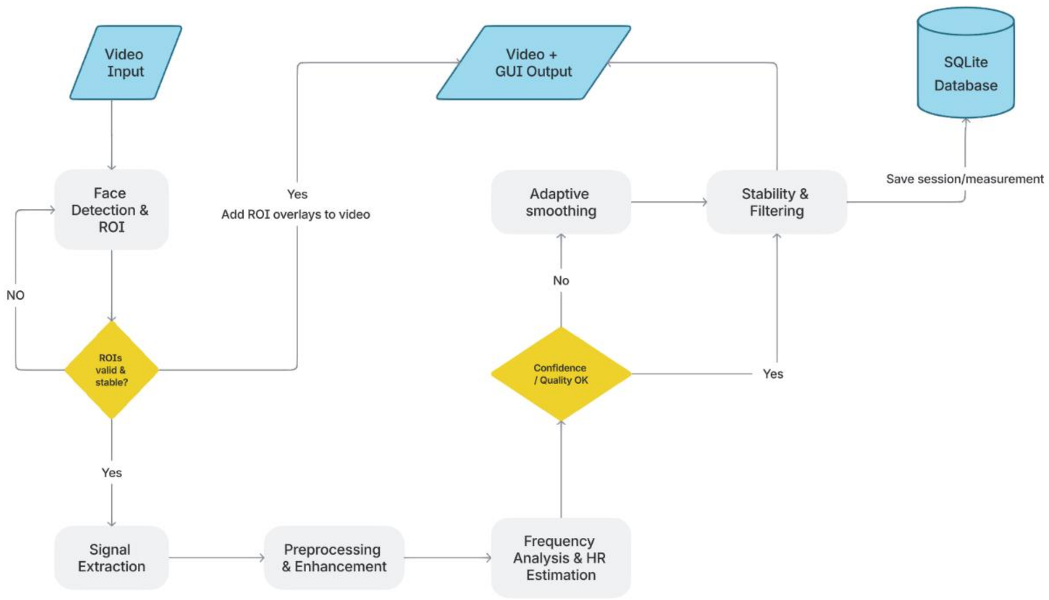


Figure 7: System processing pipeline for heart rate estimation

4.2.5 Heart Rate Monitoring Application (MVC Overview)

Rationale: We retain an MVC structure to separate persistent data, processing logic, and presentation. This improves maintainability and allows components (e.g., face detector or HR estimator) to be swapped with minimal impact.

Model (Data Layer)

- Registration Database (SQLite): users, patients, measurements; timestamps and status (Normal/Brady/Tachy).
- Configuration & Logs: runtime settings (sampling rate, thresholds) and structured logs for observability and debugging.
- Video I/O Metadata: source, FPS, resolution; non-image state needed by controllers.

Controller (Logic Layer)

- Video I/O: OpenCV wrapper with frame pacing and recovery (webcam or file).

- Face & ROI Service: MediaPipe FaceMesh (468 landmarks). ROIs: forehead, left cheek, right cheek. EMA smoothing and stability checks (grayscale std with size-adaptive thresholds).
- Signal Preprocessing: Savitzky-Golay temporal smoothing. adaptive IIR notch at 1/2/3 Hz, robust normalization (median/MAD), bandpass 0.67–3.0 Hz.
- Heart-Rate Estimation: Welch PSD in HR band, peak scoring (prominence + separation), convergence rules.
- Outlier Filtering & Smoothing: z-score rejection with median fallback, baseline HR smoothing, confidence handling.
- Application Logic: start/stop, patient linking, measurement save, alert triggers.

View (Presentation Layer)

- PyQt GUI: login/home/measurement/add user/add patient windows.
- Real-Time Displays: video with ROI overlays, raw/HR plots, BPM and frequency readout, signal-quality indicators.
- Usability & Safety: color-coded alerts for abnormal HR, simple controls, status messages.

Note on changes from Phase A. Optical flow, GrabCut, Haar, and ICA were removed. They are replaced by MediaPipe FaceMesh for ROI, adaptive notch filtering, robust normalization, and Welch-based HR estimation, which improved stability under flicker and motion.

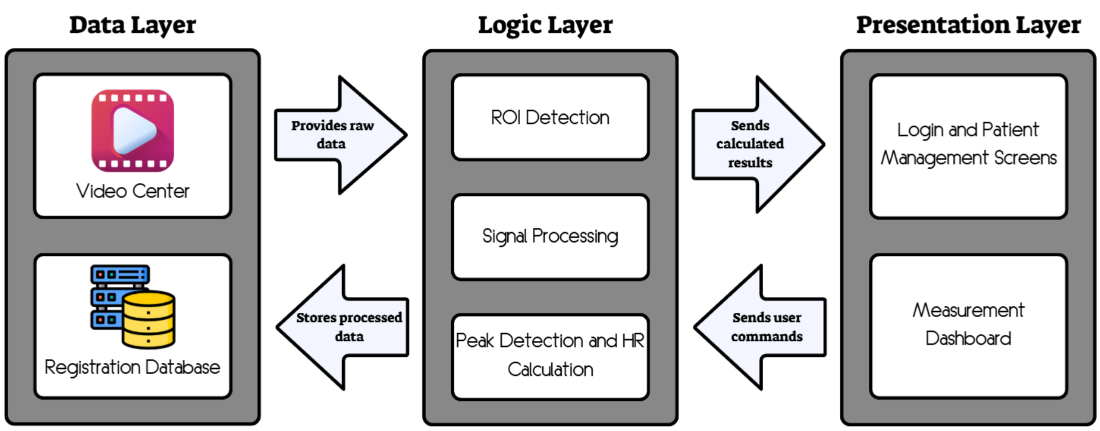


Figure 8: MVC-based architecture of the heart rate monitoring application

4.2.6 Databases

PulseVision uses a single SQLite database to manage user authentication, patient records, and heart rate measurements. SQLite was selected for its portability, zero-configuration setup, and reliable ACID compliance, which together support a desktop clinical workflow without requiring a dedicated server. The database file is created at implementation/src/data/users.db during first run and is initialized automatically.

4.2.6.1 Users

This table manages secure access and roles for clinical staff.

- Schema
  id INTEGER primary key auto increment
  username TEXT unique not null
  password_hash TEXT not null
  role TEXT not null
  last_login DATETIME
  created_at DATETIME default CURRENT_TIMESTAMP
- Security
  Passwords are stored as bcrypt hashes. On first run a default administrator account is created with username admin and password admin123. Successful logins update last_login, enabling basic auditing.
- Roles
  Role based access control separates administrative tasks from clinical use. Common roles are Administrator and Doctor.

4.2.6.2 Patients

This table stores patient demographics and clinician assignment.

- Schema
  id TEXT primary key
  first_name TEXT not null
  last_name TEXT not null
  dob DATE (date of birth)

assigned_doctor TEXT references users(username)

created_at DATETIME default CURRENT_TIMESTAMP

- Linkage

  The clinician relationship is maintained through assigned_doctor, which supports filtering by provider in the user interface.

4.2.6.3 Measurements

This table records individual heart rate readings produced by the pipeline.

- Schema

  id INTEGER primary key auto increment

  patient_id TEXT not null references patients(id)

  timestamp DATETIME not null

  heart_rate INTEGER not null

  status TEXT not null

- Usage

  Each row captures a single BPM estimate with its acquisition time and a status label such as Normal, Bradycardia, or Tachycardia.

4.2.6.4 Measurement Sessions

This table aggregates readings into clinically meaningful sessions.

- Schema

  id INTEGER primary key auto increment

  patient_id TEXT not null references patients(id)

  avg_heart_rate REAL not null

  status TEXT not null

  measurement_date DATE not null

  measurement_time TIME not null

  duration_seconds REAL not null

  total_measurements INTEGER not null

  created_at DATETIME default CURRENT_TIMESTAMP

- Purpose
  Sessions provide summary metrics and duration to support longitudinal review and reporting.

4.2.6.5 Data Relationships and Retrieval

The scheme establishes clear one-to-many relationships from patients to measurements and from patients to sessions. Queries use primary and foreign keys for efficient joints. For convenient retrieval in the application, JSON aggregation is used to return a patient together with an array of measurement rows in a single query, which reduces round trips and simplifies the view model.

4.2.6.6 Initialization and Maintenance

At application startup the database class performs the following steps.

1. Create the data directory if needed
2. Open or create the SQLite file
3. Create all tables with CREATE TABLE IF NOT EXISTS
4. Ensure a default admin user exists
5. Maintain connections with proper cleanup on shutdown

A standalone init_db.py script is also provided for manual initialization and for development workflows.

4.2.6.7 Security and Audit Features

- Passwords are hashed with bcrypt before storage
- A default admin is created only when no users exist
- `last_login` and `created_at` fields provide a basic audit trail
- The application layer enforces role checks before sensitive operations

4.2.6.8 Rationale

Moving from JSON files to SQLite improved integrity, concurrent access safety, and query flexibility. The design supports both granular analysis through individual measurements and higher-level summaries through sessions, which matches clinical review needs and enables future analytics without restructuring the data model.

4.2.6.9 Future Considerations for Improving Data Security and Reliability

The current implementation of PulseVision uses SQLite with bcrypt password hashing, role-based access control, login auditing, and structured patient–doctor relationships. While this represents a significant improvement over the previous JSON-based system, several areas remain open for future enhancement to align with best practices for healthcare systems:

1. Advanced Role-Based Access Control (RBAC)
   Expand existing role definitions to include more granular permissions (e.g., nurses vs. doctors vs. read-only staff).
2. Audit Logging
   Introduce detailed logs for login attempts, patient record modifications, and measurement session creation to strengthen accountability.
3. Database Backup & Recovery
   Implement automated backup scheduling with encrypted off-site storage, and provide disaster recovery procedures to ensure data persistence.
4. Multi-Factor Authentication (MFA)
   Add MFA mechanisms (e.g., SMS or email verification) and session expiration policies to mitigate risks of credential theft.
5. Data Encryption Beyond Passwords
   Encrypt sensitive patient information (e.g., identifiers, medical history) at the database level using AES-256, and ensure end-to-end encryption in client-server communication.

4.2.7 Project Diagrams

4.2.7.1 Use Case

The use case diagram models two role-based actors Clinician and Administrator with a general User ancestor to capture shared capabilities. Clinicians manage patients, run measurement sessions, view live HR and signal quality, and review historical trends. Administrators additionally manage users and roles, assign patients to clinicians, and configure system defaults. A compact Authenticate use case is referenced via «include» from all protected flows, reflecting the system's bcrypt-based login and audit trail. The technical stages of the rPPG pipeline are encapsulated within Run Analysis to keep the diagram task-oriented while the processing details are covered in the architecture and process sections.

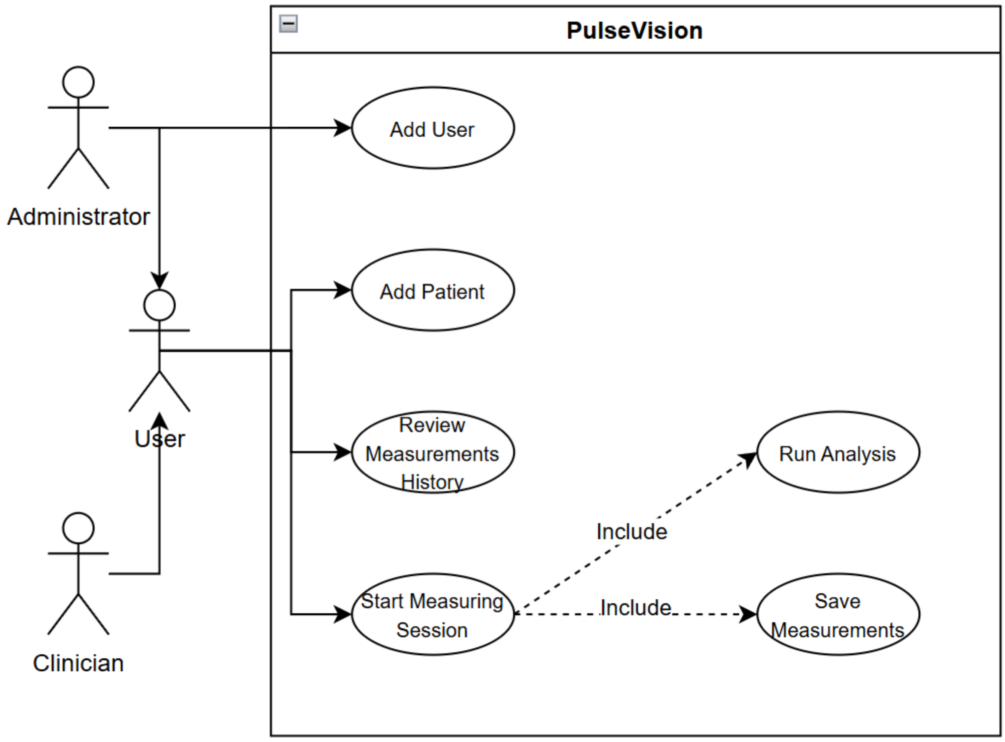


Figure 9: Use Case Diagram

4.2.7.2 Activity Diagram

The activity diagram illustrates the complete workflow of the system, from video acquisition to heart rate measurement and storage. The process begins when the user enters a specific patient profile and initiates measurement by pressing the start button. The system receives video input either from a live stream or a recorded file. Face detection is performed, followed by locating and validating the regions of interest (ROIs), specifically the forehead and cheeks. If the ROIs are stable, the green channel signal is extracted and combined across multiple ROIs to improve robustness.

Signal preprocessing and enhancement are then applied, including smoothing, notch filtering, and normalization, before proceeding to frequency analysis and heart rate estimation. A confidence check evaluates the quality of the detected signal. If the signal quality is insufficient, adaptive smoothing is applied to stabilize the result. Otherwise, the system advances to stability and filtering, ensuring that the heart rate remains consistent and reliable over time.

The final output is presented through the graphical user interface (GUI), where real-time results are displayed to the user. In parallel, the processed measurements are updated in the user's database for persistence and future analysis. This structured flow ensures that the system achieves accurate and reliable heart rate monitoring, even under challenging conditions such as motion artifacts or flickering illumination.

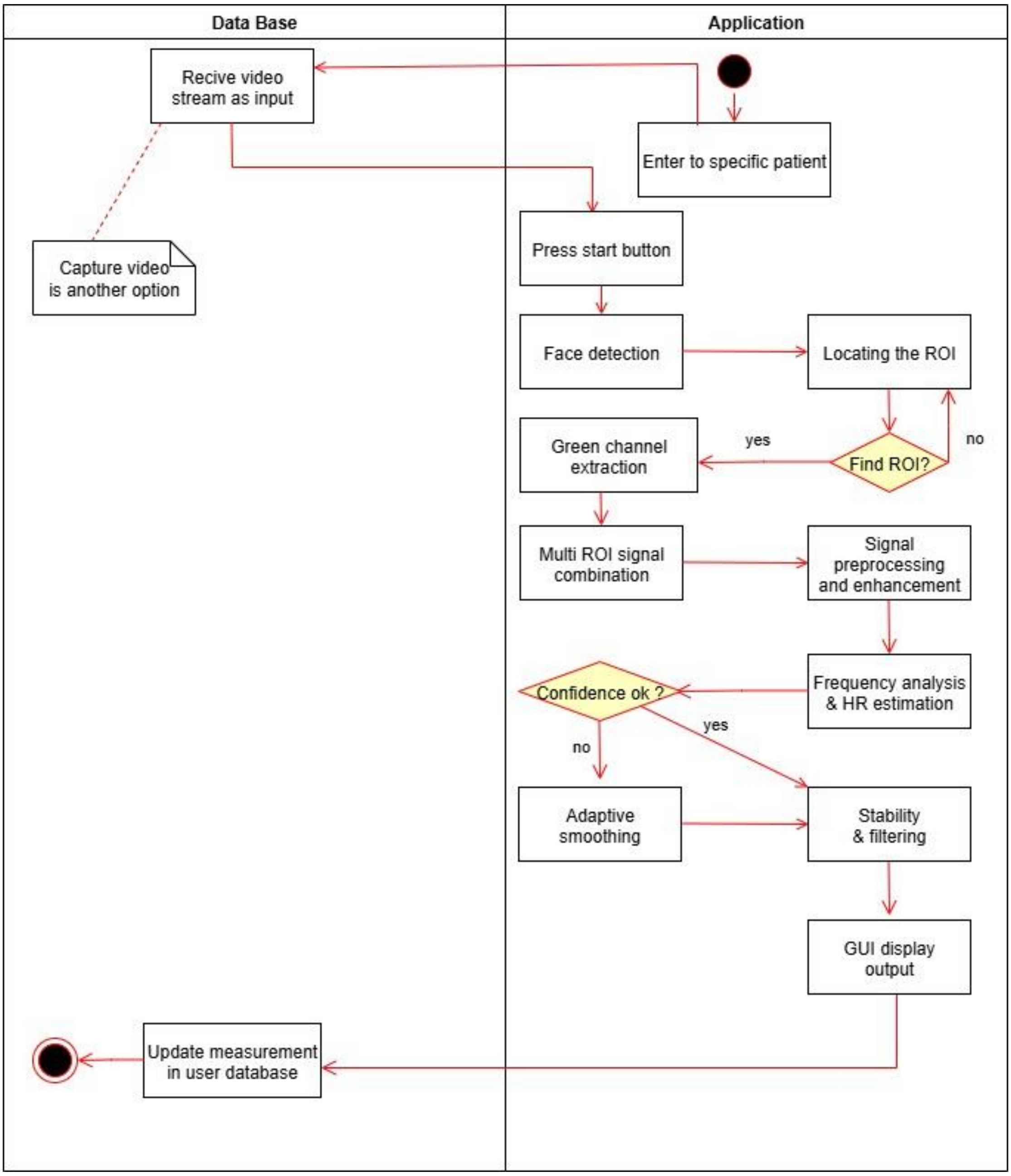


Figure 10: Activity Diagram

5 Evaluation / Verification plan

The primary goal of PulseVision was to develop a system capable of accurately estimating heart rate from facial video using remote photoplethysmography (rPPG). The evaluation focused on accuracy, robustness under real-world conditions, and usability.

The system was tested using both ~30 internal subjects (ages 20–65, diverse skin tones) and the UBFC-rPPG Dataset 2, which contains 42 subjects recorded during interactive gameplay with lighting variations.

Accuracy:

- In stable environments, the system achieved error within ±5 BPM for ~90–92 % of measurements.
- Under challenging conditions (motion or unstable illumination) the error sometimes increased to ±10 BPM, with around 80–85 % of measurements within ±5 BPM in those cases.

Robustness: The adaptive notch filters (1–3 Hz), robust normalization, and EMA smoothing ensured performance remained reliable under flickering LED/fluorescent lighting, and across subjects of varied skin tones.

Performance: Real-time operation was confirmed at 30 FPS input, satisfying requirements for live monitoring.

Usability: Informal user testing showed that the GUI is intuitive, with live video overlays, BPM and confidence displays, and automatic data logging. Users with different skin tones and facial features reported consistent visibility of ROI overlays.

These results confirm PulseVision met its design objectives, demonstrating reliable performance across a diverse population and dataset, and under variable lighting conditions.

5.1 Verification

We verified the system by dividing it into independent modules:

- User Authentication & Data Management
- Face & ROI Detection
- Heart Rate Extraction & Signal Processing
- Flicker Compensation & Non-Continuous Lighting Tests
- Real-Time Processing & Performance

- User Experience & Usability

Here is the verification table:

Test	Module	Tested Function	Expected Result	Result
User Authentication & Data Management				
1	Login	User login	Only authorized users can log in to the application	Achieved
2	Registration	User registration	Registered user cannot be re-registered	Achieved Note: Username is unique
3	Database	Patient data created	Patient information is successfully saved	Achieved
4	Database	Patient data not created	Cannot register a patient if the ID already exists in the system	Achieved Note: Patient ID is unique
Face & ROI Detection				
5	Face detection	Face detection accuracy	System accurately detects and locates faces	Achieved
6	Face detection	Low lighting conditions	System accurately detects and locates faces	Achieved
7	Face detection	Different skin tones	System accurately detects and locates faces across diverse populations	Achieved
8	Face detection	Fast-moving subjects	System maintains face tracking despite movement	Achieved
9	ROI segmentation	ROI segmentation accuracy	The ROI is accurately segmented by the system	Achieved
10	ROI segmentation	Head movement	The ROI is accurately segmented despite minor head movements	Achieved
11	ROI segmentation	Non-relevant facial exclusion	System excludes non-relevant facial features (background, hair, glasses)	Achieved

12	ROI segmentation	ROI not found	Error handling message displayed	Achieved
Heart Rate Extraction & Signal Processing				
13	Heart rate extraction	Heart rate measurement	System accurately extracts and displays the heart rate (compared to the pulse-oximeter results, in range 60-100 bpm)	Achieved Note: Motion or unstable light (TV/phone) may cause ±10 bpm noise in heart rate
14	Heart rate extraction	Heart rate alert	When the user's heart rate exceeds the limit, an alert is given	Achieved
15	Heart rate extraction	Artificial lighting conditions (LED/fluorescent flicker)	System maintains accurate heart rate readings despite artificial lighting flicker	Achieved
16	Heart rate extraction	Dynamic lighting variations	System adapts to sudden changes in lighting while preserving signal integrity	Achieved Note: HR stabilizes after a short adaptation period to lighting changes.
17	Heart rate extraction	Motion artifacts	System compensates for minor head movements to ensure stable heart rate readings	Achieved
18	Heart rate extraction	Varying camera resolutions	System maintains heart rate accuracy across different camera qualities (HD, low-res)	Achieved
19	Heart rate extraction	Multiple background environments	System extracts HR data in various indoor/outdoor settings	Achieved
20	Heart rate extraction	Different frame rates (15fps, 30fps, 60fps)	System maintains stable HR extraction across frame rate variations	Achieved
Flicker Compensation &				

Non-Continuous Lighting Tests				
21	Flicker compensation	50Hz LED flicker (Europe)	System detects and compensates for flickering noise	Achieved
22	Flicker compensation	60Hz LED flicker (US)	System detects and compensates for flickering noise	Achieved
23	Flicker compensation	Variable frequency flicker (20-100Hz)	System accurately extracts HR despite changing light frequencies	Achieved Note: The system needs short conversion time for the HR to settle.
24	Flicker compensation	Alternating bright/dim LED conditions	System stabilizes HR readings when brightness fluctuates	Not Implemented
Real-Time Processing & Performance				
25	Real-time processing	Frame rate stability	System maintains at least 20fps processing speed	Achieved
26	Performance efficiency	CPU/GPU utilization	System optimizes resource use and maintains smooth operation	Achieved
27	Mobile compatibility	Heart rate processing on mobile devices	System works on smartphones and tablets with acceptable accuracy	Not Implemented Note: Accuracy verified using mobile/tablet-captured video, but the app itself was executed on a desktop.
User Experience & Usability				
28	User interface	GUI readability	Users can clearly view and interpret HR data	Achieved
29	User interface	Alert system	System provides visual and audio alerts for abnormal HR readings	Achieved Note: Visual alert available, while

				audio alert not implemented.
30	User experience	User feedback survey	Users find the system intuitive, clear, and easy to use	Achieved
31	Integration potential	Compatibility with healthcare systems	System can export data for integration with medical applications	Not Implemented

Table 3: Verification Table

5.2 Results

To evaluate the performance of the proposed PulseVision system, we conducted experiments both on controlled test scenarios and on publicly available benchmark data (UBFC-rPPG Dataset 2). The evaluation focused on diverse conditions, including stable environments, mild motion, artificial flickering light, and illumination from TV/phone screens. In addition, we tested across subjects of different ages and skin tones to ensure robustness in real-world scenarios. Results are presented in two complementary forms:

- **Table 4** summarizes the system's accuracy under various test conditions, highlighting its ability to maintain reliable heart rate measurements across environmental and demographic variations.
- **Table 5** provides a detailed breakdown of individual test cases in a video-by-video format, demonstrating the accuracy of the system when compared with ground truth heart rate values.

Condition	Error Range	Accuracy (% of measurements within ±5 BPM)	Notes
Stable environment	±5 BPM	~ 90-94 %	Consistently achieved in controlled lighting
Mild head motion	±7 BPM	~ 85-88 %	Some fluctuation, aided by filtering
TV/Phone screen illumination	±10 BPM	~ 80 %	Unstable lighting remained challenging

Table 4

Video	Ground truth HR [BPM]	Evaluated HR [BPM]	Ground truth HR [Hz]	Evaluated HR [Hz]	HR Variation [BPM]	HR Accuracy [Percentage]
1	65	62	1.083	1.033	3	95.38
2	69	73	1.15	1.217	4	94.2
3	79	76	1.317	1.267	3	96.2
4	76	72	1.267	1.2	4	94.74
5	81	86	1.35	1.433	5	93.83
6	108	101	1.8	1.683	7	93.52
7	92	89	1.533	1.483	3	96.74
8	64	72	1.067	1.2	8	87.5
9	84	82	1.4	1.367	2	97.62
10	72	77	1.2	1.283	5	93.06

Table 5

6 User guide

This document provides detailed instructions on how to use the PulseVision system. PulseVision is a desktop Python application designed for non-invasive heart rate measurement using facial video streams. The system applies computer vision and signal processing techniques to extract photoplethysmographic (PPG) signals and outputs heart rate results in beats per minute (BPM), along with supporting graphs. In addition to real-time analysis, PulseVision includes user management, patient management, and measurement history features.

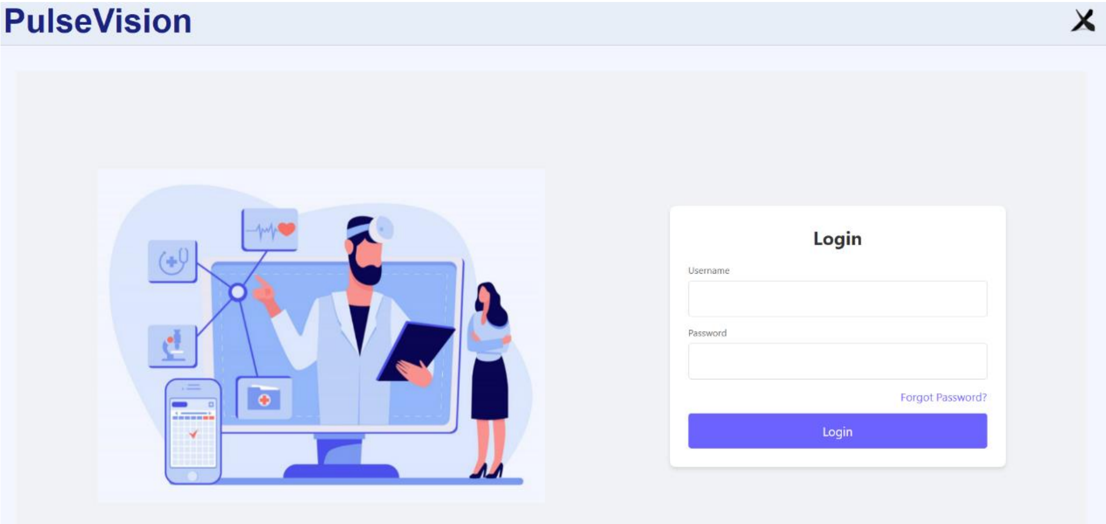
6.1 Accessing The System

PulseVision is a standalone desktop application. To run the system:

1. Download or clone the repository from GitHub: [PulseVision GitHub].
2. Install the required Python dependencies (listed in requirements.txt).
3. Launch the application by running:

python main.py

4. The Login Page will appear. Enter your registered username and password.
   - Only authorized users (doctors or administrators) can log in.

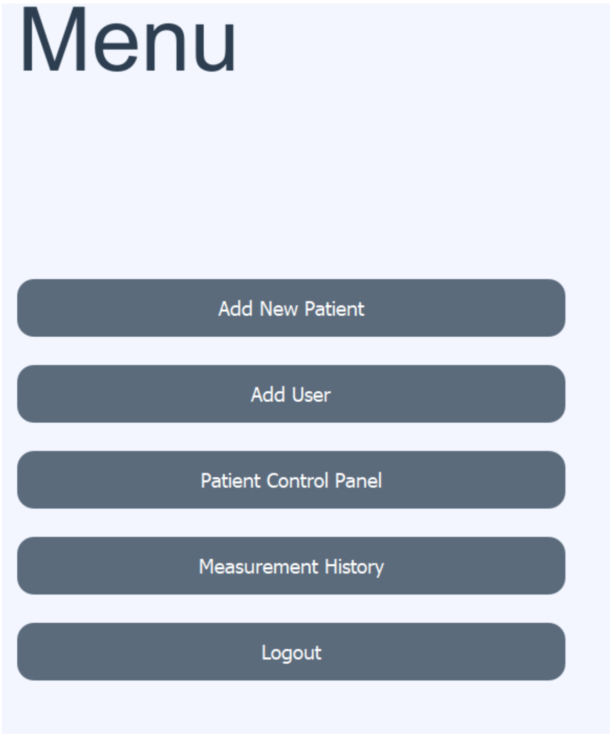


6.2 Main Menu Overview

After logging in, users arrive at the Menu page. This page serves as the central hub of the system and provides the following options:

- Add New Patient - Register new patients in the system.
- Add User - Create new user accounts (Doctor or Administrator).
- Patient Control Panel - Start and manage heart rate measurements for selected patients.
- Measurement History - Review historical results for patients, including average BPM, duration, and status.

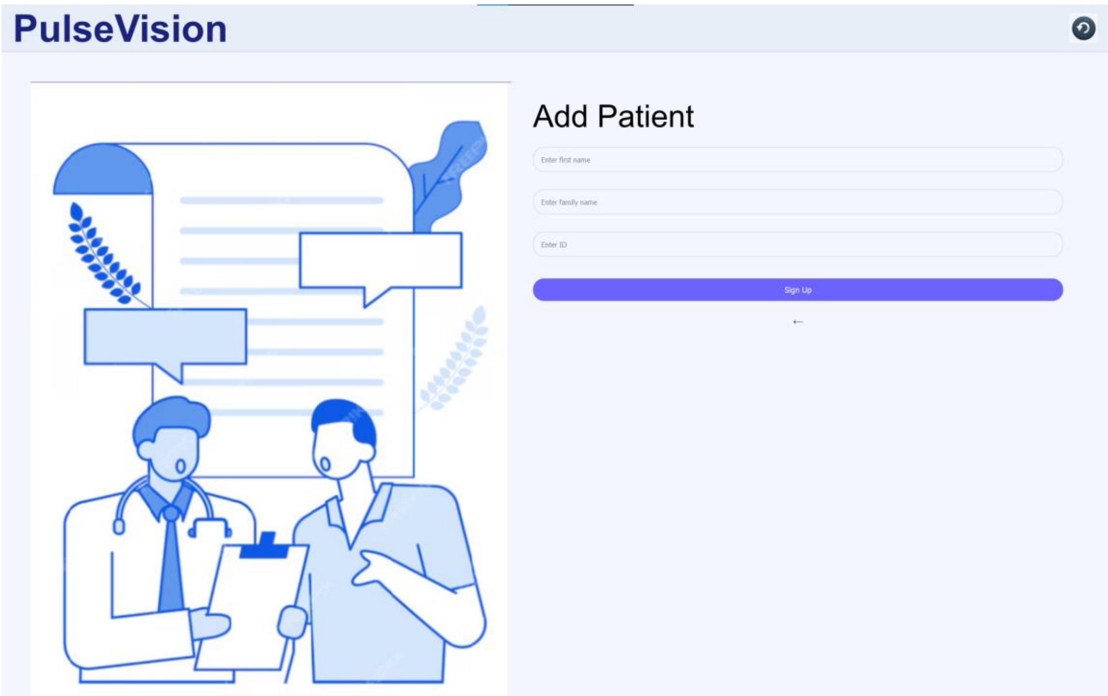
- Logout - Exit the system securely.



6.3 Adding a New Patient

Selecting Add New Patient navigates to the registration page.

- Enter the patient's first name, family name, and ID.
- Click Sign Up to add the patient to the database.
- Once saved, the patient record becomes accessible in the Patient Control Panel and Measurement History.

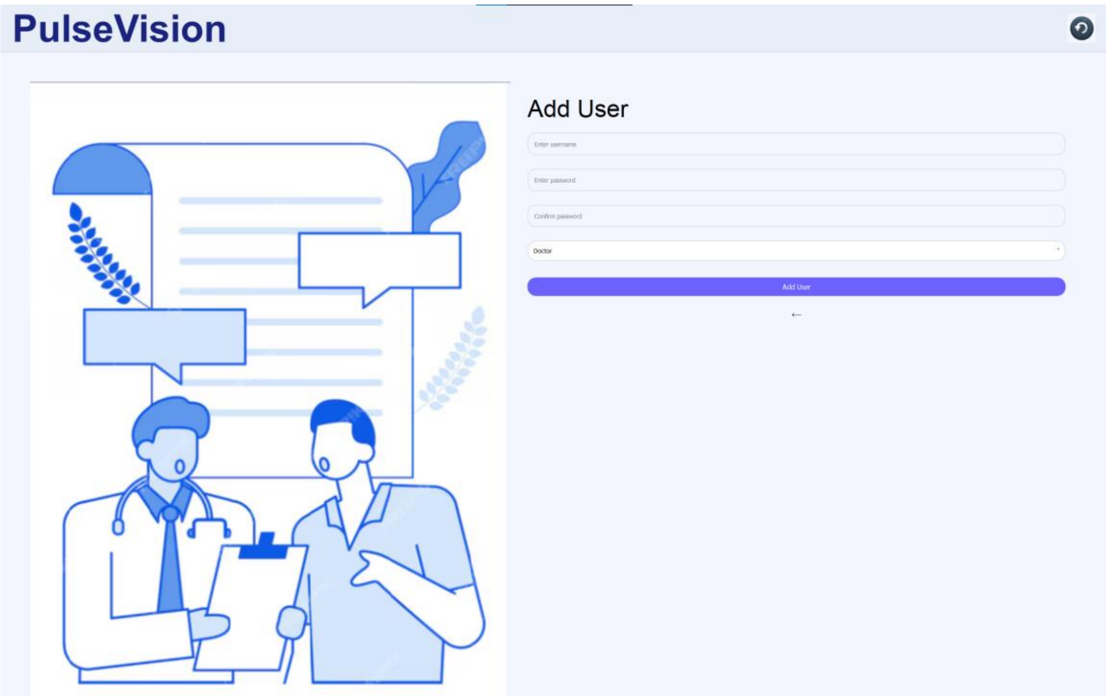


6.4 Adding a New User

System administrators can add new users (e.g., doctors, additional admins).

- Enter a username and password (with confirmation).
- Select the role: Doctor or Administrator.
- Click Add User to create the account.

Administrators have full system privileges, while doctors focus on patient monitoring and analysis.



6.5 Patient Control Panel

The Patient Control Panel displays all registered patients and allows doctors to initiate and monitor heart rate measurements. From here, doctors can:

- Select a patient to start a new heart rate analysis.
- Review and monitor measurement results in real time.
- Manage patient details.

6.6 Recording Or Uploading Video For Heart Rate Measurement

Within the measurement interface, users can choose between:

- Camera Mode - Use a connected webcam to capture real-time facial video.
- Open File - Upload a pre-recorded video file for analysis.

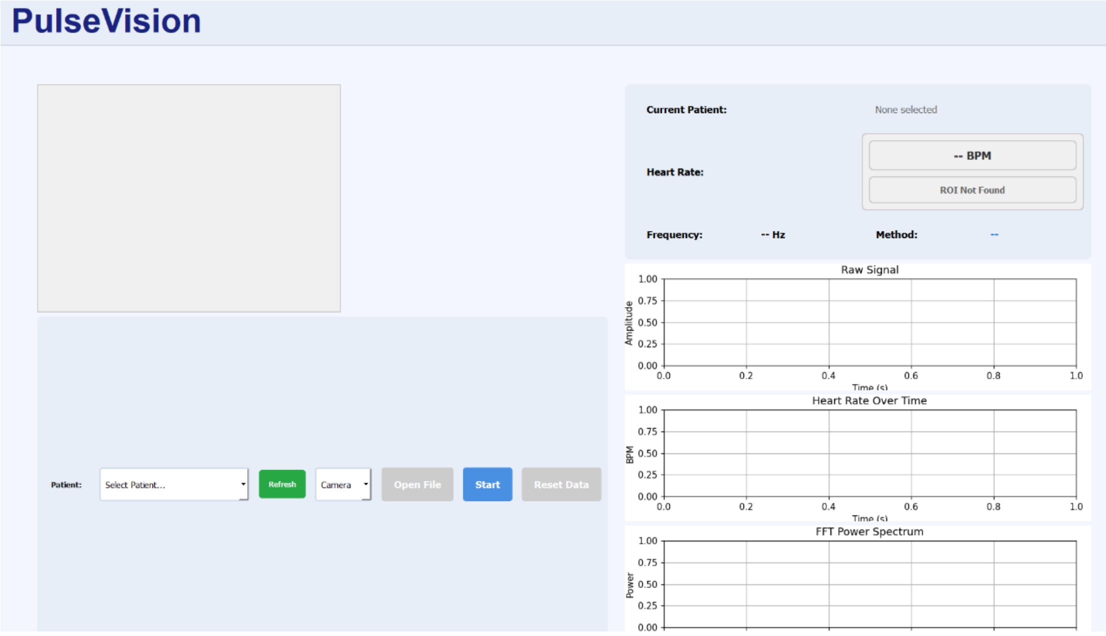
Once the video source is selected:

1. Click Start to begin capturing data.
2. The system will process the video, extract the rPPG signal, and estimate heart rate.

3. To stop the current session, click Stop.

4. To clear the session and reset the plots, click Reset Data.

The live video preview will also display face detection bounding boxes over the regions of interest (forehead, cheeks), used to calculate the signal.

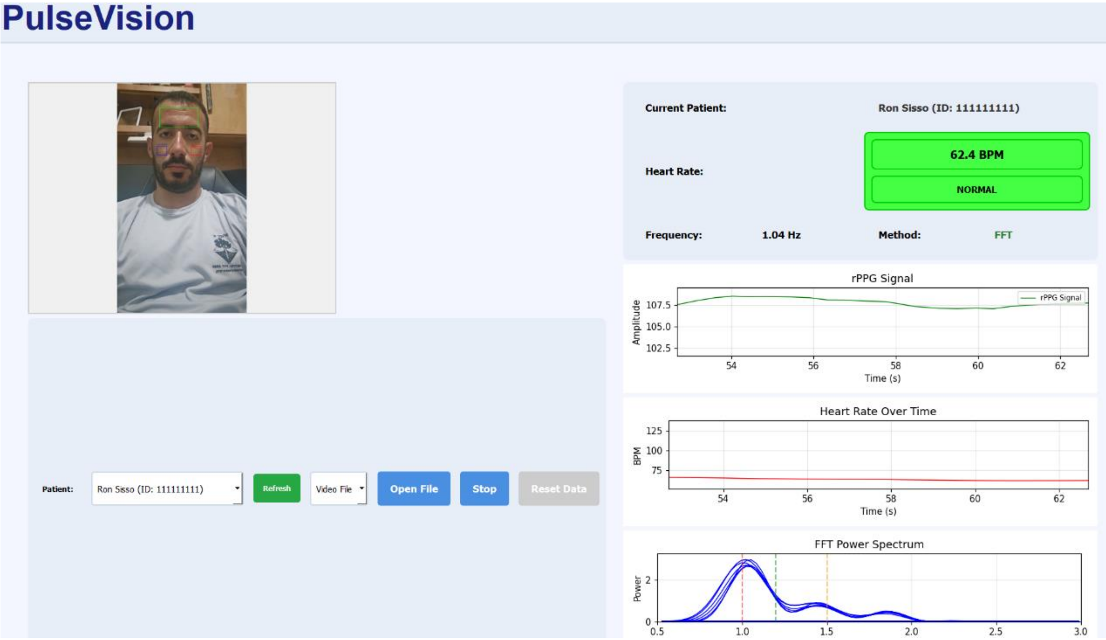


6.7 Viewing Analysis Results

After analysis begins, the system displays results directly in the GUI:

- Heart Rate (BPM) - Real-time calculation of the user's pulse.
    - If the BPM is below 120, the box is green and marked Normal.
    - If the BPM is 120 or higher, the box turns red with the alert "ALERT: High HR".
- Frequency (Hz) - Signal frequency associated with the detected pulse.
- Raw Signal Graph - Shows the extracted PPG signal over time.
- Heart Rate Over Time Graph - Displays BPM progression during the session.
- FFT Power Spectrum Graph - Visualizes the frequency-domain representation of the signal for additional validation.

These graphs provide clear insight into signal quality, heart rate dynamics, and stability during the measurement.



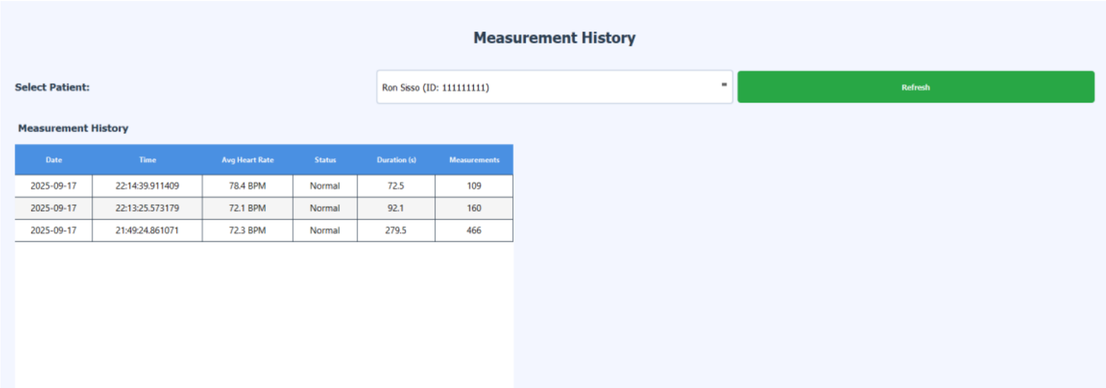
6.8 Measurements History

The Measurement History page allows doctors to review past results for each registered patient.

• Select Patient - Choose a patient from the dropdown list. The table will update to show their recorded sessions.
• Refresh - Updates the patient list and measurement records.
• History Table – Displays previous measurements with the following details:

- Date - The date the measurement was taken.
- Time - The exact time of recording.
- Average Heart Rate (BPM) - The mean BPM calculated during the session.
- Status - Indicates the measurement result (e.g., *Normal* or *Alert: High HR*).
- Duration (s) - Total recording time of the session in seconds.
- Measurements - Number of data points collected during the session.

This feature provides doctors with a structured overview of a patient's heart activity over time, enabling trend monitoring and clinical decision support.



6.9 Logging Out

When finished, return to the Menu page and select Logout. This ensures that your session ends securely and that patient/user data is protected.

7 Maintenance Guide

This guide is intended to ensure the continued use and maintenance of the PulseVision Real-Time Heart Rate Measurement System after the completion of the project. It provides clear instructions for applying updates, improvements, and ongoing maintenance to support the system's lifecycle and future usability.

7.1 System Overview

The PulseVision system is a desktop application that measures heart rate in real time using remote photoplethysmography (rPPG) from video of a person's face. It consists of:

- Video Input: Real-time capture from webcam or pre-recorded video files.
- Face Detection: MediaPipe Face Mesh for tracking 468 facial landmarks.
- Signal Processing: Multi-ROI extraction (forehead, cheeks), green-channel analysis, noise filtering, FFT-based frequency analysis, and confidence-based validation.
- GUI: A PyQt5 application that displays:
    - Live video feed with ROI overlays
    - Real-time heart rate display with confidence indicator
    - Three synchronized plots (rPPG signal, HR trend, FFT spectrum)
- Database: Patient management system for storing and retrieving patient data and past measurements.

7.2 Operating Environment

Hardware Requirements

- Processor: Modern multi-core CPU (recommended for real-time performance)
- Memory: Minimum 2 GB RAM/ 4 GB or more recommended for smoother processing
- Webcam: Standard external or integrated webcam, 720p resolution or higher
- GPU (optional): Not required, CUDA-enabled GPUs may accelerate video and signal processing tasks

Software Requirements

- Operating System: Windows 10 or later, macOS 12 or later, or Linux (Ubuntu 20.04 or later)

- Python: Version 3.11 (mandatory)
- Pip: Python package manager for dependency installation
- Dependencies: Installed via requirements.txt (including OpenCV, MediaPipe, NumPy, SciPy, PyQt5, Matplotlib, and related packages)

Additional Notes

- No external database or server infrastructure is required.
- SQLite is used internally for lightweight data persistence (user, patient, and measurement records).

7.3 Installation Instruction

The following steps describe how to install and run the PulseVision system.

Manual Setup:

- Clone Repository

```
git clone https://github.com/RonSisso/PulseVision.git

cd PulseVision/implementation
```

- Create and activate a virtual environment (Python 3.11 required)
  Windows (PowerShell):

```
python -m venv venv_311

venv_311\Scripts\activate.ps1
```

  macOS/Linux:

```
python3 -m venv venv_311

source venv_311/bin/activate
```

- Install dependencies

```
pip install -r requirements.txt
```

- Run the application

```
python src/main.py
```

7.4 Updating the System

PulseVision can be improved or maintained by updating different components:

7.4.1 Updating Signal Processing or GUI

- Modify relevant modules in src/signal_processing/ or src/gui/.
- Re-run the application to validate stability.

7.4.2 Updating Database

- Database logic is implemented in src/database/.
- Schema extensions (e.g., adding new patient/user/measurements attributes) require updating both database code and GUI panels.

7.4.3 Updating Dependencies

- Update requirements.txt if new packages are required.
- Reinstall dependencies:
- pip install -r requirements.txt --upgrade

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