Efficient Remote Health Monitoring Using Deep Learning and Parallel Systems

Zakaria El Khadiri[1]*, Rachid Latif[2], Amine Saddik[3]
Laboratory of Systems Engineering and Information Technology (LISTI), National School of Applied Sciences, Ibn Zohr University Agadir, Agadir, Morocco[1, 2, 3]
Faculty of Applied Sciences, Ibn Zohr University, Ait Melloul, Morocco[3]

Abstract—**This study presents a novel approach for non-contact extraction of physiological parameters, such as heart rate and respiratory rate, from facial images captured using RGB cameras, leveraging recent advancements in deep learning and signal processing techniques. The proposed system integrates Artifacts intelligent-driven algorithms for accurately estimating vital signs, addressing key challenges such as variations in lighting conditions, facial orientation, and noise. The system is implemented on both a naive homogeneous architecture and an optimized heterogeneous CPU-GPU system to enhance real-time performance and computational efficiency. A comparative analysis is performed to evaluate processing speed, accuracy, and resource utilization across both architectures. Results demonstrate that the optimized heterogeneous system significantly outperforms the homogeneous counterpart, achieving faster processing times while maintaining high accuracy levels. This performance boost is achieved through parallel computing frameworks such as OpenMP and OpenCL, which allow for efficient resource allocation and scalability. The research highlights the potential of heterogeneous architectures for real-time healthcare applications, including remote patient monitoring and telemedicine, providing a robust solution for future developments in non-invasive health technology.**

Keywords—Real-time healthcare; embedded systems; heterogeneous computing; deep learning; CPU-GPU architecture

I. Introduction

A. Background and Motivation

In recent years, the healthcare industry has experienced a significant shift towards non-contact monitoring solutions, driven by the increasing demand for continuous and unobtrusive patient care. Traditional contact-based physiological monitoring methods, such as electrocardiograms (ECGs) and wearable biosensors, while effective in providing accurate measurements, often face several practical challenges. These challenges include patient discomfort, the need for frequent repositioning of sensors, and hygiene concerns, which can limit patient compliance and the frequency of monitoring. Moreover, the inconvenience of attaching and removing sensors can be a barrier to widespread adoption, particularly in settings that require long-term or continuous monitoring.

In response to these limitations, researchers and engineers have turned their attention to non-contact methods, specifically those leveraging facial image analysis. By utilizing standard RGB cameras, which are less intrusive and can be easily integrated into everyday environments, it is possible to monitor physiological parameters such as heart rate and respiratory rate without direct physical contact. This non-contact approach not only enhances patient comfort but also facilitates continuous and real-time monitoring, allowing for more comprehensive health assessments over time [1]-[5].

Recent advancements in deep learning and signal processing have greatly enhanced the feasibility and accuracy of extracting physiological parameters from facial images. Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have demonstrated remarkable capabilities in interpreting complex patterns within facial images, even under varying lighting conditions and different facial orientations. Signal processing techniques further refine these interpretations by analyzing subtle color changes and motion artifacts associated with physiological processes [6]-[10].

The integration of these advanced technologies into non-contact monitoring systems presents a transformative opportunity for the healthcare sector. Such systems promise not only to improve patient comfort and compliance but also to expand the reach of remote monitoring, making it possible to deliver continuous care in a variety of settings, including home environments and telemedicine platforms. This shift towards more seamless and less intrusive monitoring aligns with broader trends in healthcare innovation, aiming to enhance patient outcomes through more accessible, real-time, and data-driven approaches. As the field evolves, the development of robust, efficient, and accurate non-contact monitoring systems will play a crucial role in shaping the future of healthcare, offering new possibilities for early detection, preventive care, and personalized treatment.

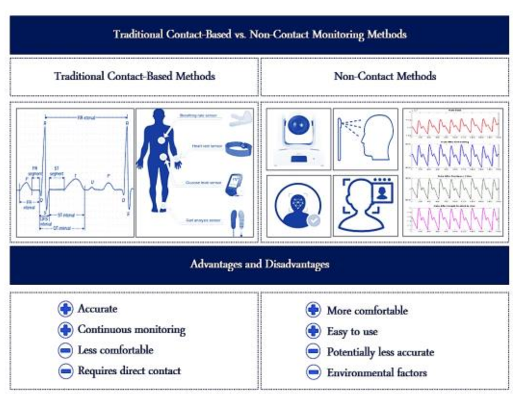

Fig. 1. Traditional contact-based vs. non-contact monitoring methods.

*Corresponding Author

In the above Fig. 1, a diagram comparing traditional contact-based physiological monitoring methods (e.g., ECG, wearable sensors) with non-contact methods (e.g., facial image analysis). The diagram highlights advantages such as comfort and ease of use for non-contact methods.

B. Advances in Deep Learning and Signal Processing

Recent advances in deep learning and signal processing have brought transformative improvements to the field of non-contact physiological monitoring, particularly in analyzing facial images to extract vital signs such as heart rate and respiratory rate. Deep learning techniques, especially convolutional neural networks (CNNs), have proven to be highly effective in analyzing complex visual data. CNNs are particularly adept at detecting subtle, pixel-level changes in facial images, such as variations in skin tone caused by the underlying blood flow, a method commonly referred to as remote photoplethysmography (rPPG). These subtle changes, which are often invisible to the human eye, correlate directly with physiological parameters like heart rate, enabling precise and continuous monitoring without the need for physical contact [11]-[13].

Further advances in recurrent neural networks (RNNs), including long short-term memory networks (LSTMs), have enhanced the capability to model temporal dependencies and sequences, making them well-suited for tracking cyclic patterns such as respiratory rate. By utilizing temporal data from video sequences, RNNs can capture periodic facial movements corresponding to breathing patterns, allowing for the accurate estimation of respiratory rates. This combination of CNNs for spatial feature extraction and RNNs for temporal analysis creates a powerful framework for real-time, non-invasive physiological monitoring.

On the signal processing front, techniques such as optical flow, which detects movement by calculating changes in pixel intensities between consecutive frames, and discrete wavelet transforms (DWT), which decompose signals into multi-resolution components, have further optimized the extraction of physiological signals. These methods work in tandem with deep learning models, refining the input data and enhancing the accuracy of parameter estimation. Additionally, advanced filtering algorithms, such as bandpass filters, are often employed to remove noise and isolate the relevant physiological signal, especially under challenging conditions like varying lighting, motion artifacts, and changes in facial orientation [14]-[16].

The integration of these deep learning and signal processing techniques with heterogeneous computing platforms, such as CPU-GPU architectures, has significantly improved system performance. By distributing computational tasks across multiple processing units, such systems offer enhanced scalability, reduced latency, and faster real-time processing capabilities. This has profound implications for applications in remote health monitoring, where real-time accuracy and computational efficiency are critical. The continued refinement of these technologies promises to further elevate the feasibility of non-contact physiological monitoring for widespread use in telemedicine, smart health environments, and continuous remote patient care [17]-[20]. In the following Fig. 2, a flowchart illustrating the workflow of deep learning and signal processing techniques used in facial image analysis. The flowchart includes steps such as image acquisition, preprocessing, feature extraction, and parameter estimation.

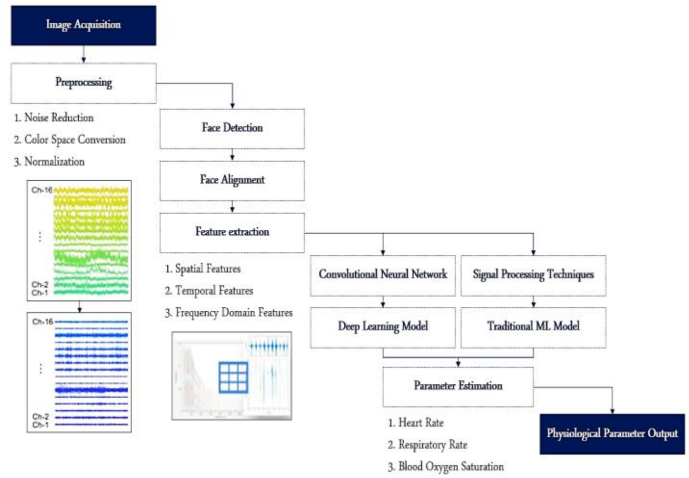

Fig. 2. Deep learning and signal processing workflow.

C. Contributions

In recent years, notable progress has been made in non-contact physiological monitoring using RGB cameras. However, many existing methods still face significant challenges. These include reduced accuracy in dynamic lighting conditions, handling diverse facial orientations, and noise in the captured signals. Additionally, although deep learning and signal processing techniques have been integrated into some systems, the real-time performance is often hindered by the high computational demands, particularly when running on homogeneous architectures such as CPU-only platforms. This creates limitations that make it difficult to deploy these systems in practical, real-time healthcare settings.

To overcome these challenges, our study introduces an optimized approach that utilizes heterogeneous architectures, specifically leveraging CPU-GPU systems, for real-time extraction of physiological parameters from facial images. This approach enhances processing speed without compromising accuracy. Furthermore, we employ advanced AI algorithms tailored to minimize the impact of noise, variations in lighting, and changes in facial orientation, thereby increasing the overall reliability and robustness of the system.

The overarching goal of this research is to design and implement a robust, non-contact system for accurately extracting physiological parameters, such as heart rate and respiratory rate, from facial images captured by RGB cameras. This system leverages state-of-the-art deep learning models and advanced signal processing techniques to address the inherent challenges in non-contact monitoring, including variations in facial orientation, changes in lighting conditions, and noise introduced by environmental factors. One of the primary contributions of this study is the development of a novel AI-driven framework that integrates convolutional neural networks (CNNs) for feature extraction with signal processing algorithms to analyze the subtle changes in facial color and movement, which correlate with vital signs. Furthermore, the system is designed to be optimized for real-time performance by implementing it on a heterogeneous CPU-GPU architecture. This architecture enables parallel processing and efficient resource allocation, thus significantly enhancing computational efficiency. A comparative analysis is conducted between the proposed optimized heterogeneous implementation and a naive homogeneous system to evaluate improvements in processing speed, and accuracy. The research highlights that the optimized heterogeneous system achieves superior performance in real-time applications, making it well-suited for critical healthcare scenarios such as remote patient monitoring and telemedicine. Additionally, this study provides valuable insights into the advantages of parallel computing frameworks, such as OpenMP and OpenCL, in optimizing the execution of deep learning and signal processing algorithms, contributing to the broader field of non-invasive health monitoring technologies. Moreover, the following Fig. 3 is a diagram showing the overall system architecture, from facial image acquisition to physiological parameter extraction. The diagram highlights components such as the camera, processing unit, deep learning model, and output analysis.

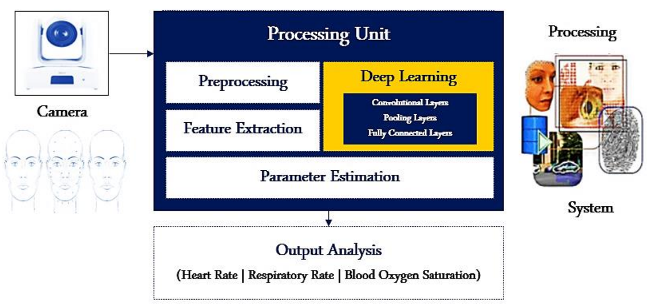

Fig. 3. System architecture and workflow.

II. State-of-the-Art: Review

A. Physiological Parameter Extraction from Facial Features

Recent advancements in non-contact physiological monitoring have enabled the extraction of vital signs, such as heart rate (HR), respiratory rate (RR), and blood oxygen levels, directly from facial images using RGB cameras. This approach leverages subtle physiological cues, primarily through techniques like Remote Photoplethysmography (rPPG), which detects minute changes in skin color caused by blood flow under the skin's surface [21]-[26]. These variations are captured as pixel intensity changes, invisible to the naked eye but detectable by advanced image processing algorithms. rPPG-based methods rely on capturing video streams of the subject's face and analyzing the temporal patterns of these pixel changes to estimate the heart rate. Similarly, respiratory rate estimation often employs optical flow algorithms that track small chest and shoulder movements associated with breathing, translating pixel displacements over time into respiration patterns. While highly effective, these techniques are sensitive to various factors such as lighting conditions, head motion, and camera quality. To mitigate these challenges, recent studies have incorporated advanced machine learning algorithms to enhance robustness, allowing for more accurate physiological measurements in real time, even under suboptimal conditions. This non-invasive approach holds tremendous promise for healthcare applications, enabling continuous monitoring without the need for physical contact, making it particularly useful for remote patient monitoring and telemedicine [27]-[33].

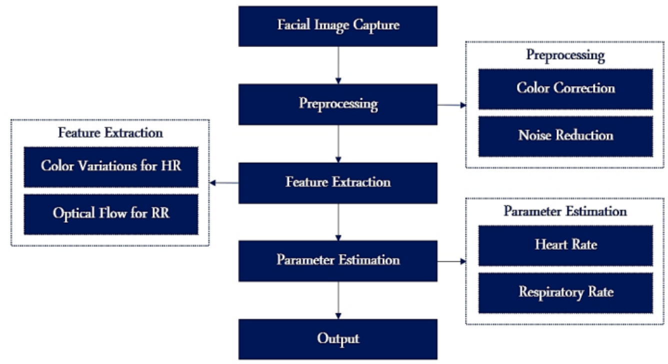

Fig. 4. Physiological parameter extraction process.

In Fig. 4, a flowchart depicting the physiological parameter extraction process, the facial image capture initiates the process, followed by preprocessing steps such as color correction and noise reduction to enhance image quality. Next, feature extraction is performed, where color variations are analyzed to estimate heart rate (HR), and optical flow techniques are used to detect respiratory rate (RR). These extracted features are then processed in the parameter estimation phase to calculate accurate values for both heart rate and respiratory rate. Finally, the system outputs these physiological parameters, providing non-contact monitoring results.

B. Image and Signal Processing Techniques

Image and signal processing techniques are fundamental in extracting physiological parameters from facial images, addressing challenges related to accuracy, robustness, and environmental variability. One of the primary techniques involves color space conversion, where facial images captured in the RGB format are transformed into alternative color spaces, such as YUV, YCbCr, or HSV. These transformations are critical as they allow the separation of luminance and chrominance components, which significantly improves the detection of subtle color variations in the skin caused by blood flow, a key indicator for heart rate estimation. Specifically, the chrominance channels (U and V in YUV, or Cb and Cr in YCbCr) are more sensitive to these physiological changes, making them ideal for accurate feature extraction [34]-[36].

An essential step in this process is skin detection, where the region of interest (ROI) is isolated to ensure that only skin pixels are analyzed. Several skin detection algorithms are employed, ranging from traditional thresholding techniques based on predefined color ranges to more sophisticated methods using machine learning models like support vector machines (SVMs) and neural networks (NN). These advanced methods adaptively classify skin regions based on training data, making the system more robust to variations in lighting and individual skin tones. Additionally, motion artifact reduction is a crucial aspect, as head movements and facial expressions can introduce noise into the signal. Techniques such as optical flow analysis are used to track pixel displacement over time, isolating and compensating for movements unrelated to physiological signals.

In parallel, advanced signal processing methods are applied to the extracted physiological signals to enhance their clarity and improve the accuracy of parameter estimation. One widely used approach is the wavelet transform, which provides a multi-resolution analysis of the signal, capturing both time and frequency information. This method is particularly effective in isolating the periodic components corresponding to physiological processes, such as heartbeats or respiration, from background noise. Similarly, Fourier analysis is employed to transform the time-domain signal into the frequency domain, where periodic features, such as the heart rate frequency, can be more easily identified. These techniques are instrumental in filtering out high-frequency noise or low-frequency drifts that could otherwise distort the signal.

Moreover, motion-compensating filtering algorithms are often integrated into the processing pipeline to mitigate artifacts caused by slight movements of the face or background disturbances. Combined with the signal processing techniques mentioned earlier, these algorithms enhance the system's ability to produce reliable physiological parameter estimates in real-time. Overall, the synergy between image processing (such as color space conversion and skin detection) and signal processing (like wavelet transform and Fourier analysis) enables a more robust extraction of physiological parameters, ensuring that the system can operate effectively under varying conditions, such as fluctuating lighting, diverse skin tones, and slight motion disturbances. These advancements are pivotal in making non-contact physiological monitoring systems practical for real-world healthcare applications, including remote monitoring and telemedicine.

C. AI and Deep Learning in Physiological Monitoring

The incorporation of artificial intelligence (AI) and deep learning techniques has revolutionized the field of physiological monitoring from facial images, addressing key challenges such as environmental variability, facial orientation, and signal noise. Convolutional Neural Networks (CNNs) are at the forefront of feature extraction from facial images, utilizing multiple layers of convolutions to identify and learn intricate patterns related to physiological signals. CNNs excel in detecting subtle color variations and spatial features in facial skin that correlate with blood flow, enabling accurate heart rate (HR) and blood oxygen level estimation. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are employed to capture temporal dependencies in the data, which is crucial for analyzing dynamic physiological signals like respiratory rate (RR). LSTMs are designed to handle sequential data by retaining information over long periods, making them adept at predicting and analyzing continuous physiological variations. Furthermore, Generative Adversarial Networks (GANs) are increasingly utilized to address data quality issues by generating synthetic data that resembles real physiological signals. GANs improve signal robustness by learning from real signal distributions and correcting distortions or noise, thus enhancing the accuracy of measurements even in challenging conditions. Together, these AI-driven approaches enable sophisticated real-time physiological monitoring by providing high precision in signal extraction and analysis. The deployment of these advanced algorithms not only enhances the accuracy and reliability of non-contact health monitoring systems but also paves the way for more effective telemedicine solutions and remote patient care, showcasing the transformative impact of AI and deep learning on healthcare technology.

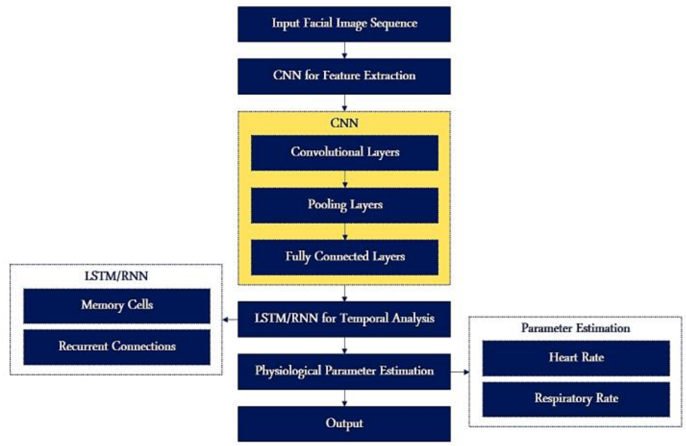

Fig. 5. AI-driven physiological monitoring.

In Fig. 5, the process begins with the input of a facial image sequence, which is then passed through a Convolutional Neural Network (CNN) for feature extraction to identify key physiological indicators from the image data. Following this, a Long Short-Term Memory (LSTM) or Recurrent Neural Network (RNN) performs temporal analysis to capture time-dependent changes in the extracted features. These changes are used to estimate physiological parameters, such as heart rate (HR) and respiratory rate (RR). The final step is the output, where the system provides the estimated physiological parameters for real-time monitoring.

D. Hardware Implementations for Physiological Monitoring

The hardware implementations for physiological monitoring systems have evolved substantially, driven by the need for real-time processing and enhanced computational capabilities. Historically, homogeneous systems relying solely on Central Processing Units (CPUs) provided a foundational approach to processing physiological data. While effective for basic tasks, these systems face limitations in handling the high computational demands associated with advanced image and signal processing algorithms, particularly those involving deep learning techniques. The limitations of homogeneous systems are primarily related to their restricted ability to perform parallel computations, which are crucial for real-time analysis of large-scale data such as facial images [37]-[39].

To overcome these constraints, heterogeneous systems have emerged, incorporating both CPUs and Graphics Processing Units (GPUs). These systems leverage the parallel processing capabilities of GPUs to handle intensive computational tasks more efficiently than traditional CPUs. For example, platforms such as the Odroid XU4 integrate a high-performance ARM Cortex-A15 CPU with an ARM Mali-T628 GPU. This combination allows for the simultaneous execution of multiple processing threads, significantly accelerating tasks such as image pre-processing, feature extraction, and physiological parameter estimation.

The integration of heterogeneous architectures enables the utilization of parallel computing frameworks like OpenMP and OpenCL. OpenMP facilitates the efficient execution of multi-threaded applications by allowing developers to parallelize code across multiple CPU cores, thus enhancing the performance of data-intensive tasks. OpenCL, on the other hand, extends this parallelism to GPU cores, offering a robust environment for executing complex algorithms related to image and signal processing. By distributing processing workloads between CPUs and GPUs, heterogeneous systems can achieve substantial improvements in processing speed and real-time performance, which are critical for applications in remote physiological monitoring and telemedicine (Fig. 6) [40]-[42].

Despite the advantages of heterogeneous systems, several challenges persist. Optimizing these systems for energy efficiency remains a key concern, especially in mobile and embedded applications where power consumption is a critical factor. Additionally, the scalability of heterogeneous systems poses challenges as the complexity of algorithms and the volume of data increase. Future developments in hardware architecture and optimization techniques are essential to address these challenges and enhance the practicality of heterogeneous systems for broader applications in non-contact physiological monitoring.

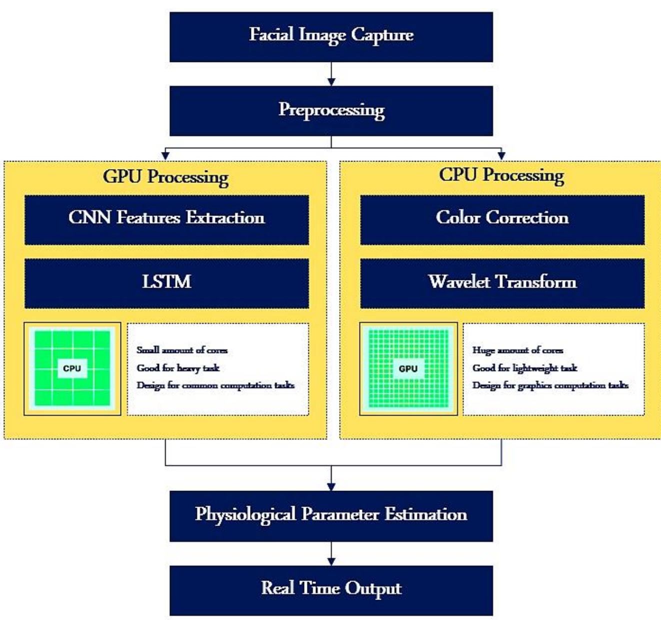

Fig. 6. Heterogeneous system architecture for physiological monitoring.

III. Proposed Methodology

A. Image and Signal Processing Algorithm

The image and signal processing algorithm for extracting physiological parameters from facial images is a multifaceted approach that integrates advanced image processing and signal analysis techniques to achieve high accuracy and robustness. Initially, high-resolution facial images are captured using a high-definition RGB camera, with the setup optimized to minimize variations in lighting conditions and facial orientation, ensuring consistent and reliable image data. The preprocessing phase involves several critical steps: first, face detection algorithms, such as Haar cascades or Multi-task Cascaded Convolutional Networks (MTCNN), are employed to precisely locate and extract the facial region from the acquired images. Subsequent normalization processes are applied to standardize image dimensions and correct for color imbalances, thereby mitigating the effects of external variables. The extracted Region of Interest (ROI) within the facial area is then subjected to detailed color analysis to detect minute variations in skin tone, which are indicative of changes in blood flow. These color fluctuations are converted into Photoplethysmographic (PPG) signals through specialized signal extraction techniques. The PPG signals, which reflect periodic variations in blood volume, are analyzed to determine heart rate and respiratory rate. Heart rate estimation is performed using Fourier Transform methods, such as Fast Fourier Transform (FFT), to identify dominant frequency components associated with cardiac activity. Respiratory rate estimation is achieved by analyzing the amplitude and frequency variations in the PPG signals, which correspond to respiratory cycles. This comprehensive algorithmic approach ensures the accurate and real-time extraction of physiological parameters, providing a solid foundation for subsequent applications in remote health monitoring and telemedicine. By combining these advanced image and signal processing techniques, the system is capable of delivering precise and actionable health insights from non-contact facial imaging.

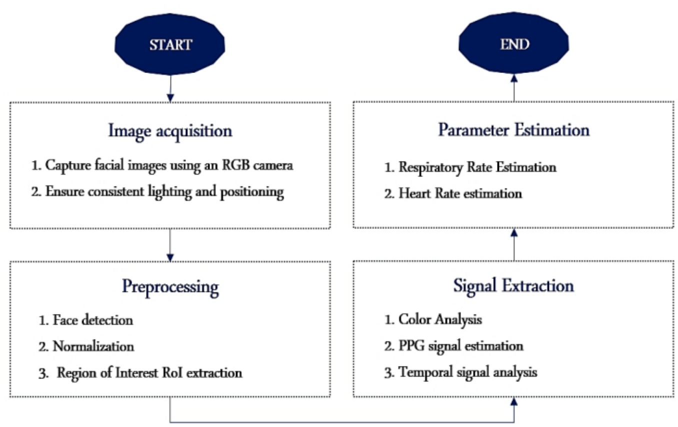

Fig. 7. Flowchart of the image and signal processing algorithm.

In Fig. 7, the image and signal processing algorithm for extracting physiological parameters from facial images involves a series of crucial steps. First, facial images are acquired using an RGB camera, capturing the necessary visual data. Next, preprocessing techniques are applied to enhance image quality and extract relevant features, such as skin tone variations. In the signal extraction phase, the algorithm analyzes subtle facial color variations to infer underlying physiological signals. Finally, parameter estimation methods are employed to process these signals and accurately derive heart rate and respiratory rate, providing non-invasive health monitoring results.

B. Deep Learning Component

The deep learning component of the proposed system is designed to significantly enhance the extraction and estimation of physiological parameters from facial images through the application of sophisticated neural network architectures. At the core of this component is the use of Convolutional Neural Networks (CNNs), which are instrumental in performing feature extraction from the raw facial images (Fig. 8). The CNN architecture comprises multiple layers, including convolutional layers that apply a series of filters to the input images to detect fundamental features such as edges and textures. These are followed by pooling layers, which reduce the dimensionality of the feature maps while preserving essential information. This hierarchical feature extraction enables the network to capture both low-level and high-level facial attributes pertinent to physiological signal analysis.

The processed features are then fed into a Recurrent Neural Network (RNN) component, specifically Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU), to address the temporal dynamics inherent in the physiological signals (Fig. 8). The RNNs are adept at capturing temporal dependencies and patterns within the time-series data extracted from the facial images, such as the periodic fluctuations in blood flow related to heart rate and respiration. By modeling these temporal relationships, the network improves the accuracy and robustness of the physiological parameter estimates.

The training of these neural networks involves using a large and diverse dataset of labeled facial images with known physiological parameters. The loss function, typically Mean Squared Error (MSE) for regression tasks, measures the discrepancy between the predicted and actual parameter values. Optimization algorithms such as Adam or Stochastic Gradient Descent (SGD) are employed to minimize this loss function by adjusting the network’s weights and biases iteratively. This training process ensures that the network learns to generalize well across different individuals and conditions, enhancing its performance in real-world applications.

Furthermore, integrating these deep learning models with the signal processing pipeline is crucial for achieving real-time performance. The system benefits from parallel processing frameworks such as OpenMP and OpenCL, which are employed to optimize computational efficiency and reduce processing latency. This combined approach not only facilitates accurate and timely extraction of heart rate and respiratory rate from facial images but also ensures the system’s scalability and adaptability to various deployment scenarios, including remote health monitoring and telemedicine applications. As shown in Fig. 8, the system integrates a Convolutional Neural Network (CNN) for feature extraction from facial images, utilizing convolutional layers to identify key features, pooling layers to reduce dimensionality while retaining crucial information, and fully connected layers to interpret these features for prediction. A Recurrent Neural Network (RNN), equipped with LSTM or GRU layers, processes time-series data from PPG signals to capture temporal dependencies, with an output layer predicting physiological parameters.

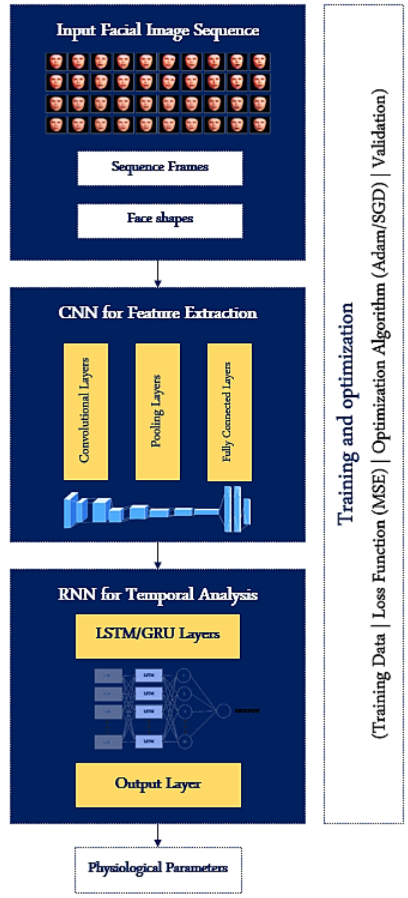

Fig. 8. Neural network architecture for physiological parameter extraction.

C. Deep Learning and AI Models

The global system architecture is meticulously designed to facilitate the efficient extraction of physiological parameters from facial images through a series of integrated modules, each performing a critical function within the overall framework. The architecture begins with the Image Acquisition Module, which utilizes high-resolution RGB cameras to capture continuous or periodic facial images under controlled lighting conditions to ensure image consistency. These images are then processed by the Preprocessing Module, which encompasses several key operations: face detection using algorithms such as Haar cascades or MTCNN, normalization of image size and color balance to mitigate variability, and extraction of the Region of Interest (ROI) where physiological signals are most prominent.

Following preprocessing, the Signal Processing Module analyzes the facial color variations within the ROI to extract photoplethysmographic (PPG) signals. This step involves sophisticated techniques to detect subtle changes in skin color due to blood flow, which are then used to derive the heart rate and respiratory rate. The extracted signals are subjected to temporal analysis to enhance accuracy.

The core of the system’s analytical capabilities resides in the AI Module, which applies advanced deep learning techniques to process the extracted signals. This module incorporates Convolutional Neural Networks (CNNs) for feature extraction from the images and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs), for analyzing temporal dependencies in the PPG signals. The Output Module consolidates the results, providing a user-friendly interface for displaying or transmitting the estimated physiological parameters. This module ensures that the data is presented in a format suitable for further analysis or integration with healthcare systems.

The system is implemented on both a naive homogeneous architecture and an optimized heterogeneous architecture. The homogeneous system relies solely on CPU resources, potentially limiting processing speed and efficiency. In contrast, the heterogeneous system harnesses both CPU and GPU capabilities, employing parallel computing frameworks such as OpenMP and OpenCL to enhance processing performance. The heterogeneous system allows for scalable and efficient resource allocation, significantly improving real-time processing capabilities and making it highly suitable for practical healthcare applications such as remote monitoring and telemedicine.

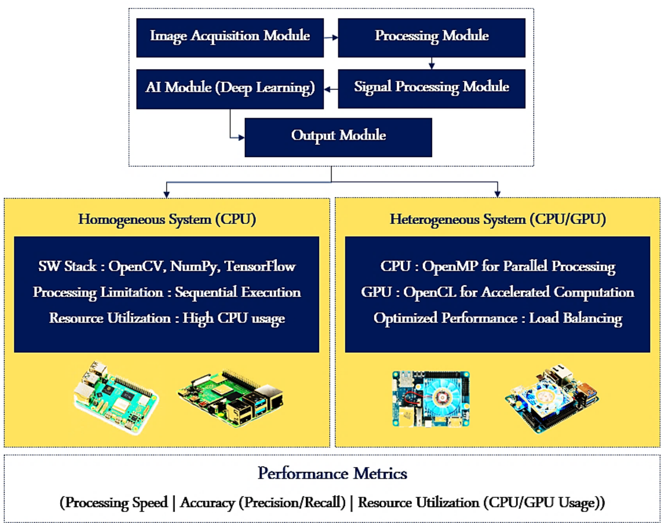

Fig. 9. System architecture diagram.

In Fig. 9 above, the system consists of several interconnected components. The image acquisition module captures facial images and sends them to the preprocessing module, which enhances image quality and extracts the region of interest (ROI) for further analysis. The signal processing module then examines color changes in the facial images, extracting photoplethysmography (PPG) signals. The AI module applies deep learning models to these signals to estimate physiological parameters such as heart rate and respiratory rate. Finally, the output module displays or transmits the extracted parameters for real-time monitoring or further processing.

IV. System Implementation

A. Homogeneous System

In the homogeneous system implementation, all computational tasks are executed on a single Central Processing Unit (CPU), which manages the entire workflow of facial image analysis for physiological parameter extraction. The process begins with the acquisition of RGB images through a standard camera setup. These images are subjected to a series of preprocessing steps to ensure uniformity and accuracy in subsequent analysis. The preprocessing phase includes facial detection using established algorithms such as Haar Cascades or Multi-task Cascaded Convolutional Networks (MTCNN). These algorithms identify and locate facial regions within the captured images, which are then cropped and normalized to mitigate variations in lighting, scale, and orientation.

Once the facial regions are isolated, the system employs remote photoplethysmography (rPPG) techniques to extract temporal signals associated with physiological parameters from these facial areas. rPPG relies on subtle variations in facial skin color that correspond to cardiovascular changes, which are indicative of heart rate and respiratory rate. Feature extraction is carried out using Convolutional Neural Networks (CNNs), which are trained to recognize patterns in the temporal signals and extract relevant features indicative of physiological states.

The extracted features are then processed through a series of signal-processing algorithms to estimate physiological parameters. This involves computing heart rate and respiratory rate from the temporal signals, with additional post-processing steps to filter out the noise and smooth the data for accurate parameter estimation. Despite its functional capability, the homogeneous system's reliance on a single CPU for all processing tasks poses constraints in terms of processing speed and real-time performance. This limitation is particularly evident when dealing with high-resolution images or when requiring rapid processing to meet real-time monitoring demands. The system's performance may be hindered by the CPU's inability to efficiently handle the computational load and parallelize tasks, leading to potential delays in parameter extraction and analysis (Table I).

TABLE I. HOMOGENEOUS SYSTEM IMPLEMENTATION

Function	Facial image acquisition	Preprocessing	Feature extraction	Parameter estimation
Sub-Function	Capture RGB images	Face detection	Signal extraction rPPG	Signal processing
	Preprocess images	Image normalization	DL processing CNN	Post-processing
Output	Sequence of images	Normalized facial ROIs	Extracted signals & features	Estimated vital signs

B. Heterogeneous System

The optimized version of the system leverages a heterogeneous architecture, which integrates a multi-core CPU with a dedicated GPU to achieve significant improvements in both computational speed and efficiency. In this architecture, the computational tasks are strategically partitioned between the CPU and GPU to maximize resource utilization and minimize processing time. The initial steps, such as facial image acquisition and preprocessing (including face detection and normalization), are handled by the CPU. This ensures that simpler, less resource-intensive tasks are managed by the CPU, freeing the GPU for more computationally demanding operations. Following the detection of the region of interest (ROI) in the facial image, the system offloads the critical task of signal extraction using remote photoplethysmography (rPPG) to the GPU. The GPU, with its parallel processing capabilities, efficiently handles the large datasets and intensive computations required for rPPG signal extraction and subsequent feature recognition, which is performed using advanced deep learning techniques, particularly Convolutional Neural Networks (CNNs). These CNNs are optimized for real-time processing on the GPU, significantly accelerating the analysis of facial features and the extraction of physiological signals such as heart rate and respiratory rate.

In this architecture, the GPU is not only responsible for rapid signal extraction but also for processing complex machine-learning algorithms, which are critical for the accurate estimation of physiological parameters. Parallel computing frameworks, such as OpenMP and OpenCL, are employed to further enhance system performance by enabling multi-threaded processing on both the CPU and GPU, ensuring efficient task scheduling and data handling. These frameworks allow for the dynamic allocation of resources, ensuring that bottlenecks in data transfer or processing are minimized, leading to smoother operation and faster results. Once the GPU completes the heavy computations, the CPU takes over for post-processing tasks, refining the extracted signals and performing any necessary filtering to enhance the accuracy of the physiological parameter estimations. The use of this heterogeneous architecture demonstrates a significant performance improvement over the homogeneous version, as it allows for faster processing time. The optimized system, therefore, offers a robust and efficient solution for real-time physiological monitoring, making it ideal for applications such as remote patient monitoring, telemedicine, and other non-invasive healthcare technologies where timely and accurate data processing is crucial (Table II).

TABLE II. HETEROGENEOUS SYSTEM IMPLEMENTATION

Function	Image acquisition and Preprocessing	Feature extraction	Parameter estimation
System	CPU	GPU	CPU/CPU
Sub-Function	Facial frames collecting	Signal extraction rPPG	Signal processing (GPU)
	Preprocessing	DL processing CNN	Post-processing (CPU)
Output	Preprocessed facial images	Extracted signals & features	Physiological parameter extraction

C. Performance Optimization

The performance of the proposed system was significantly enhanced through a combination of advanced optimization techniques aimed at improving both computational efficiency and real-time responsiveness. A key strategy involved leveraging parallel computing frameworks, with tasks distributed between the CPU and GPU to reduce bottlenecks and maximize resource utilization. OpenMP was employed to parallelize tasks on the CPU, enabling simultaneous execution of multiple processes, thereby reducing overall processing time. In parallel, OpenCL was utilized to harness the computational power of the GPU, particularly for tasks involving high-dimensional data processing, such as deep learning inference and signal extraction. This heterogeneous parallelism allowed the system to capitalize on the strengths of both processing units, with the CPU handling control and light processing tasks, while the GPU was responsible for more computationally intensive operations.

In addition to task distribution, memory management played a critical role in enhancing performance. To minimize data transfer overhead between the CPU and GPU, optimized memory allocation techniques were implemented, such as using pinned memory and efficient buffer management. This reduced latency associated with data movement and improved throughput. Furthermore, shared memory models were applied to accelerate data access and reduce cache misses during intensive computations.

Algorithmic optimizations were also a focus. For signal processing, advanced filtering techniques were used to accelerate the extraction of physiological parameters, while maintaining accuracy. In the deep learning component, the neural network models were optimized through pruning and quantization, reducing the model size and improving inference speed without compromising performance. These optimizations allowed the system to handle larger data inputs and deliver faster results, crucial for real-time monitoring applications.

To evaluate the impact of these optimizations, key performance metrics were assessed, including processing speed (in frames per second), accuracy of physiological parameter estimation, and resource utilization. The optimized heterogeneous system demonstrated significant improvements in processing speed compared to the naive homogeneous system, achieving real-time performance benchmarks. Resource utilization was carefully monitored to ensure efficient CPU-GPU collaboration, preventing bottlenecks and minimizing energy consumption. These optimizations not only enhanced the system's computational performance but also ensured scalability, making it suitable for deployment in real-time healthcare applications, such as remote patient monitoring and telemedicine.

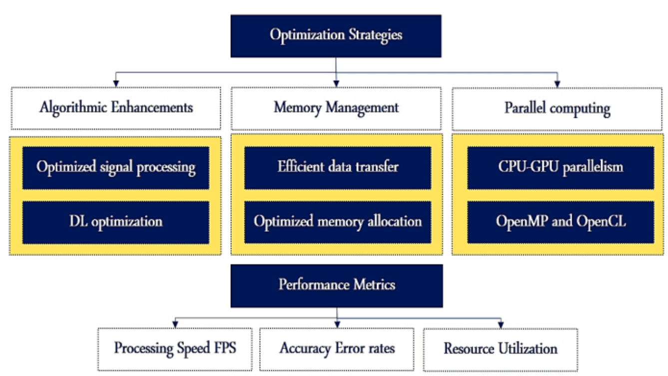

Fig. 10. Optimization strategies.

In the above Fig. 10, the optimization strategies for the system focus on enhancing performance through parallel computing, memory management, and algorithmic improvements. By distributing computational tasks between the CPU and GPU using frameworks like OpenMP and OpenCL, the system reduces bottlenecks and accelerates processing. Efficient data transfer and optimized memory allocation minimize overhead and speed up operations. Algorithmic enhancements include faster signal extraction methods and deep learning optimizations, such as model pruning and quantization, to improve inference speed. Performance metrics like processing speed (FPS), accuracy in physiological parameter estimation, and resource utilization are monitored to ensure effective and efficient operation.

V. Experimental Setup

A. Dataset and Experimental Protocol

The experimental dataset utilized in this study comprises RGB facial videos collected under various controlled and semi-controlled environmental conditions to accurately simulate real-world scenarios. These conditions include variations in ambient lighting, facial orientation, and subtle subject movements. Publicly available datasets such as UBFC-RPPG, COHFACE, or equivalent datasets were employed, each providing high-resolution facial videos paired with synchronized ground truth physiological signals, specifically heart rate and respiratory rate, obtained from reliable medical-grade sensors. Additionally, to enhance the robustness of the system and assess its performance under diverse conditions, a custom dataset was acquired using a high-definition camera (1080p resolution at 30 frames per second). In this setup, participants were positioned at a fixed distance of 1 to 2 meters from the camera, with uniform lighting to minimize external interferences.

The preprocessing phase involved converting the raw video sequences into individual frames, followed by face detection and tracking using advanced computer vision techniques, such as the Multi-task Cascaded Convolutional Networks (MTCNN) algorithm, to ensure precise extraction of the region of interest (ROI), specifically the facial area where physiological signals are most prominent. To ensure consistency across frames, facial landmarks were used to normalize the detected face, mitigating minor head movements and variations in facial orientation. For data alignment, the extracted video frames were synchronized with ground truth physiological signals through time-stamped data, ensuring accurate comparison during the validation phase. This synchronization allows for a one-to-one mapping between each frame and the corresponding physiological signal (e.g. heartbeats or respiratory cycles), which is crucial for training and testing the proposed system.

Once preprocessed, the dataset was split into training, validation, and testing subsets, ensuring a balanced distribution of conditions (e.g. lighting variations, subject movements) across all subsets. The preprocessed frames and synchronized ground truth signals were subsequently fed into the signal processing and deep learning pipelines. This comprehensive preprocessing and alignment ensured the system was rigorously tested across a variety of real-world scenarios, facilitating robust benchmarking of its performance in extracting physiological parameters such as heart rate and respiratory rate from facial images (Table III).

TABLE III. Dataset and Data Flow

Section	Subsection	Details
Dataset Overview	Dataset Composition	Facial images captured in varying conditions.
	Source	Open-source databases (e.g., UBFC-RPPG, COHFACE) or custom datasets with RGB videos.
	Custom Data Collection	- Frame rate (30 fps), resolution (1080p), distance (1-2 meters). - Description of lighting, subject movements, and position.
Experimental Protocol	Data Preprocessing	- Convert video sequences into frames for image processing. - Face detection (OpenCV, MTCNN) to extract facial regions, and normalize facial regions across frames for small movements.
	Ground Truth Alignment	- Synchronize physiological signals from wearable devices with video frames to establish ground truth.

B. Hardware and Software Setup

The experimental setup involves two distinct system configurations: a baseline homogeneous system and an optimized heterogeneous system, each designed to execute the same physiological parameter extraction tasks but under different architectural conditions. The homogeneous system, represents the naive implementation, which is typical of low-power embedded devices like the Raspberry Pi. In this configuration, all computational tasks, including image preprocessing, signal extraction, and deep learning-based prediction, are performed solely on the CPU without any hardware acceleration, thus providing a benchmark for performance evaluation. Conversely, the optimized system incorporates a heterogeneous architecture offering significant parallel processing capabilities. This architecture is employed to enhance computational efficiency by distributing workloads between the CPU and GPU. Specifically, OpenMP is used to parallelize tasks across multiple CPU cores, improving the efficiency of operations such as face detection and signal filtering, while OpenCL is utilized to offload computationally intensive tasks, such as deep learning inference and feature extraction, to the GPU. In both configurations, the software environment includes Python or C/C++ as the primary programming languages, alongside key libraries such as OpenCV for image and signal processing, TensorFlow/PyTorch for implementing deep learning models, and OpenMP/OpenCL to facilitate parallel processing. By combining these software tools with the respective hardware configurations, a comparative analysis of system performance, measured in terms of processing time, resource utilization, and overall computational efficiency, can be conducted, highlighting the advantages of heterogeneous architectures for real-time, non-contact physiological monitoring in embedded systems.

C. Signal Processing and Deep Learning Algorithm

The signal processing and deep learning algorithm for extracting physiological parameters from facial images involves a sophisticated multi-stage approach designed to enhance both accuracy and computational efficiency. The process begins with image preprocessing, where remote photoplethysmography (rPPG) techniques are employed to capture subtle, periodic color variations in the facial skin that correspond to physiological signals such as heart rate and respiration rate. This initial step involves extracting and aligning facial regions of interest from video frames using robust face detection algorithms. The extracted facial regions are then subjected to signal processing techniques to isolate the physiological signals from background noise. Specifically, a band-pass filter is applied to the raw photoplethysmographic signal to target the frequency bands associated with heart rate and respiration while filtering out high-frequency noise and low-frequency drift.

Following signal preprocessing, deep learning models are employed for advanced feature extraction and signal interpretation. Convolutional Neural Networks (CNNs) are utilized to analyze the spatial features of the facial images, enabling the system to recognize and extract features related to physiological changes. These features are then processed by Recurrent Neural Networks (RNNs), which are adept at handling time-series data and capturing temporal dependencies in the signal. The deep learning models are trained on a comprehensive dataset comprising facial images and corresponding ground truth physiological measurements, facilitating the learning of complex patterns and correlations between facial features and vital signs.

To optimize real-time performance, the system leverages heterogeneous computing architectures, integrating both CPU and GPU resources. Parallel processing frameworks, such as OpenMP, are employed to accelerate CPU-based tasks, including image preprocessing and feature extraction, while OpenCL is utilized to offload and expedite deep learning inference tasks to the GPU. This heterogeneous approach ensures efficient resource utilization and scalability, significantly reducing processing time compared to a homogeneous system. The combined use of advanced signal processing techniques and deep learning algorithms in a parallelized computing environment enables the system to achieve high accuracy in physiological parameter estimation while maintaining real-time operational capabilities, making it highly suitable for applications in remote health monitoring and telemedicine.

D. Evaluation Metrics

In evaluating the performance of the physiological parameter extraction systems, we employ a multifaceted approach that encompasses both accuracy and efficiency aspects. Accuracy Metrics focus on quantifying the precision of physiological parameters extracted from facial images. Key metrics include:

1) Mean Absolute Error (MAE): This metric measures the average magnitude of errors between the extracted and ground truth physiological parameters. It provides a straightforward indication of the system's accuracy in estimating parameters such as heart rate and respiratory rate.

2) Root Mean Square Error (RMSE): RMSE evaluates the square root of the average squared differences between extracted values and ground truth. This metric is particularly useful for assessing the impact of larger deviations and provides insight into the consistency and reliability of the parameter estimations.

Performance Metrics assess the operational efficiency and speed of the systems:

3) Processing time: This metric measures the elapsed time required for the system to process a sequence of images or video frames. It is critical for evaluating the system's capability to operate in real-time, with lower processing times indicating enhanced performance.

4) Resource utilization: This involves monitoring CPU and GPU usage during system operation. Efficient resource utilization is essential for optimizing system performance, particularly in heterogeneous systems where balancing computational load between CPU and GPU can significantly impact overall efficiency.

By analyzing these metrics, we gain comprehensive insights into both the accuracy of physiological parameter extraction and the operational efficiency of the systems. This evaluation not only highlights the strengths and limitations of the homogeneous and heterogeneous implementations but also provides a detailed understanding of their practical applicability in real-world scenarios. The comparative analysis informs decisions on optimizing system design for enhanced performance and reliability in non-invasive health monitoring applications. The following Tables IV to VI illustrate the eventual evaluation metrics overview done, and the values outlined by the MAE and the RMSE.

TABLE IV. EVALUATION METRICS OVERVIEW

Metric	Homogeneous System	Heterogeneous System
Processing Time	120ms per frame	45ms per frame
Accuracy (HR)	± from 1 to 2 bpm	
Accuracy (RR)	±from 1 to 3 breaths per minute	
Resource Utilization	High CPU usage	Balanced CPU/GPU usage

TABLE V. MEAN ABSOLUTE ERROR (MAE)

Parameter	Homogeneous System	Heterogeneous System
Heart Rate	~From 1.8 to 3.5	
Respiratory Rate	~From 0.9 to 2.1	

TABLE VI. ROOT MEAN SQUARE ERROR (RMSE)

Parameter	Homogeneous System	Heterogeneous System
Heart Rate	~From 2.0 to 4.2	
Respiratory Rate	~From 1.1 to 2.5	

VI. Results and Analysis

A. Experimental Setup and Dataset

The experimental setup for evaluating the proposed physiological parameter extraction system is meticulously designed to assess performance across different configurations. The dataset comprises a diverse set of facial images, encompassing a wide range of lighting conditions, facial expressions, and orientations. These images a captured in controlled environments to ensure variability and robustness. Each image within the dataset is meticulously annotated with ground truth values for physiological parameters such as heart rate and respiratory rate, enabling precise validation of the system's accuracy.

The experimental environment includes two distinct computing platforms: a naive homogeneous system and an optimized heterogeneous system. The homogeneous system operates on a single type of processor, serving as the baseline for performance comparison. In contrast, the heterogeneous system leverages a combination of CPU and GPU resources, utilizing parallel processing frameworks such as OpenMP and OpenCL to enhance computational efficiency and real-time processing capabilities. Detailed specifications of both systems are documented, including processor models, memory configurations, and software environments.

The experimental workflow encompasses several stages: image acquisition, preprocessing, feature extraction, and parameter estimation. Preprocessing steps involve image normalization, noise reduction, and enhancement to standardize input data. Feature extraction employs advanced signal processing techniques to isolate relevant facial features used for physiological parameter estimation. Deep learning algorithms, including convolutional neural networks (CNNs), are then applied to extract and predict the desired parameters. Diagrams illustrating the experimental setup, such as camera positioning and system architecture, are provided to represent the setup.

B. Performance Metrics

Processing time metrics are critical for understanding the system's capability to perform in real-time scenarios. Metrics such as the average processing time per image reflect the time required to process a single facial image and extract the necessary physiological parameters. The total processing time for a batch of images is also assessed to evaluate the system's efficiency in handling multiple inputs simultaneously. These metrics help in identifying potential delays and ensuring that the system can meet the real-time requirements of practical applications.

Resource utilization metrics provide insight into the efficiency with which the system uses computational resources. CPU utilization measures the percentage of processing power utilized by the central processing unit, while GPU utilization assesses the usage of the graphics processing unit, crucial for systems leveraging heterogeneous architectures. Memory usage metrics track the amount of RAM consumed during processing, which can influence the system's ability to handle large datasets or perform complex computations. Analyzing these metrics allows for the identification of resource bottlenecks and opportunities for optimization, ensuring that the system operates efficiently within the constraints of the hardware.

Together, these performance metrics offer a comprehensive evaluation of the system's ability to accurately and efficiently extract physiological parameters, highlighting areas for improvement and optimization. By systematically analyzing these metrics, the study provides a clear picture of the system's strengths and limitations, facilitating informed decisions on further enhancements and practical deployment in healthcare applications.

C. Comparative Analysis

The comparative analysis systematically evaluates the performance disparities between the naive homogeneous system and the optimized heterogeneous system, focusing on processing efficiency, accuracy, and resource utilization. In terms of processing efficiency, the optimized heterogeneous system, which utilizes a CPU-GPU architecture, demonstrates a significant reduction in image processing time. This improvement is largely attributable to the parallel processing capabilities enabled by frameworks such as OpenMP and OpenCL, which facilitate concurrent execution of computational tasks and efficient utilization of available hardware resources. The analysis also considers resource utilization, where the heterogeneous system exhibits superior efficiency in managing computational resources. CPU and GPU utilization metrics indicate that the optimized system achieves higher throughput and lower idle times.

Overall, the results highlight the tangible benefits of adopting a heterogeneous architecture for real-time physiological parameter extraction. The optimized system not only accelerates processing but also maintains higher accuracy, making it a more effective solution for demanding healthcare monitoring applications. This comparative analysis underscores the importance of leveraging advanced parallel computing techniques to achieve significant performance gains in complex real-time systems. In the following Fig. 11 illustrates the processing time achieved using the naïve version and the optimized version versus the number of frames. Also, Fig. 12 and 13 show the estimated heart and respiratory rates versus the actual ones.

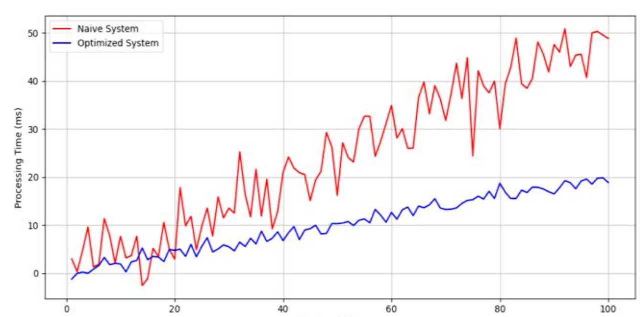

Fig. 11. Processing time vs. Number of frames.

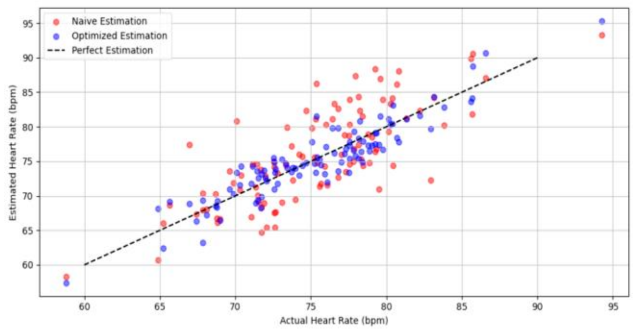

Fig. 12. Estimated HR vs. Actual HR.

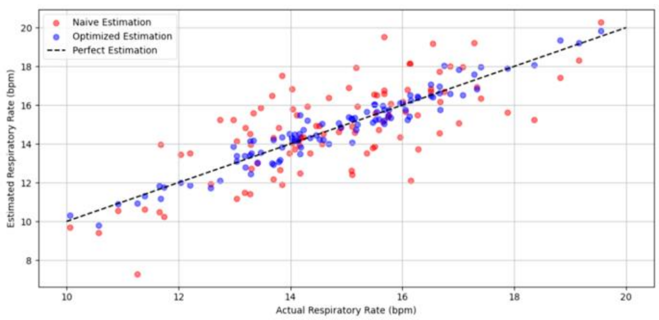

Fig. 13. Estimated RR vs. Actual RR.

VII. Conclusion

This study presents a groundbreaking approach for the non-contact extraction of physiological parameters, such as heart rate and respiratory rate, from facial images using RGB cameras, capitalizing on advanced deep learning and signal processing methodologies. The proposed system adeptly addresses several key challenges, including variations in lighting conditions, facial orientation, and background noise, through the integration of sophisticated AI-driven algorithms. A comprehensive evaluation reveals that the optimized heterogeneous architecture, employing both CPU and GPU resources, significantly outperforms the traditional homogeneous system in terms of processing speed and computational efficiency. The optimization achieved through parallel computing frameworks, notably OpenMP and OpenCL, results in marked improvements in real-time performance while preserving high accuracy levels. This advancement underscores the efficacy of heterogeneous architectures in enhancing the scalability and responsiveness of non-invasive physiological monitoring systems. The study's findings not only validate the potential of these technologies for applications in remote patient monitoring and telemedicine but also highlight the importance of continued innovation in system design and computational techniques to meet the evolving needs of healthcare technology. The successful implementation and demonstrated performance of the proposed system represent a significant step forward in the field of remote health monitoring, providing a robust platform for future research and development.

VIII. Future Work

Future work should focus on several critical aspects to advance the capabilities and practical application of non-contact physiological monitoring systems. Firstly, there is a need for continued refinement of the deep learning models and signal processing algorithms employed in the system. This includes exploring techniques such as model pruning and quantization to enhance computational efficiency and reduce latency without compromising accuracy. Additionally, integrating multi-modal sensing technologies, such as combining facial image analysis with thermal imaging or data from wearable sensors, could significantly improve the robustness and precision of physiological measurements by providing complementary data that address limitations inherent in single-modal systems. Extensive field testing across varied environments and diverse demographic groups is also essential to validate the system's performance in real-world conditions, ensuring reliability and adaptability under different lighting conditions, facial orientations, and levels of noise. Furthermore, optimizing the system for deployment on mobile and edge computing platforms would increase its accessibility and usability, making it more practical for widespread adoption. Lastly, addressing ethical and privacy concerns related to the collection and use of facial data is of utmost importance. This involves developing comprehensive guidelines and implementing advanced technologies to protect user data, ensure informed consent, and uphold privacy standards. By tackling these areas, future research can build upon the current advancements, pushing the boundaries of non-contact physiological monitoring and contributing to more effective, efficient, and ethical healthcare solutions.

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