What are the existing methods of sleep detection?

- **Medical Approach**
  - Process called "polysomnography" to detect sleep cycles
  - Makes determination based on brain activity (primary measure), eye activity, blood oxygen levels, heart rate and rhythms, breathing rate, respiratory effort, body movements, and snoring

- **Smartwatch Approach**
  - Makes an estimate using a combination of heart rate, heart rate variability, and motion detection

What are RR intervals and how do they help with sleep detection?

- RR intervals represent the time between successive heartbeats, measured via ECG. Long RR intervals are a fundamental feature of Heart Rate Variability (HRV) from which various HRV metrics are calculated.

- Fluctuations in RR intervals reflect changes in autonomic nervous system activity, which varies during different sleep stages.

**METHOD**

**PART 1 - PULSE EXTRACTION (RRP PIPELINE)**

The pipeline starts with capturing video input using OpenCV with idle, activity landmarks for data detection and sleep onset location.

We then extract the green channel from the RR video for preprocessing. This is performed on each window with the intention that the green channel most accurately represents and captures the motion of the human heart.

For training, we collected 12 channels through 22 wireless attachments to the patient.

In the preprocessing step, the heart detection is performed first to then optimally align and integrate the trends to make more immediate and sophisticated estimations. The heart detection method uses a 3x3 Convolutional Neural Network (CNN) model for better identification of significant peaks.

In the first stage, we conduct a Fast Fourier Transform (FFT) on the processed green channel data through window-based analysis. The data is zoomed in to 80-second windows, and the result is divided by a second for each subsequent window. The system does not forget the largest peak windows and extract a heart backdrop, correlating to heartbeat 48 to 180 beats per minute.

**PART 2 - SLEEP STAGE DETERMINATION**

**EEG PIPELINE**

**ECG to HRV FEATURES DATA PRE-PROCESSING PIPELINE**

- Using the raw ECG data, we collect RR intervals. The RR intervals are used to calculate two new features: HRV and the sleep stage.

- The RR intervals are then used to determine the sleep stage.

**PART 3 - SLEEP STAGE VERIFICATION**

**EEG PIPELINE**

- We analyze the EEG data to determine the sleep stage.

- The EEG data is divided into sections, and each section is analyzed to determine the sleep stage.

**COMPARING RESULTS, WITH EPOCH INDEX VS. WITHOUT**

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**RESULTS & FINDINGS**

Using the remote photoplethysmography (RRP pipeline) described above, we achieved an average error rate of 5% in heart rate measurements across 50 trials conducted under ideal conditions. The pipeline accurately captured both active and passive heart rate trends over time. Building upon the RRP pipeline, the study incorporated Heart Rate Variability (HRV) data to classify sleep stages, employing the AUTOMATE sleep preprocessing pipeline, incorporating eeg stress and epoch analysis, the research surpassed notable precision in sleep stage classification:

- **Test Accuracy**: A said 94.87%, indicating a high rate of correct predictions by the model.
- **Cohen’s Kappa**: At 0.76, this reflects good agreement, surpassing random chance significantly.
- **Macro F1 Score**: With a score of 0.81, the balance between precision and recall across all sleep stages indicates reliable performance.

The incorporation of the epoch index improves model predictability as evidenced by higher Cohen’s Kappa and F1 scores. The implementation effectively synthesized a feature into the preprocessing pipeline, demonstrating the potential of non-invasive sleep stage classification through HRV analysis. This approach could lead to improved patient comfort and accessibility in sleep studies. These methods will be integrated to conduct a sleep study and demonstrate a complete pipeline that can identify sleep stages autonomously.

**CONCLUSION**

The emergence of smartwatch technology and portable health monitors has sparked a significant shift in the landscape of sleep analysis. Companies like Fitbit and Garmin have spearheaded this movement, showcasing the efficacy of leveraging metrics such as heart rate, heart rate variability, and motion detection as indicators of sleep and its various stages. Simultaneously, researchers, notably those at MIT, have been diligently analyzing data to extract vital signs like pulse, opening up a novel avenue for sleep monitoring.

However, despite these promising advancements, there has been a notable gap in integrating these disparate technologies into a unified system capable of extracting sleep stages directly from raw video feeds. Our Capstone project has sought to bridge this gap, demonstrating that it is indeed feasible to construct such a system with a commendable level of accuracy. By combining insights from both the research and sensor technologies and vision-based pulse extraction methods, we have taken a significant step towards realizing our overarching objective: democratizing and streamlining sleep analysis.

We are optimistic that our project serves as a catalyst for future endeavors in this domain, encouraging further exploration and innovation towards making sleep analysis more accessible and seamless for individuals worldwide. By harnessing the potential of diverse technologies and interdisciplinary collaboration, we can unlock new frontiers in understanding and optimizing sleep health, ultimately enhancing overall well-being and quality of life.