T.C.

MARMARA UNIVERSITY

FACULTY of ENGINEERING

COMPUTER ENGINEERING DEPARTMENT

CSE4197 Engineering Project I

Project Specification Document

rPPG BASED HEART RATE ESTIMATION USING DEEP LEARNING

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1. Problem Statement

With the development of technology, new techniques are rapidly developing for the heart rate measurement process, which is vital especially in hospitals. Heart rate estimation is of great importance in determining a person's mental and physiological state. In some cases, it is not possible to use many medical devices such as the finger pulse oximeter with PPG technology due to the patient's delicate health conditions. As we can see the way of work of rPPG in Figure1, remote PPG studies (rPPG), which will bring us a solution in such sensitive situations, make it possible to measure heart rate monitoring with less need for medical devices and without causing infection.

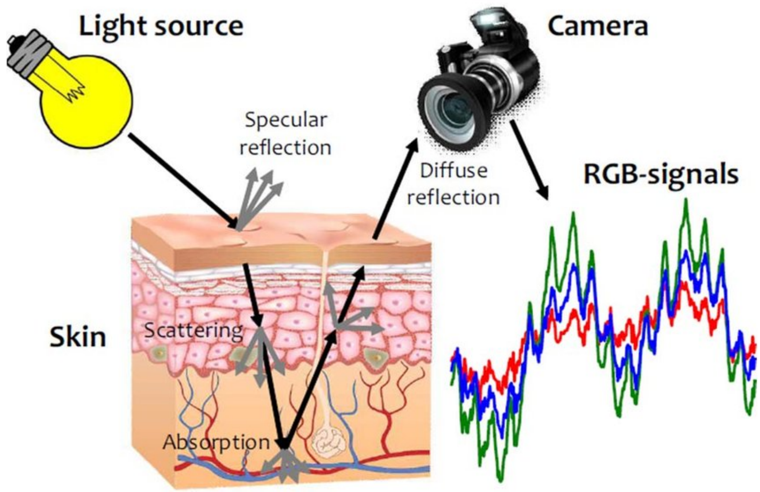

Figure 1: The rPPG setup which normally consists of the light source, camera, and pulsating skin area [1]

rPPG, which has been studied for a long time, does not give exactly the right result when it comes to there are factors such as the person's movements and changes in ambient light. In this project, we will work on the factors that cause errors in the measurement results and apply various methods to improve the results of the measurements made under these factors.

2. Problem Description and Motivation

In the results of the experiments conducted in rPPG studies, while the heart rates obtained from stable subjects and videos with good light were mostly correct, the error rates in the results increased in more realistic scenarios. The factors in these realistic scenarios are generally related to the person's movements and ambient lighting.

It is very important to choose the region of interest (ROI) to be used when measuring. Heart rate is determined by the change of colour signals. This area becomes difficult to detect when the person turns their head, moves, laughs, speaks.

The colour signals we get from the ROI are important. These colour signals change as the heart pumps blood. We cannot see these colours with our eyes, but it is possible to obtain the colour signals of the pixels in the ROI with certain methods. However, in some cases, it is difficult to analyze these signals. For example, the colour signals we get from the face of a person watching a movie in front of a screen are quite confused. Because the change of light reflected from the film affects the colours of the pixels in the ROI. Or when we try to measure in a low light environment, the signals we receive will be quite weak. We can see taking the face frame from a video with ROI in Figure2.

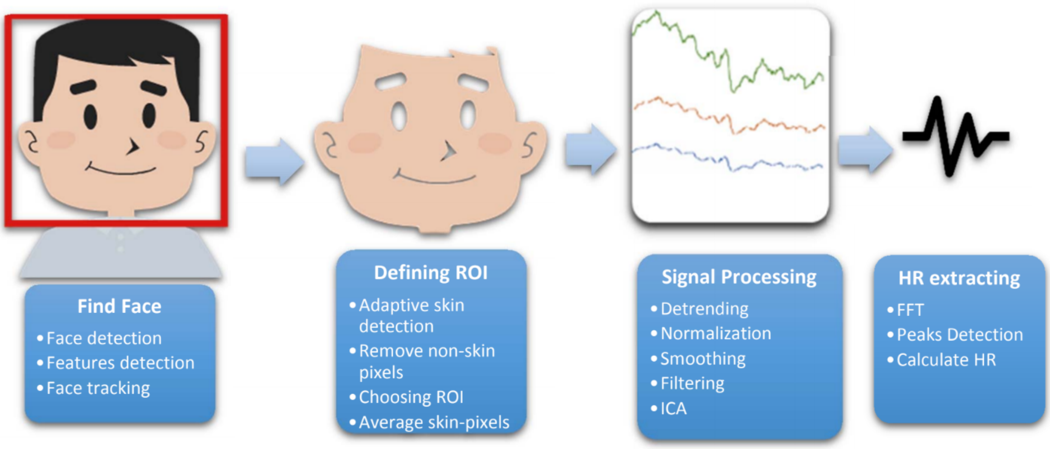

Figure 2: Block diagram of the proposed rPPG method. [1]

A person's skin colour is also an important factor in detecting heartbeat signals. While the changes in light skin create stronger signals, it is more difficult to obtain these signals in darker skin.

PPG technology is one of the most important methods used in heart rate measurement. PPG technology is often used in pulse oximeters in hospitals. Pulse oximeters measure according to whether the haemoglobin in the red blood cells can hold oxygen or not. The sensor in the device determines the number of beats per minute of the artery. However, it is not possible to measure heart rate with pulse oximetry under all conditions. For example, since the epidermis and dermis of a patient with a third-degree burn are completely destroyed, and so, it is not possible to measure the heart rate with a pulse oximeter due to the injury to the underlying tissue or muscle. On the other hand, patients in pediatric intensive care units, especially premature babies in the incubator, are very sensitive to infections. In such sensitive situations, the heart rate must be measured in a way that does not come into contact with the patient. We can see the basic framework of rPPG measurement in Figure3. We decided to work on this issue in order to find a solution to this vital problem in the healthcare industry. Our main motivation is to contribute to human health.

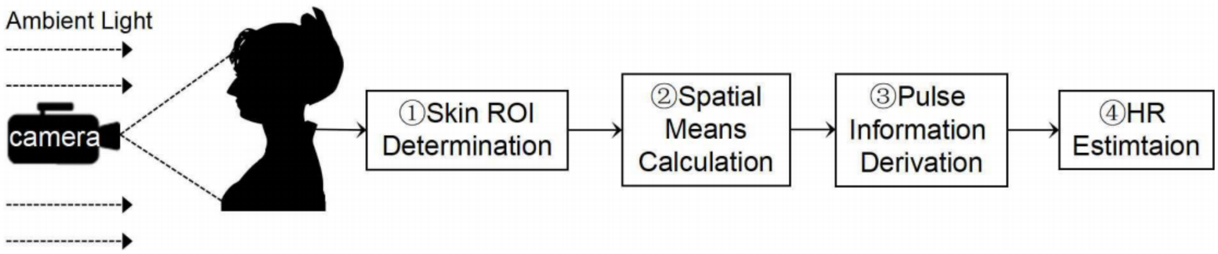

Figure 3: The basic framework of rPPG measurement. [2]

As we can see in Figure 4, according to the research of WHO in 2018, cardiovascular diseases are the number one cause of death globally. The most important step to prevent and treat is early diagnosis. Measurement of heart rate is of vital importance for the evaluation of human cardiovascular status. Photoplethysmography (PPG) is one of the most preferred methods to measure the heart rate, breathing rate, the amount of blood flowing in the vessels and their change over time. Studies have shown that photoplethysmography can be done remotely by means of a camera. There are a lot of benefits of measuring without contact. For example, oximeters usually measure through finger-mounted probes. However, with pulse oximeters, if there is a problem in the patient's blood circulation, it will not be possible to measure with probes. In addition, the need for expensive disposable probes increases the cost [3]. On the other hand, remote measurement is very important for contact-sensitive patients such as newborns, patients in intensive care units etc. With rPPG (remote PPG), heart rate monitoring is possible with less need for medical devices and without causing infection. In light of these benefits, measuring the remote PPG signal will make a serious contribution to the healthcare industry. We believe that the remote PPG pulse estimation method will be an indispensable application in the healthcare industry by eliminating certain problems and improving methods.

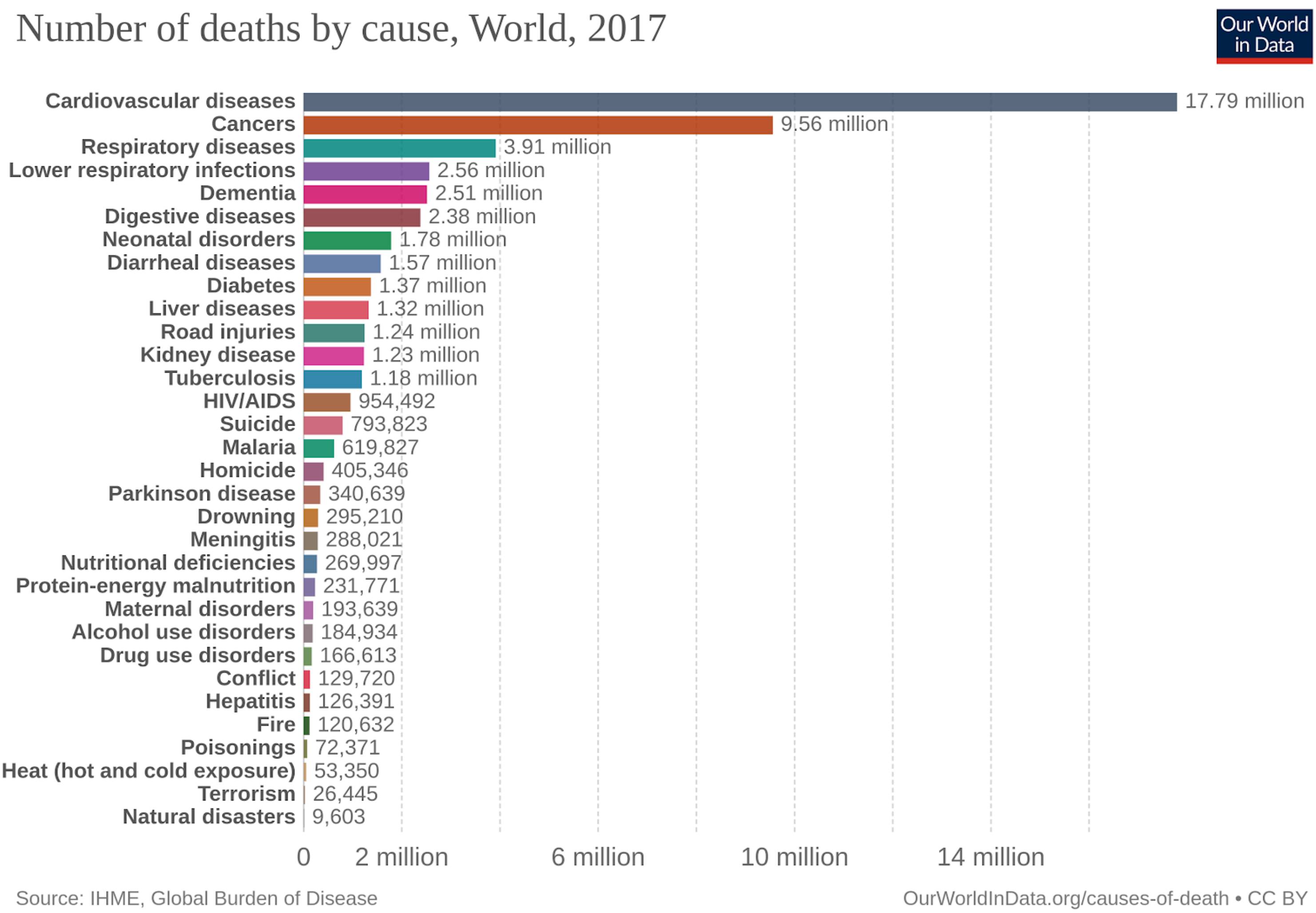

Figure 4: information from individuals sentenced to death and their families and representatives; reporting by other civil society organizations; and media reports. [4]

We have been searching the literature for a while. We have read many articles, examined the studies, and seen the methods. We have several datasets. Using these datasets, we will test the methods we have determined as the most useful in line with our research results. We will identify the deficiencies and insufficient situations of these methods and try to improve them.

3. Aims of the Project

Project Aim 1: The heart rate that we can get from the video of the face of a person standing still in a well-lit environment should be measured close to the reference heart rate. We aim to achieve an RMSE error of less than 5 bpm on PURE [5] and UBFC datasets [6].

Project Aim 2: In a well-lit environment, the heart rate that we can get from the video of the face of a person who moves his / her head right and left up and down without rotating his / her head should be measured close to the reference heart rate.

Project Aim 3: In a well-lit environment, a result close to the reference heart rate should be obtained by taking into account the person's speech or facial expressions such as laughing or being surprised.

Project Aim 4: In a well-lit environment, the heart rate of a person wearing glasses should be measured close to the reference heart rate.

4. Related Work

4.1 Datasets

- **PURE**

This data set consists of 10 persons (8 male, 2 female) that were recorded in 6 different setups (steady, talking without head movements, slow translation, fast translation - twice slow translation speed - average speed was %7 of the face height per second, small head rotation - 20°, medium head rotation - 35°) resulting in a total number of 60 sequences of 1 minute each.

The videos were captured with an eco274CVGE camera by SVS-Vistek GmbH at a frame rate of 30 Hz with a cropped resolution of 640x480 pixels and a 4.8mm lens. Reference data have been captured in parallel using a finger clip pulse oximeter (phlox CMS50E) that delivers pulse rate wave and SpO2 readings with a sampling rate of 60 Hz.

The test subjects were placed in front of the camera with an average distance of 1.1 meters. Lighting condition was daylight through a large window frontal to the face with clouds changing illumination conditions slightly over time.

Minimum pulse rate measured using the oximeter is at 42 BPM and the maximum rate was 148 BPM. [5]

- **UBFC**

The UBFC-RPPG database was created using a custom C++ application for video acquisition with a simple low-cost webcam (Logitech C920 HD Pro) at 30fps with a resolution of 640x480 in uncompressed 8-bit RGB format. A CMS50E transmissive pulse oximeter was used to obtain the ground truth PPG data consisting of the PPG waveform as well as the PPG heart rates.

The subject sits in front of the camera (about 1m away from the camera) with his/her face visible and is required to play a time-sensitive mathematical game that aimed at augmenting their heart rate while simultaneously emulating a normal human-computer interaction scenario. 42 videos (among 46 videos) of this dataset are shared for research purposes. All experiments are conducted indoors with a varying amount of sunlight and indoor illumination. [6]

4.2 Heart Rate Estimation Methods

4.2.1 Contact Methods

- **Electrocardiography (ECG or EKG)**

Electrocardiography (ECG or EKG) is a graph of voltage versus time of the electrical activity of the heart using electrodes placed on the skin. These electrodes detect the small electrical changes that are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle (heartbeat). [8]

- **Photoplethysmogram (PPG)**

A photoplethysmogram (PPG) is an optically obtained plethysmogram that can be used to detect blood volume changes in the microvascular bed of tissue. A PPG is often obtained by using a pulse oximeter which illuminates the skin and measures changes in light absorption. A conventional pulse oximeter monitors the perfusion of blood to the dermis and subcutaneous tissue of the skin.

With each cardiac cycle, the heart pumps blood to the periphery. Even though this pressure pulse is somewhat damped by the time it reaches the skin, it is enough to distend the arteries and arterioles in the subcutaneous tissue. If the pulse oximeter is attached without compressing the skin, a pressure pulse can also be seen from the venous plexus, as a small secondary peak.

Figure 5: Finger pulse oximeter [15]

The change in volume caused by the pressure pulse is detected by illuminating the skin with the light from a light-emitting diode (LED) and then measuring the amount of light either transmitted or reflected by a photodiode. Each cardiac cycle appears as a peak, as seen in the figure. Because blood flow to the skin can be modulated by multiple other physiological systems, the PPG can also be used to monitor breathing, hypovolemia, and other circulatory conditions. Additionally, the shape of the PPG waveform differs from subject to subject and varies with the location and manner in which the pulse oximeter is attached as we can see in Figure 5.

4.2.2 Remote Methods

- **Independent component analysis (ICA)**

Independent component analysis (ICA) is a technique for uncovering independent signals from a set of observations that are composed of linear mixtures of the underlying sources. The underlying source signal of interest is the BVP that propagates throughout the body. During the cardiac cycle, volumetric changes in the facial blood vessels modify the path length of the incident ambient light such that the subsequent changes in the amount of reflected light indicate the timing of cardiovascular events. By recording a video of the facial region with a webcam, the red, green, and blue (RGB) colour sensors pick up a mixture of the reflected plethysmographic signal along with other sources of fluctuations in light due to artefacts. Given that haemoglobin absorptivity differs across the visible and near-infrared spectral range, each colour sensor records a mixture of the original source signals with slightly different weights. [9]

- **Meta-Learning**

The authors propose a method based on Meta-Learning. rPPG signals are usually collected using a video camera with a limitation of being sensitive to multiple contributing factors, e.g. variation in skin tone, lighting condition and facial structure. End-to-end supervised learning approach performs well when training data is abundant, covering a distribution that doesn't deviate too much from the distribution of testing data or during deployment. To cope with the unforeseeable distributional changes during deployment, the researchers propose a transductive meta-learner that takes unlabeled samples during testing (deployment) for a self-supervised weight adjustment (also known as transductive inference), providing fast adaptation to the distributional changes. Using this approach, they achieve state-of-the-art performance on MAHNOB-HCI and UBFC-rPPG. The approach of meta-learning rPPG estimation framework is to perform a fast adaptation of weights when the network is deployed in a setting that is not covered by the training distribution. [10]

- **Heart Rate Variability**

The HR counts the total number of heartbeats in a given time period, which is a very coarse way of describing cardiac activity. On the other side, HRV features describe heart activity on a much finer scale, which is computed from the IBIs of pulse signals. Most common HRV features include low frequency (LF), high frequency (HF), and their ratio LF/HF, which are widely used in many medical applications. Besides, the respiratory frequency (RF) can also be estimated by analyzing the frequency power of IBI. Apparently, compared with the task of estimating the average HR (only one number), measuring HRV features is more challenging, which requires an accurate measurement of the time location of each individual pulse peak. For the needs of most healthcare applications, average HR is far from enough. [11]

Since the measurement of heart rate is a sensitive and important issue for human health, studies should be done carefully. Many methods used for many years have provided great benefits in the health sector. With the PPG technology that came into our lives in 1930, heart rate measurement was carried out in a contact manner until the latest technological developments. With the development of technology, it has been focused on non-contact measurement techniques. ECG devices used in contact measurement make a pulse estimation by giving a graph of the electrical activity of the heart against time by using electrodes placed on the skin. Oximeters, another commonly used method, monitor the perfusion of blood into the dermis and subcutaneous tissue of the skin. Makes heart-rate estimates with the data it obtains. This method is called PPG and it constitutes the basic working principle of rPPG. The logic is the same in rPPG. The only difference is that we try to extract the signals returning from the skin from the image recorded from the camera, not with the oximeter. After passing the image obtained through many different stages, we estimate the pulse rate from the amount of blood flowing under the skin with the result we obtain. In methods such as EKG and PPG, the necessity of being connected to physical mechanisms both causes limitation of movement and the use of transportation is more costly. In rPPG methods, we find the opportunity to estimate the heart rate using a simple webcam or phone camera without getting stuck in these restrictions. The different methods and approaches we explained above have been cited from different studies. As we can see here, although each of them is closely related, they have advantages and disadvantages compared to each other. We aim to make an rPPG application where we can make a pulse estimation with the least error margin by focusing on the methods that will minimize the errors among these methods.

5. Scope of the Project

The scope of our project is estimating the heart rate of the person using a properly shot video. We have two public datasets as PURE and UBFC-rPPG. In the PURE dataset, there are 60 records of 1 minute each with 10 persons (8 male, 2 female) and 6 different setups as steady, talking without head movements, slow translation, fast translation - twice slow translation speed - average speed was %7 of the face height per second, small head rotation - 20°, medium head rotation - 35°. In this dataset, the minimum pulse rate measured using the oximeter is at 42 BPM and the maximum rate was 148 BPM. In the UBFC-rPPG dataset, there are 42 records about 1 m away from the camera. All experiments are conducted indoors with a varying amount of sunlight and indoor illumination.

Firstly, we will implement the ICA method using these two datasets and then compare these two datasets. Then we will implement the deep learning-based iPHYS and 3D-CNN methods on these two data sets and then compare them. In the first part of our study, we expect the subjects to stand upright in front of the camera and the ambient lighting to be sufficient. In this scope, after achieving our goal, we can focus on the necessary improvements. In addition, at this stage, we consider cases where the subjects do not have a beard, moustache, makeup, facial type disorder or birthmark. Different approaches and solution techniques for such special cases are not currently within our scope.

Finally, we will implement our project by taking the SynRythm [12] method as a reference with all the experiences we have gained and the different perspectives we have acquired. We will make the necessary improvements and tests. Our goal is estimating the heart rate in immobile subjects with a maximum margin of error is +-5 beats per minute and in moving experiments, our goal is to see that the margin of error can be accepted up to 10 hits.

6. Success Factors and Benefits

6.1. Measurability / Measuring Success

The main objective of the project is to develop a contactless photoplethysmography method that can monitor heart rate using a webcam using deep learning methods. The project will be considered successful if our requirements listed below are fulfilled:

- We will determine the ROI(region of interest) area(e.g. forehead area and cheeks area) on the face correctly.
- We will track the detected ROI region throughout the video.
- The heart rate root means squared error(RMSE) measured by our method is less than 5 beats per minute.
- The heart rate means absolute error(MAD) measured by our method.
- The Pearson correlation measured by our method.

6.2. Benefits / Implications

The benefits of our project are:

- It will minimize the changes in heart rate due to the stress of being connected to a device.
- Remotely measuring heart rate for sensitive individuals and babies in intensive care units.
- Measuring the remote heart rate of a person who has a burn because he or she can’t wear pulse oximeters.
- Other applications: measuring the heart rate of a person at a gym, and drivers.

7. Methodology and Technical Approach

7.1 Implementation and Comparison of Signal Decomposition Based Methods

First of all, we will detect the face with a Viola-Jones face detector [13] using a simple webcam. We will detect ROI from the face we have obtained and we will follow this ROI throughout the video. We will create colour signals from the colour channels coming from the ROI and after applying Independent Component Analysis (ICA) to these signals, it will generate separated source signals. We will select the most traceable BVP of these signals and find the frequency domain of this signal from the power spectral density (PDS) distribution, which we obtained using Welch's method. We will be able to access HR from the frequency domain.

As a result of our literature reviews, these techniques have been used in many studies. We have explained the steps related to ICA through the studies made by referring to the article 'Noncontact, automated cardiac pulse measurements using video imaging and blind source separation' by MIT [14].

In this article, experiments were conducted with people of different ages and different groups, including men and women. BVP sensor was used to measure the actual heart rate of the person. In addition, experiments were carried out indoors and with well-adjusted ambient light. The experimental area is as Figure 6:

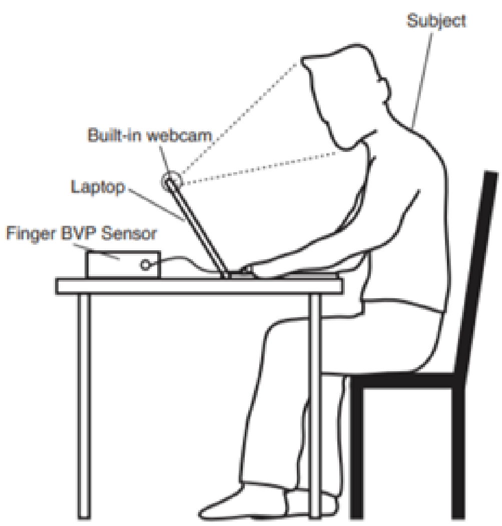

Figure 6: Experimental setup [14]

The main source for this study is the radiating vascular pulse wave throughout the body. Volumetric changes are observed in facial vessels during the cardiac cycle. RGB colour sensors take a mix of the plethysmographic signal from the face area with the web camera.

Haemoglobin absorptivity differs across visible and infrared rays. Each colour sensor records a mixture of signals of different weights. Signals recorded from red, green, and blue are denoted by $x_1(t)$, $x_2(t)$ and $x_3(t)$. respectively. In conventional ICA the number of recoverable sources cannot exceed the number of observations, thus source signals are represented by $s_1(t)$, $s_2(t)$ and $s_3(t)$.

The ICA model assumes that the observed signals are linear mixtures of the sources i.e. $x_i(t) = \Sigma a_{ij} s_j(t)$ for each *i = 1,2,3.* This can be represented compactly by the mixing equation:

$$x(t) = As(t) \tag{1}$$

where the column vectors $x(t) = [x_1(t), x_2(t), x_3(t)]T$, $s(t) = [s(t), s(t), s(t)]T$ and the square *3 × 3* matrix A contains the mixture coefficients a_{ij}. The aim of ICA is to find a separating or demixing matrix W that is an approximation of the inverse of the original mixing matrix A whose output

$$s(t) = Wx(t) \tag{2}$$

We should maximize the non-Gaussian resource.

Automatic face tracker was used to find each measurement area in the video. OpenCV face detection algorithm is used. Previous face coordinates were used to reduce segmentation errors in the face area. If more than one face was detected while waiting for a single face, the algorithm chose the closest face coordinates from the previous frame.

Then the face region was divided into three RGB channels red, blue and green, respectively $x_1(t)$, $x_2(t)$ and $x_3(t)$. Then they normalized the RGB traces as follows.

$$x_i'(t) = \frac{x_i(t) - \mu_i}{\sigma_1} \tag{3}$$

for each *i = 1,2,3* where μi and σi are the mean and standard deviation of $x_i(t)$ respectively. The normalization transforms $x_i(t)$ to $x_i'(t)$ which is zero-mean and has a unit variance.

The raw traces are then split into three different signals using ICA. We can see the methodology of ICA in Figure 7.

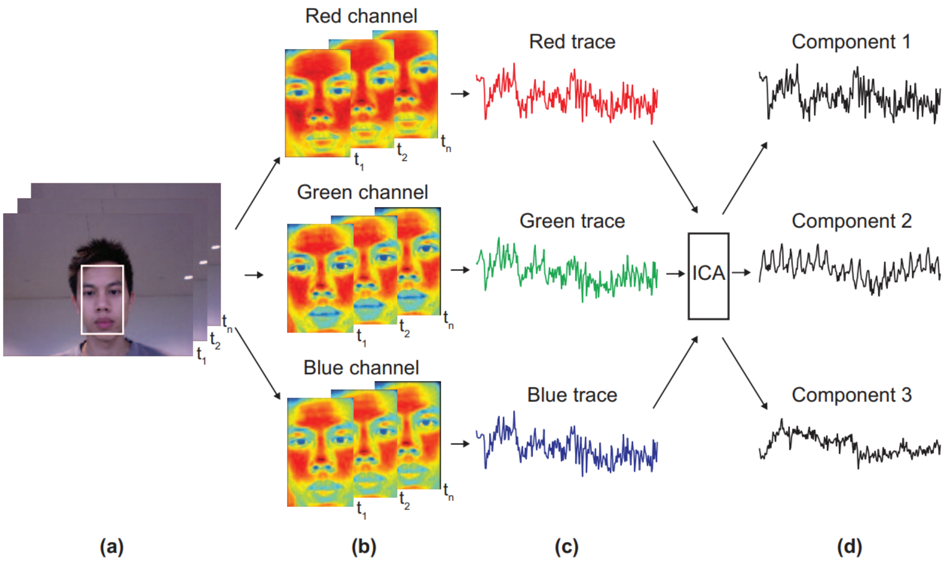

Figure 7: Cardiac pulse recovery methodology. (a) The region of interest (ROI) is automatically detected using a face tracker. (b) The ROI is decomposed into the RGB channels and spatially averaged to obtain (c) the raw RGB traces. ICA is applied on the normalized RGB traces to recover (d) three independent source signals.[14]

Finally, FFT was applied to the selected signals to obtain the power spectrum. The pulse frequency was designated as the frequency that corresponded to the highest power of the spectrum within an operational frequency band. We can see an example of recovering the cardiac pulse rate from a webcam video recording in Figure 8.

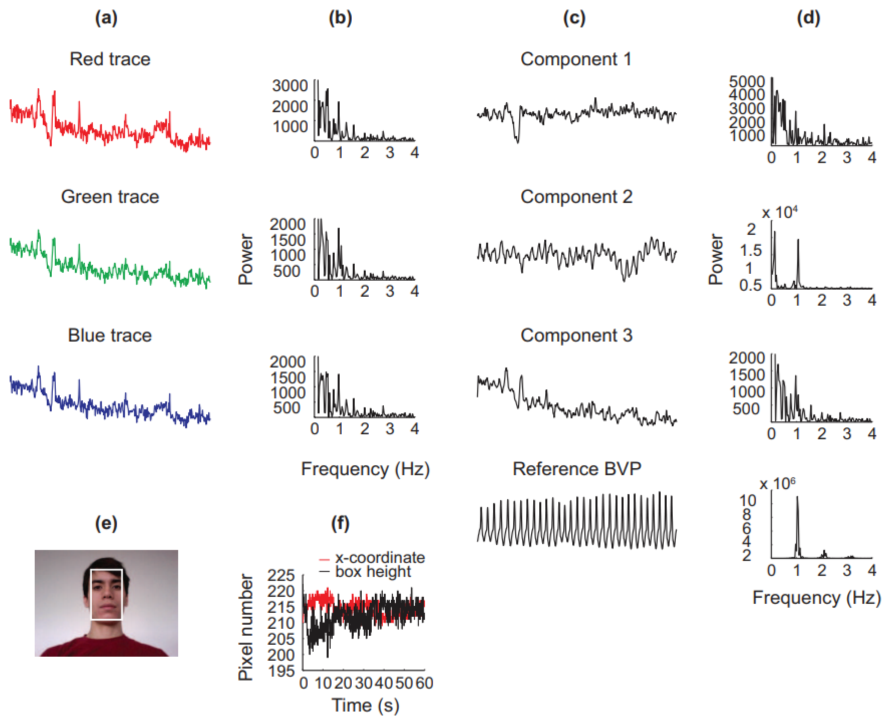

Figure 8: Recovery of the cardiac pulse from a webcam video recording of a participant at rest. (a) 30 s raw RGB traces and (b) their respective power spectra. (c) The independent components recovered using ICA along with the reference finger BVP signal and (d) their respective power spectra. (e) (Media 1) A single-frame excerpt from the webcam video recording with localized ROI (white box). (f) Evolution of the localized ROI over 1 min.

7.2 Implementation and Comparison of Deep Learning-Based Methods

We plan to carry out our measurements with deep learning methods, which is our main approach. We hope that deep learning will reduce error rates as a result of these measurements.

We have explained a Deep learning method we plan to use from the article 'Learning a Deep Heart Rate Estimator from General to Specific' [12].

First, in Figure 9, they used ImageNet to train the model and a large amount of synthetic rhythm spatial-temporal maps to pre-train deep HR regression models. Then the pre-trained model was transferred to the real HR estimation task where only a small portion of operational face video data is available in this target domain.

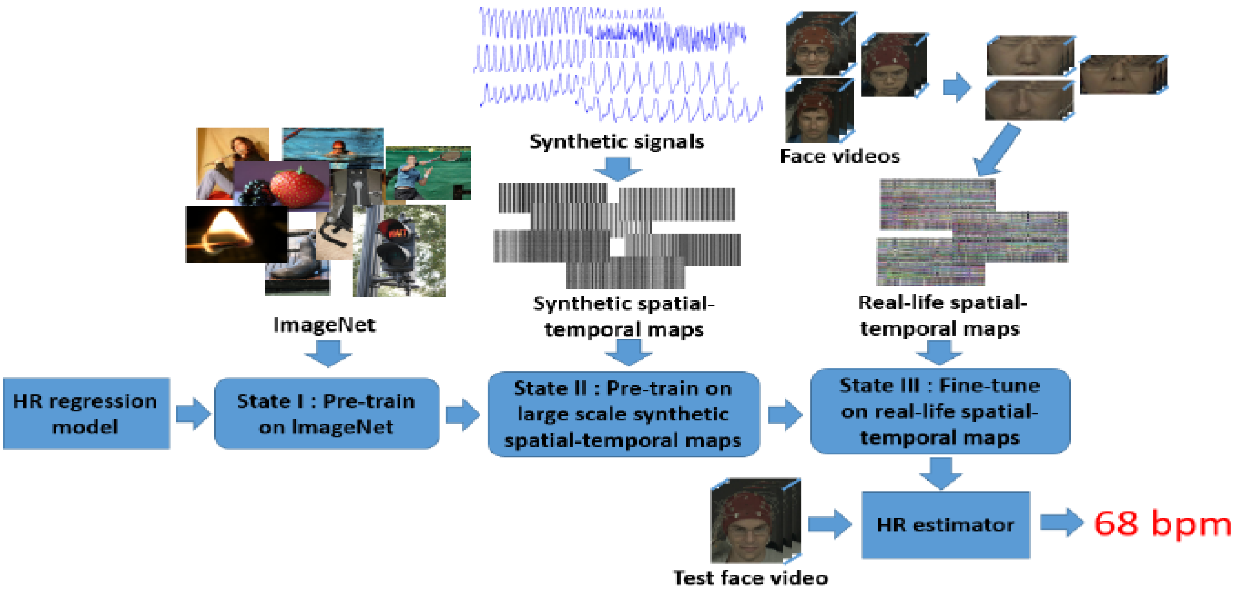

Figure 9: A diagram of the proposed deep heart rate estimator using a spatial-temporal representation and general-to-specific transfer learning.[12]

The face area that shows the colour changes in the best way is the cheek area. This area is much less active than the eye area.

After the cheek area was obtained, they resized $M * N$ into a rectangular shape. Then they divided the cheek rectangle by n ROI. Based on the n blocks, they generated a spatial-temporal representation map for each face video sequence. Average pooling is helpful to reduce the sensor noises of heart rhythm signals. Let $C(x, y, t)$ denotes the value at location (x, y) of the the frame from one of the R, G and B channels, and the average pooling of the ith block ROI for each channel at time t can be presented as

$$\overline{C_i}(t) = \frac{\Sigma_{x,y \in ROI_i} C(x, y, t)}{|ROI_i|} \quad (4)$$

Where $||ROI||$ denotes the area of a block (the number of pixels). So, for each face video they obtain temporal *3*n* sequences with the length of for R, G, and B channels, e.g., $C_i = \{\overline{C_i}(1), \overline{C_i}(2), ... \overline{C_i}(T)\}$ where C donates one of the R, G and B channels and *i* donates the index of the ROI.

They propose a synthetic heart rhythm-generating algorithm to replicate the colour changes caused by the actual heart rhythm. In order to overcome the noise introduced by facial movement or illumination changes, a random step signal and a random Gaussian noise are added to the original signal. The final formulation of the generated signal S can be presented as follow,

$$S = M_1 sin(\omega_1 t + \phi) + 0.5 M_1 sin(2\omega_1 t + \phi) + M_2 sin(\omega_2 t + \phi) + P_1 Step(t - t_1) + P_2 Step(t - t_2) + N(t) \quad (5)$$

Where M1 and M2 are the magnitudes randomly sampled from [0,1]; ω_1 and ω_2 are the frequencies of the cardiac cycle and breath activity; Step(t) is a step signal and t_1 and t_2 are randomly chosen in the range of $[0; T]$. P_1 and P_2 are the probabilities from a Bernoulli distribution. N donates the Gaussian noise function. We can see that the synthetic signals generated by the proposed approach are able to replicate the real signals when the subject is stable.

8. Professional Considerations

8.1. Methodological Considerations / Engineering Standards

- We will use GitHub to manage version control
- We will use Python to develop the software.
- We will use UBFC and PURE datasets.

- We will use the Waterfall Project Management Model for the software development process.
- We will use Gantt charts for our management plan.

8.2. Societal / Ethical Considerations

8.2.1. Economical

Since our studies do not require the use of devices such as pulse oximetry used in hospitals, it is an economically viable study as we can measure it using a simple webcam.

8.2.2. Environmental

The equipment we will use in our work does not contain any substances that can pollute the environment.

8.2.3. Health and Safety

Since the main purpose of rPPG is to calculate heart rate for non-contact patients, it is a method that can be used for every patient. In addition, it does not pose any threat to patients in terms of health and safety.

8.2.4. Legal Considerations

Since the datasets and libraries we will use are open source, they do not pose a legal problem. Python source code and installers are available for download for all versions and we have a free license for students on GitHub.

9. Management Plan

9.1. Phases

Phase 1: Deciding the project subject, then understanding and identifying the problem. Making the literature survey of rPPG. Investigation of previous studies about the project. Analyzing the current methods and different approaches.

Phase 2: Reading the reviews of the related works and planning general methodology. Finding the dataset to be used in the project. Preparing and submission project specification document (PSD).

Phase 3: Provision of equipment and establishment of development environments. Studying and comparing on the UBFC and PURE datasets with iPhys and CNN libraries.

Phase 4: Evaluation of the results and deciding the detailed process. Presentation of the first part of the project. Preparing analysis and design document (ADD).

Phase 5: Implementation of rPPG algorithm based on SynRhythm study in Python. Applying deep learning approaches.

Phase 6: Testing on real data. Observing the results and generating decision logic. Detection and improvement of the errors.

Phase 7: Preparation for final presentation, report and poster of the project.

9.2. Gantt Chart & Timeline

As we can see in Chart 1, the general management and time plan of the project can be described as follows:

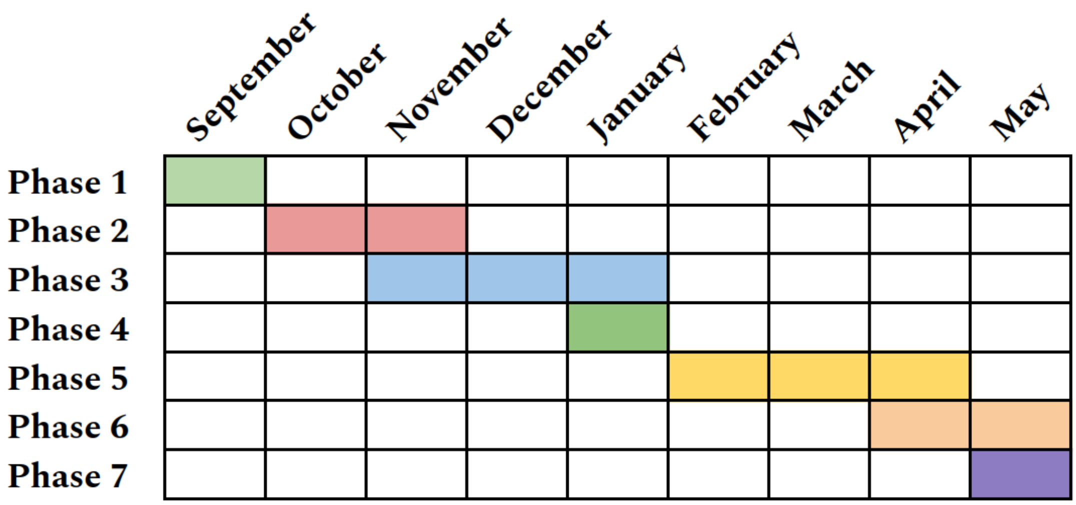

Chart 1: The gantt chart of general management and time plan

9.3. Division of Responsibilities Among Team Members

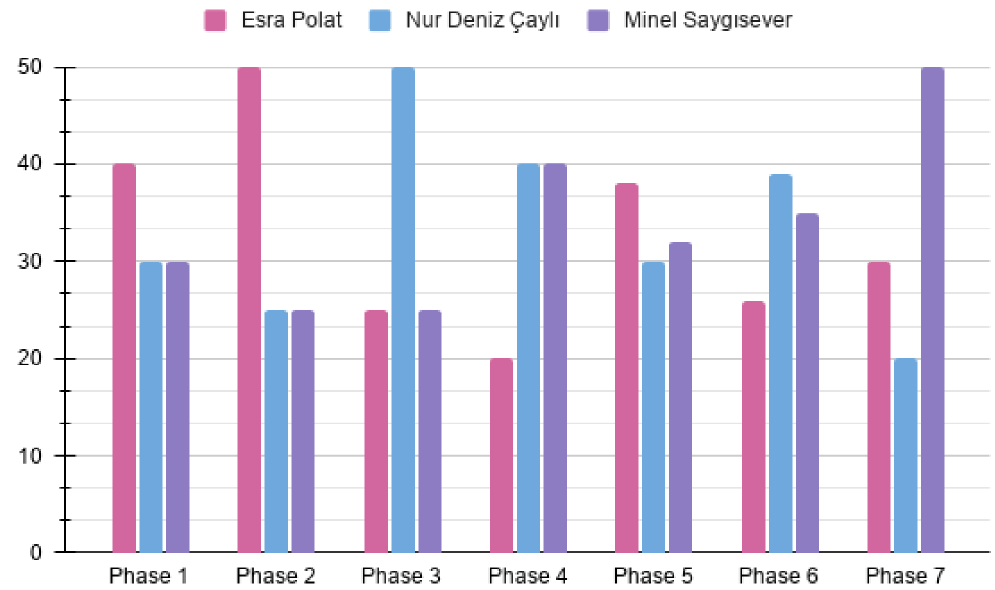

Chart 2: Division of responsibilities of phases among team members

<table>
<tr><th></th><th>Esra Polat</th><th>Nur Deniz Çaylı</th><th>Minel Saygısever</th></tr>
<tr><td rowspan="4">Phase 1</td><td colspan="3">deciding the project subject</td></tr>
<tr><td colspan="3">understanding and identifying the problem</td></tr>
<tr><td colspan="3">the literature survey of rPPG</td></tr>
<tr><td colspan="3">analyzing the current methods and different approaches</td></tr>
<tr><td rowspan="3">Phase 2</td><td colspan="3">planning general methodology</td></tr>
<tr><td colspan="3">preparing project specification document (PSD)</td></tr>
<tr><td>finding the dataset</td><td></td><td></td></tr>
<tr><td rowspan="3">Phase 3</td><td></td><td>provision of equipment</td><td>establishment of development environments</td></tr>
<tr><td>studying on the UBFC dataset</td><td>studying on the PURE dataset</td><td>comparing UBFC and PURE datasets</td></tr>
<tr><td>checking over iPhys</td><td>checking over CNN</td><td></td></tr>
<tr><td rowspan="3">Phase 4</td><td></td><td>evaluation of the results</td><td>evaluation of the results</td></tr>
<tr><td colspan="3">presentation</td></tr>
<tr><td colspan="3">preparing analysis and design document (ADD)</td></tr>
<tr><td>Phase 5</td><td>implementation of SynRhythm</td><td>implementation of SynRhythm</td><td>applying deep learning approaches</td></tr>
<tr><td>Phase 6</td><td></td><td>improvement of the errors</td><td>testing on real data</td></tr>
<tr><td rowspan="2">Phase 7</td><td colspan="3">presentation</td></tr>
<tr><td>preparation of poster</td><td></td><td>preparation of report</td></tr>
</table>

Cooperation Esra Polat Nur Deniz Çaylı Minel Saygısever

Table 1:Division of responsibilities of phases among team members

We can see the timeline that visualizes the intervals of project steps in Figure 10.

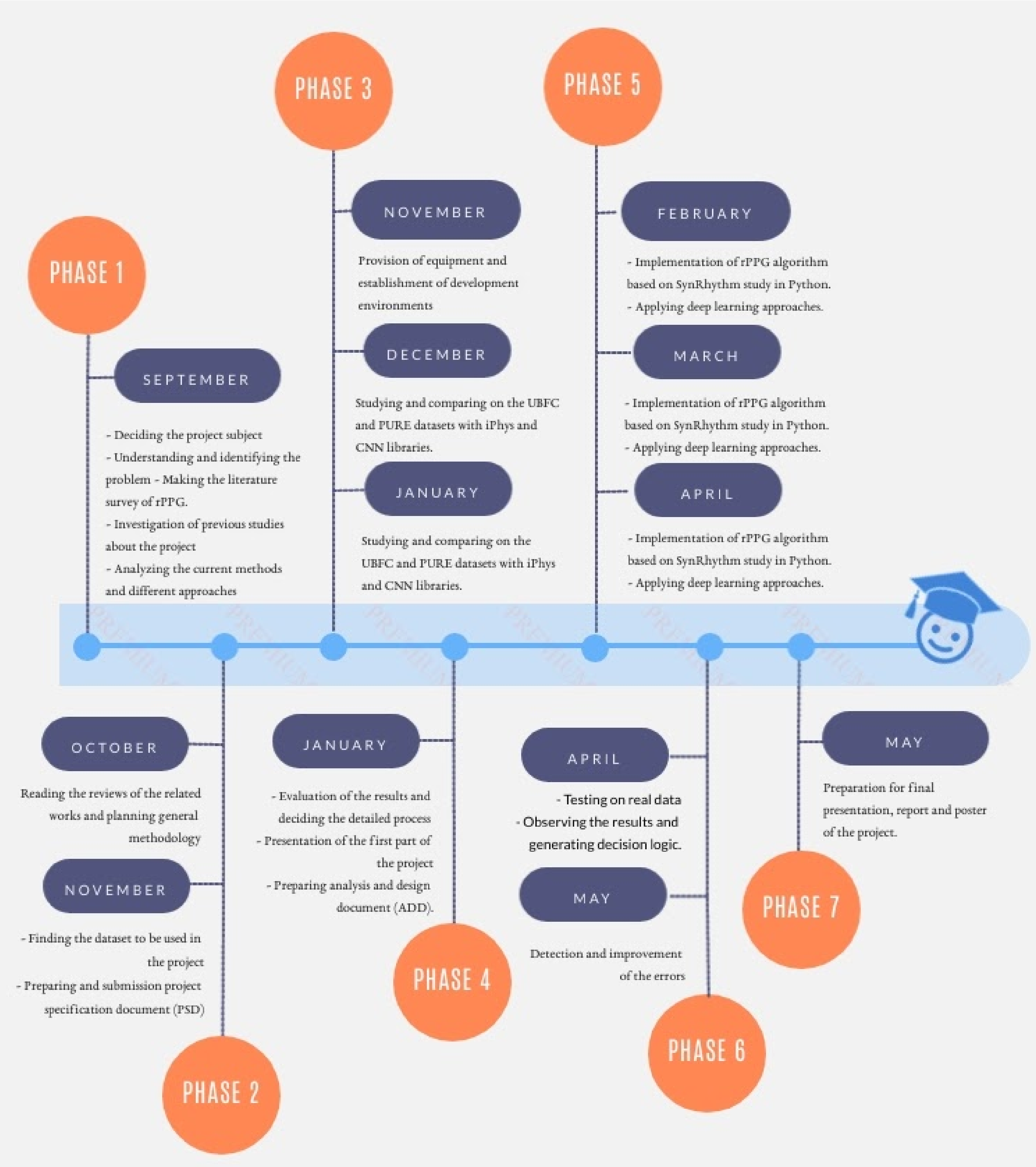

Figure 10:Timeline of the project

9.4. Risk Management

LIKEHOOD		POSSIBLE RISKS
	HIGH	unpredictable changes in lighting conditions
	HIGH	moving of subject during the experiment
	MEDIUM	darker the skin color
	LOW	unknown disease, using glasses, birthmark or deformity on face

Table 2: Possible risks and likelihood of these

The first risk that we face to face is unpredictable changes in lighting conditions. Our study is not aimed at a system that is compatible with different light conditions. However, we will focus on maximum improvement for a system that works consistently in all conditions. In the learning and testing parts, we will prefer quality and diverse data sets. Another risk is that the human subject moves too much during the experiment. This can negatively affect results. The results may also be miscalculated if the human subject has an unknown disease, using glasses, birthmark or deformity on his face. In addition, the darker the skin color, the harder the prediction will be. We will try different techniques to deal with these problems. We will search for the region that gives the most accurate result by making measurements from different parts of the face. We aim to design a system where we will reach the lowest margin of error by performing many tests with a variety of human subjects and unlabeled data. We can see the summary of possible risks in Table 2.

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