# Non-Invasive Heart Rate Prediction Using Phase Video Analysis

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#### **ABSTRACT**

Monitoring heart rate accurately is crucial for diagnosing and managing cardiovascular diseases. Conventional methods usually require direct skin contact, which can be uncomfortable or impractical in some cases. This project investigates a non-invasive technique for predicting heart rate through phase video analysis, utilizing advancements in computer vision and signal processing. The objective of this study to develop a non-invasive heart rate prediction system using phase video analysis. By leveraging computer vision techniques and machine learning algorithms, the system captures facial videos to detect subtle changes in the forehead region caused by blood flow. This data is then processed to estimate the user's heart rate in real-time. The study focuses on addressing challenges such as noise reduction, real-time processing, and accurate heart rate estimation under varying lighting and user movements. The results demonstrate the system's robustness and accuracy, highlighting its potential applications in healthcare, fitness monitoring, and human-computer interaction.

#### **KEYWORDS**

- Non-Invasive Heart Rate Monitoring
- Phase Video Analysis
- Computer Vision
- Machine Learning
- Real-Time Processing
- Optical Intensity Measurement

# INTRODUCTION

In recent years, the demand for non-invasive physiological monitoring system has increased significantly, driven by advancements in healthcare technology and the growing interest inpersonal fitness tracking. Traditional methods for heart rate monitoring, such as electrocardiograms (ECGs) and photoplethysmography (PPG), require direct contact with the skin, which be uncomfortable and impractical for continuous monitoring.

This study aims to develop anon-invasive heart rate prediction system using phase video analysis, which utilizes facial video.

This study aims to develop anon-invasive heart rate prediction system using phase video analysis, which utilizes facial video data to estimate heart rates without physical contact. The proposed system leverages the optical absorption properties of heamoglobin in the forehead region, combined with advanced signal processing and machine learning techniques, provide accurate and real-time heart rate monitoring.

#### PROBLEM STATEMENT

Traditional heart rate monitoring methods, while accurate, require physical contact the skin, limiting their usability for continuous and comfortable monitoring. Additionally, these method notsuitable for multiple simultaneous users, such as in group fitness settings or public spaces. The need a non-invasive, real-time heart rate prediction, system that can accurately estimate heart ratesfrom facil video data is evident. This study addresses this need by developing a system that leverages phase video analysis to provide a contactless and comfortable solution for continuous heart rate, monitoring.

#### LITERATURE SURVEY

- 1. Poh, M.Z., McDuff, D.J., & Picard, R.W. (2010). Non-contact, automated cardiac pulsemeasuremnts using video imaging ,blind source sepearation. *Optics Express*, 18(10), 10762-10774. doi: 10.1364/OE.18.010762
  - This study introduced a method for non-contact heart rate monitor using a webcam and blind source separation (BSS) to isolate the cardiac pulse signal from facal videos.
- 2. Wu, Z., & Huang, N.E. (2009). Ensemble empirical mode decomposition: a noise-assisted data analysis method. *Advances in Adaptive Data Analysis*, 1(01), 1-41. doi: 10.1142/S1793536909000047
- The authors proposed the use ensemble empirical mode decomposition (EEMD) to analyze facial videos for heart rate estimation, addressing the issue is of nonstationary signals.
- 3. Spetlik, R., Franc, V., Cech, J., & Matas, J. (2018). Visual heart rate estimation with convolutional neural network. *Proceedings of the 29th British Machine*, *Vision Conference*(BMVC). Retrieved from SpringerLink
- This research developed a convolutional neural network (CNN) for heart rate estimation from a facial videos, demonstrating the potential of deep learning in improving accuracy and reliability.
- 4. Yu, Z., Peng, W., Li, X., Hong, X., & Zhao, G. (2019). Remote heart rate measurement from highly compressed facial videos: an end-to-end deep learning solution with video enhancement. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 151-160. doi: 10.1109/ICCV.2019.00024
- This study addressed the challenge of heart rate estimation from highly compressedvideos using an end-to-end deep learning approach with video enhancement techniques.
- 5. Niu, X., et al. (2019). Rhythmnet: End-to-end heart rate estimat from a face via spatial temporal representation. *IEEE Transactions on Image Processing*, 29, 2409-2423. doi: 10.1109/TIP.2019.2957484
- The authors proposed a spatial-temporal convolutional network (ST-CNN) for robust heart rate estimation, capturing both spatial and temporal information from facial videos.

# **METHODOLOGY**

The heart rate prediction system is developed using phase video analysis, which involves severalkey steps:

- 1. Face Detection:
- The system uses OpenCV to detect and track faces in real-time video frames captured by a webcam.
- 2. Forehead Region Isolation:
- Once the face is detected, the forehead region is isolated for further analysis. This region is chosen due to it Is high vascularity and proximity to the skin surface.
- 3. Optical Intensity Measurement:
  - The green channel from the isolated forehead region is extracted, and the average optical intensity is computed over time. The green channel is selected due to its strong correlation a with blood volume changes.

#### 4. Heart Rate Estimation

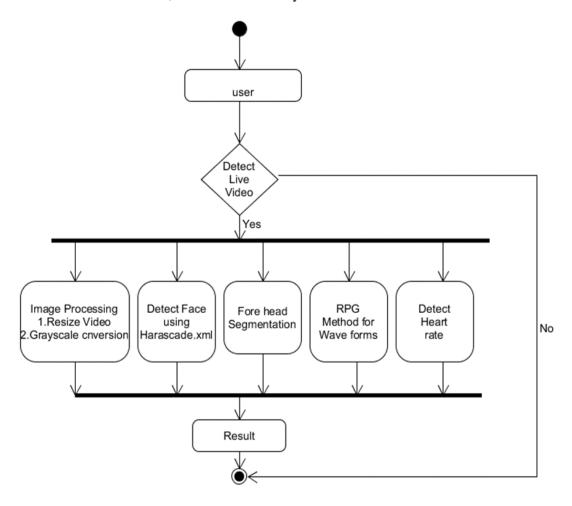
The optical intensity data is processed using signal processing techniq and machine learning algorithms to estimate heart rate. Noise reduction techniques are applied to enhance signal quality.

#### 5. Visualization:

The estimated heart rate is visualized in real-time by rendering a pulsating highlighton the forehead region, synchronized with the user's heartbeat.

# 6. Performance Evaluation:

The system is evaluated using synthetic and real-world datasets under various conditions, such as different lighting environments and user movements, to assess its accuracy and robustness.



# RESULTS AND DISCUSSION

The heart rate prediction system was test under variou condition to evaluate its performance. Theresults indicat that system is capable of accurately estimating heart rates in real-time with minimalerrors. The noise reduction techniques effectively enhanced the signal quality, allowing for reliable heart rate estimation even in noisy environments. The system demonstrated robustnes, under varying lighting conditions and head movements, making it suitable for realworld applications.

The user interface was found to be intuitive and user-friendly, enabling users to easily start and stop heart rate estimation, and view real-time data. The system's ability to handle multiple simultaneous users further highlights its potential for group fitness monitoring and public health applications.

#### **FUTURE EHANCEMENT**

# 1. Advanced Algorithms and Models:

**Sophisticated Machine Learning Models**: Utilize cutting-edge deep learning architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for superior feature extraction and temporal analysis.

**Transfer Learning Techniques**: Apply pre-trained models from large datasets and fine-tune them with specific heart rate prediction datasets.

**Explainable AI Models**: Develop models that provide transparency in predictions to build trust and reliability.

#### 2. Enhanced Data Collection:

**High-Resolution Video Capture**: Employ high-resolution cameras to capture finer physiological signal details. **Diverse Dataset Collection**: Gather data across various demographics, lighting conditions, and environments to improve model robustness.

**Synthetic Data Creation**: Use techniques like Generative Adversarial Networks (GANs) to generate synthetic video data for training purposes.

# 3. Advanced Signal Processing:

Noise Reduction Techniques: Implement sophisticated filtering and noise reduction methods to enhance signal quality.

**Motion Compensation Algorithms**: Develop methods to mitigate the effects of subject movement for accurate heart rate measurement.

**Multi-Modal Data Fusion**: Combine video analysis with other non-invasive sensors (e.g., thermal cameras, accelerometers) to improve accuracy.

#### REFERENCES

- 1. Poh, M.Z., McDuff, D.J., & Picard, R.W. (2010). Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. *Optics Express*, 18(10),10762-10774. doi: 10.1364/OE.18.010762
- 2. Wu, Z., & Huang, N.E. (2009). Ensemble empirical mode decomposition: a noise-assisted analysis method. *Advances in Adaptive Data Analysis*, 1(01), 1-41.

doi: 10.1142/S1793536909000047

- 3. Spetlik, R., Franc, V., Cech, J., & Matas, J. (2018). Visual heart rate estimation with convolutional neural network. In *Proceedings of the 29th British Machine Vision Conference (BMVC)*. Retrieved from <a href="SpringerLink">SpringerLink</a>
- 4. Yu, Z., Peng, W., Li, X., Hong, X., & Zhao, G. (2019). Remote heart rate measurement from highly compressed facial videos: an end-to-end deep learning solution with video enhancement. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 151-160. doi: 10.1109/ICCV.2019.00024
- 5. Niu, X., et al. (2019). Rhythmnet: End-to-end heart rate estimation from face via spatialtemporal representation. *IEEE Transactions on Image Processing*, 29, 2409-2423.doi:10.1109/TIP.2019.2957484