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Pervasive Vision-Based System for Simultaneous Physiological Parameter Tracking in Intensive Care Units: A Dual-Site Clinical Evaluation

Lukas Schneider
Department of Computer Science and Biomedical Engineering, Technical University of Munich, Munich, Germany

Hanna Voge
Institute of Medical Informatics, Heidelberg University, Heidelberg, Germany

Markus Reinhardt
Department of Electrical Engineering and Information Technology, RWTH Aachen University, Aachen, Germany

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ABSTRACT

Continuous monitoring of physiological parameters in intensive care units (ICUs) is essential for early detection of clinical deterioration, prevention of adverse events, and optimization of patient management. Conventional monitoring systems rely primarily on contact-based sensors such as electrocardiography leads, pulse oximeters, and respiratory belts, which may cause discomfort, restrict patient mobility, and increase the risk of infection or skin injury during prolonged use. Recent advances in computer vision, biomedical signal processing, and artificial intelligence have enabled the development of camera-based contactless monitoring systems capable of measuring multiple vital signs simultaneously. However, the clinical reliability, scalability, and real-world applicability of such systems in critical care environments remain insufficiently validated.

This study presents a pervasive vision-based monitoring platform designed for simultaneous extraction of multiple physiological parameters, including heart rate, respiratory rate, oxygen saturation, and motion-related indicators, using non-contact imaging sensors in intensive care settings. The proposed system integrates multi-wavelength imaging, remote photoplethysmography, motion analysis, and machine learning–based signal reconstruction to achieve continuous monitoring without physical attachment to the patient. A dual-site clinical evaluation was conducted across two independent hospital ICUs to assess the robustness, accuracy, and clinical usability of the system under real-world conditions.

The methodological framework combines advanced video-based physiological measurement techniques with adaptive filtering, signal quality assessment, and intelligent feature extraction to ensure reliable operation in complex ICU environments characterized by varying lighting conditions, patient movement, and clinical interventions. Performance was evaluated against standard bedside monitoring equipment using statistical agreement analysis, error metrics, and event detection capability.

Results demonstrate that the proposed system achieves clinically acceptable accuracy for multiple vital parameters while significantly improving patient comfort and reducing sensor-related complications. The dual-center validation confirms the reproducibility of performance across different clinical infrastructures and patient populations. The findings support the feasibility of deploying pervasive vision-based monitoring as a complementary or alternative solution to conventional contact-based systems in critical care.

This research contributes to the advancement of non-contact medical monitoring technologies and provides evidence for their integration into next-generation intelligent ICU environments.

Keywords: Contactless monitoring, computer vision in healthcare, intensive care unit monitoring, remote photoplethysmography, physiological signal extraction, multi-parameter vital signs, clinical evaluation, non-invasive sensing, ICU surveillance systems, biomedical image processing.

INTRODUCTION

Continuous surveillance of physiological parameters is a fundamental requirement in intensive care units (ICUs), where patients are exposed to high risk of sudden clinical deterioration. Early detection of abnormal vital signs such as heart rate instability, respiratory irregularities, and oxygen desaturation is critical for preventing adverse outcomes and improving survival rates. Clinical studies have shown that abnormal physiological observations often precede severe complications, emphasizing the importance of reliable monitoring systems capable of providing uninterrupted and accurate measurements (Buist, 2004). Despite the widespread use of electronic monitoring devices, limitations associated with conventional sensor-based technologies remain a significant challenge in critical care environments.

Traditional ICU monitoring systems rely on contact-based sensors including electrocardiography electrodes, pulse oximeters, respiratory belts, and blood pressure cuffs. While these devices provide accurate measurements under controlled conditions, their long-term use may lead to discomfort, skin irritation, motion artifacts, and increased risk of infection, particularly in vulnerable patients such as neonates, elderly individuals, and those with compromised skin integrity. In addition, wired monitoring systems can restrict patient mobility and complicate clinical workflows, reducing overall efficiency in high-dependency care settings (Watkinson, 2006). Continuous electronic monitoring has been shown to improve patient safety, yet the physical burden imposed by sensor attachments remains a persistent limitation (McGrath, 2019).

Recent developments in computer vision and biomedical imaging have introduced the possibility of contactless physiological monitoring using cameras and optical sensors. These systems operate by analyzing subtle changes in skin color, motion patterns, and thermal variations to estimate vital signs without direct physical contact. Early research demonstrated that remote photoplethysmography could be used to extract heart rate information from video recordings by measuring variations in reflected light caused by blood volume changes (Poh, 2011). Subsequent studies expanded this concept to include respiratory rate estimation, oxygen saturation measurement, and blood pressure prediction using multi-wavelength imaging and signal processing techniques (Huang, 2024; Verkruysse, 2017).

The application of vision-based monitoring in critical care has attracted increasing attention due to its potential to provide continuous, non-invasive, and unobtrusive patient surveillance. Camera-based monitoring systems have been successfully tested for cardiorespiratory tracking, neonatal monitoring, and sleep analysis, demonstrating the feasibility of extracting clinically relevant parameters from video data (Zeng, 2024; Wang, 2024; Jorge, 2022). In neonatal intensive care units, where minimal physical contact is preferred, contactless monitoring has shown particular promise for measuring heart rate variability, respiration, and oxygen saturation without disturbing the patient (Ye, 2023; Zeng, 2025).

Despite these advancements, several technical and clinical challenges limit the adoption of vision-based monitoring systems in real ICU environments. Variations in lighting conditions, patient movement, occlusion by medical equipment, and differences in skin tone can significantly affect signal quality. Furthermore, ICU environments involve complex workflows where clinicians frequently interact with patients, making it difficult to maintain stable imaging conditions. Robust algorithms capable of handling noise, motion artifacts, and missing data are therefore required to ensure reliable operation (Wang, 2022). In addition, clinical validation across multiple hospital sites is necessary to demonstrate reproducibility and generalizability of performance.

Another critical limitation of existing research is the focus on single-parameter monitoring rather than simultaneous multi-parameter tracking. ICU clinicians rely on integrated information from multiple vital signs to make informed decisions, and systems that measure only one parameter cannot fully replace conventional monitoring devices. Multi-parameter vision-based monitoring requires advanced signal fusion techniques, synchronized feature extraction, and real-time processing capabilities to maintain clinical accuracy (Nishidate, 2022). The development of a unified platform capable of simultaneously estimating heart rate, respiration, oxygen saturation, and motion-related indicators represents a significant step toward intelligent ICU surveillance systems.

To address these challenges, this study proposes a pervasive vision-based monitoring platform designed for continuous multi-parameter physiological tracking in intensive care environments. The system integrates high-resolution cameras, multi-wavelength illumination, signal processing algorithms, and machine learning models to extract vital signs without physical contact. Unlike previous studies limited to laboratory settings or single-center evaluations, the present work includes a dual-site clinical validation to assess performance under diverse real-world conditions. Evaluating the system across two independent ICUs allows investigation of robustness against variations in infrastructure, patient demographics, and clinical procedures.

The objectives of this research are threefold. First, to design a vision-based monitoring architecture capable of simultaneous extraction of multiple physiological parameters in ICU conditions. Second, to develop signal processing and machine learning methods that maintain accuracy despite motion artifacts, lighting variability, and environmental noise. Third, to conduct a dual-center clinical evaluation comparing the proposed system with standard bedside monitors in order to determine clinical reliability and usability.

The significance of this work lies in its contribution to the development of next-generation non-contact monitoring technologies for critical care. By reducing reliance on wired sensors and enabling continuous unobtrusive surveillance, pervasive vision-based monitoring has the potential to improve patient comfort, enhance safety, and support the transition toward intelligent hospital environments. The findings of this study provide both technical and clinical evidence supporting the feasibility of deploying camera-based multi-parameter monitoring systems in real ICU settings.

2. Literature Review

The development of contactless physiological monitoring systems has emerged from the convergence of biomedical engineering, computer vision, and clinical monitoring technologies. The need for reliable, continuous, and unobtrusive monitoring in intensive care environments has driven extensive research into alternative sensing modalities capable of overcoming the limitations of traditional contact-based devices. This section critically reviews the existing literature related to physiological monitoring, camera-based sensing, remote photoplethysmography, multi-parameter extraction, and clinical validation of non-contact monitoring systems, with emphasis on identifying gaps that motivate the present study.

2.1 Limitations of Conventional Physiological Monitoring in ICU

Continuous monitoring of vital signs has long been recognized as essential for detecting patient deterioration in hospital environments. Early clinical investigations demonstrated that abnormal physiological observations often precede critical events, highlighting the importance of reliable monitoring systems capable of early warning detection (Buist, 2004). Conventional ICU monitoring relies on electrocardiography, pulse oximetry, blood pressure cuffs, and respiratory sensors, which provide accurate measurements but require physical contact with the patient. These sensors may cause discomfort, limit mobility, and increase the risk of skin injury during prolonged monitoring, particularly in critically ill or neonatal patients.

Electronic physiological monitoring has been shown to reduce adverse events when implemented continuously in high-risk wards; however, maintaining sensor placement and ensuring signal stability remain challenging in real-world clinical conditions (Watkinson, 2006). In addition, enhanced surveillance monitoring improves patient safety but may increase clinician workload due to frequent alarms and sensor adjustments (McGrath, 2019). These limitations have motivated the search for non-contact monitoring solutions capable of providing continuous measurements without physical attachments.

2.2 Emergence of Vision-Based Physiological Monitoring

Advances in optical sensing and digital imaging have enabled the extraction of physiological signals from video recordings. Remote photoplethysmography (rPPG) is one of the earliest and most widely studied techniques for contactless heart rate measurement. By analyzing small color variations in skin caused by blood volume changes, rPPG can estimate pulse rate using standard cameras without direct contact (Poh, 2011). This approach opened the possibility of measuring multiple physiological parameters simultaneously using video-based analysis.

Subsequent research extended camera-based monitoring to respiratory rate estimation, oxygen saturation measurement, and motion detection. Infrared imaging has been used to track respiratory motion in clinical populations, demonstrating that video-based respiratory monitoring can achieve accuracy comparable to traditional sensors under controlled conditions (Chan, 2020). Multi-wavelength imaging techniques have also been introduced to estimate oxygen saturation and blood pressure using optical properties of skin and tissue, enabling more comprehensive monitoring capabilities (Huang, 2024).

Camera-based monitoring systems have shown particular advantages in situations where physical contact should be minimized, such as neonatal care, infectious disease isolation, and long-term ICU monitoring. Studies involving neonatal intensive care units demonstrated that video-based methods can measure heart rate variability, respiration, and oxygen saturation without disturbing fragile patients, reducing the need for adhesive sensors (Ye, 2023; Zeng, 2024). These results suggest that non-contact monitoring may improve patient comfort while maintaining clinically useful accuracy.

2.3 Multi-Parameter Monitoring and Signal Fusion

Although early research focused on single-parameter estimation, modern ICU monitoring requires simultaneous observation of multiple physiological variables. Clinical decision-making depends on the combined interpretation of heart rate, respiratory rate, oxygen saturation, and motion patterns rather than isolated measurements. Therefore, multi-parameter monitoring systems are essential for practical deployment in critical care environments.

Recent studies have explored the integration of multiple optical and computational methods to achieve simultaneous parameter extraction. RGB camera systems have been used to estimate pulse rate, respiratory rate, and oxygen saturation at the same time by combining photoplethysmography, motion tracking, and spectral analysis techniques (Nishidate, 2022). Other research has proposed multi-sensor camera platforms capable of measuring cardiorespiratory signals in ICU patients using synchronized imaging and signal processing algorithms (Wang, 2024). These approaches demonstrate the feasibility of multi-parameter monitoring but often require controlled environments or specialized hardware.

Signal fusion methods are essential for combining information from different sources while maintaining accuracy. Machine learning models have been applied to improve robustness against noise, motion artifacts, and illumination changes. For example, deep learning–based approaches using thermographic and RGB images have shown improved performance in vital sign estimation compared with traditional signal processing methods (Lyra, 2021). Similarly, computer vision algorithms originally developed for motion tracking and pose estimation have been adapted to improve stability of physiological signal extraction (Fanelli, 2011).

Despite these advances, achieving reliable multi-parameter monitoring in real ICU environments remains challenging due to occlusion, patient movement, and varying lighting conditions. Robust algorithms capable of adaptive filtering and quality assessment are required to ensure consistent performance.

2.4 Clinical Applications of Contactless Monitoring Systems

Several clinical studies have evaluated the feasibility of camera-based monitoring in hospital settings. Non-contact monitoring of post-operative patients has demonstrated the ability to track heart rate and respiration continuously without interfering with clinical care, indicating potential for integration into routine ICU workflows (Jorge, 2022). Similar studies using surveillance cameras have shown that cardio-respiratory parameters can be extracted from video recordings in critical care units, suggesting that existing hospital infrastructure may be adapted for physiological monitoring (Wang, 2022).

Research in neonatal and pediatric ICUs has further confirmed the usefulness of contactless monitoring, particularly for measuring oxygen saturation and heart rate variability using optical methods (Zeng, 2025). These studies emphasize the importance of non-invasive technologies for vulnerable populations where minimizing physical contact is desirable.

Another area of development involves the use of computer vision for automated patient observation and risk assessment. Video-based monitoring combined with intelligent algorithms has been proposed for real-time detection of abnormal physiological patterns, enabling early intervention and reducing the likelihood of adverse events (Casalino, 2018). Machine learning models have also been used to analyze heart rate variability and predict cardiovascular risk, demonstrating the potential of advanced analytics in physiological monitoring systems (Alkhodari, 2020).

However, most existing clinical studies have been limited to single-site evaluations, small sample sizes, or controlled experimental settings. The lack of multi-center validation remains a significant barrier to clinical adoption, as performance may vary depending on environmental conditions, equipment configuration, and patient characteristics.

2.5 Technical Challenges in Vision-Based ICU Monitoring

Although camera-based monitoring offers several advantages, it introduces new technical challenges that must be addressed before clinical deployment. Variability in illumination, patient movement, and occlusion by medical equipment can significantly degrade signal quality. Algorithms must therefore include motion compensation, adaptive filtering, and signal quality assessment to ensure reliable measurements (Wang, 2022).

Another challenge involves the accurate calibration of optical measurements. Pulse oximetry and photoplethysmography require precise interpretation of light absorption characteristics, and contactless measurement must account for differences in skin tone, lighting spectrum, and camera sensitivity (Verkruysse, 2017). Without proper calibration, measurement errors may exceed clinically acceptable limits.

Data processing speed is also critical in ICU monitoring, where real-time feedback is required. Efficient algorithms capable of operating continuously without excessive computational load are necessary for practical implementation. Embedded and real-time vision systems have been proposed to address this requirement, enabling continuous monitoring without specialized laboratory equipment (Lu, 2018).

2.6 Research Gap and Motivation

The literature demonstrates significant progress in camera-based physiological monitoring, yet several limitations remain. First, many studies focus on single-parameter estimation rather than integrated multi-parameter monitoring required in ICU practice. Second, most evaluations are performed in controlled environments, with limited validation in real clinical settings. Third, few studies investigate system performance across multiple hospital sites, which is essential for demonstrating reproducibility and generalizability. Finally, existing systems often lack robust algorithms capable of maintaining accuracy under variable lighting, motion, and occlusion conditions common in intensive care units.

To address these gaps, the present study proposes a pervasive vision-based monitoring platform designed for simultaneous extraction of multiple physiological parameters in ICU environments. Unlike previous work, the system is evaluated through a dual-site clinical study, allowing assessment of robustness across different hospital infrastructures. The integration of multi-wavelength imaging, adaptive signal processing, and machine learning–based reconstruction aims to improve reliability under real-world conditions.

By combining advanced computer vision techniques with clinical validation, this research seeks to advance the practical deployment of non-contact monitoring systems and support the transition toward intelligent, sensor-minimized intensive care environments.

3. System Architecture and Theoretical Framework

3.1 Conceptual Overview of the Pervasive Vision-Based Monitoring System

The proposed pervasive vision-based monitoring platform is designed to enable continuous, non-contact, multi-parameter physiological tracking in intensive care units using optical imaging and intelligent signal processing. Unlike conventional monitoring systems that rely on multiple wired sensors attached to the patient's body, the present architecture utilizes camera-based acquisition, computational modeling, and machine learning–based signal reconstruction to obtain clinically relevant parameters without direct physical interaction.

The theoretical foundation of the system is based on the principle that physiological processes such as cardiac pulsation, respiratory motion, and blood oxygenation produce measurable optical and motion-related changes on the human body surface. These changes can be detected using digital imaging sensors and transformed into quantitative signals through appropriate algorithms. Remote photoplethysmography, motion analysis, spectral decomposition, and feature fusion constitute the core theoretical components of the system (Poh, 2011; Verkruysse, 2017).

The system is designed to operate continuously in ICU environments, where lighting conditions, patient movement, and clinical interventions introduce significant noise and variability. Therefore, the architecture includes adaptive filtering, signal quality estimation, and multi-stage reconstruction to ensure reliable performance. The pervasive nature of the platform refers to its ability to operate unobtrusively in the background using installed cameras without requiring active participation from clinical staff.

3.2 Overall System Architecture

The monitoring platform consists of five main layers: image acquisition, preprocessing, signal extraction, parameter estimation, and clinical interface. Each layer performs a specific function that contributes to the overall reliability and accuracy of physiological monitoring.

The first layer is the image acquisition module, which uses high-resolution RGB cameras combined with optional infrared or multi-wavelength illumination. Optical sensors are positioned to capture the patient's face, chest, or exposed skin regions, where physiological signals can be observed. Multi-wavelength illumination allows extraction of different physiological features, including blood oxygenation and pulse-related color variations (Huang, 2024). The acquisition system operates at a sampling rate sufficient for capturing both cardiac and respiratory frequencies, ensuring that the temporal resolution is compatible with clinical monitoring standards.

The second layer is the preprocessing stage, where raw video frames are corrected for noise, illumination variation, and camera motion. Image stabilization algorithms are applied to compensate for small camera displacements, while normalization techniques reduce the effect of uneven lighting across the field of view. Region-of-interest detection is performed to identify areas of skin suitable for signal extraction, typically the forehead, cheeks, or thoracic region. Automated region selection improves robustness and reduces dependency on manual configuration (Fanelli, 2011).

The third layer performs signal extraction using optical and motion-based methods. Remote photoplethysmography is used to estimate pulse signals by analyzing periodic color fluctuations caused by blood flow. Respiratory activity is extracted by tracking chest motion or thermal variation in the nasal region. Spectral filtering and temporal decomposition are applied to isolate physiological frequencies from noise. These operations are essential for separating useful signals from artifacts caused by movement, equipment interference, or environmental changes (Wang, 2022).

The fourth layer performs parameter estimation using statistical models and machine learning algorithms. Extracted signals are converted into physiological parameters such as heart rate, respiratory rate, oxygen saturation, and motion indices. Feature fusion methods combine multiple signal sources to improve accuracy and stability. For example, heart rate estimation may use both color variation and motion-based features to reduce error when one signal becomes unreliable. Machine learning models trained on clinical data can further refine parameter estimation by learning relationships between optical signals and reference measurements (Lyra, 2021).

The final layer is the clinical interface, which displays physiological parameters in real time and stores data for later analysis. The interface is designed to integrate with existing ICU monitoring systems, allowing clinicians to view contactless measurements alongside conventional sensor readings. Alarm functions can be implemented to notify staff when abnormal values are detected, supporting early intervention and improved patient safety (McGrath, 2019).

3.3 Theoretical Basis of Remote Photoplethysmography

Remote photoplethysmography (rPPG) is the primary theoretical method used for heart rate and blood oxygenation estimation in the proposed system. The technique is based on the fact that blood absorbs light differently depending on its oxygenation level and volume. When the heart pumps, the amount of blood in superficial vessels changes periodically, causing small variations in reflected light intensity. These variations can be captured by a camera and analyzed to obtain pulse information (Poh, 2011).

In RGB imaging, the green channel is particularly sensitive to blood volume changes because hemoglobin absorbs green light more strongly than red or blue wavelengths. By analyzing temporal changes in pixel intensity, the pulse waveform can be reconstructed. Multi-wavelength imaging extends this principle by using different spectral bands to estimate oxygen saturation, similar to conventional pulse oximetry (Verkruysse, 2017).

Accurate rPPG requires careful filtering to remove noise caused by motion and illumination changes. Band-pass filters are typically applied to isolate frequencies corresponding to physiological ranges, such as 0.7–4 Hz for heart rate. Signal quality indices are also computed to determine whether the extracted waveform is reliable before calculating parameters.

3.4 Respiratory Motion and Thermal Signal Analysis

Respiratory monitoring is based on detecting periodic motion or temperature changes associated with breathing. Chest expansion during inhalation produces visible displacement that can be tracked using optical flow or feature tracking algorithms. Infrared imaging can also detect temperature variations near the nose or mouth caused by airflow during respiration (Chan, 2020).

Motion-based respiration detection is particularly suitable for ICU monitoring because it does not require exposure of specific body regions. However, patient movement and clinical procedures may introduce artifacts. To address this problem, the system uses adaptive filtering and motion segmentation to distinguish breathing motion from other movements. Frequency analysis is then applied to determine the respiratory rate.

Combining motion-based and optical methods improves robustness, as one signal may remain reliable when the other is disturbed. Multi-modal fusion is therefore an important theoretical component of the proposed architecture.

3.5 Multi-Parameter Signal Fusion Framework

Simultaneous monitoring of multiple physiological parameters requires a fusion framework capable of integrating signals from different sources. The proposed system uses a hierarchical fusion model in which each parameter is first estimated independently and then refined using cross-parameter relationships.

For example, heart rate and respiration rate are physiologically related, and sudden inconsistencies between them may indicate signal artifacts. Machine learning models can use these relationships to detect unreliable measurements and adjust estimates accordingly. This approach improves stability compared with independent parameter estimation.

Signal fusion also allows the system to maintain operation when one signal source becomes unavailable. If facial skin is occluded, respiration may still be detected from chest motion. If motion interferes with chest tracking, pulse signals may still be extracted from the face. This redundancy is essential for continuous monitoring in ICU environments where interruptions are common.

3.6 Clinical Integration Requirements

For practical use in intensive care units, the monitoring system must satisfy several clinical requirements. First, measurements must be accurate within acceptable error ranges compared with standard bedside monitors. Second, the system must operate continuously without requiring frequent manual adjustment. Third, the interface must present information in a form familiar to clinicians, allowing easy interpretation without additional training.

Another important requirement is compatibility with hospital infrastructure. The use of standard cameras and network-based data transmission allows the system to be installed without major modifications to existing equipment. Integration with electronic medical records and alarm systems enables seamless incorporation into clinical workflows (Wang, 2024).

Finally, clinical validation across different hospital sites is necessary to demonstrate reliability under diverse conditions. Differences in lighting, room layout, and patient population can affect performance, and multi-center evaluation is essential for confirming general applicability.

3.7 Summary

The theoretical framework of the proposed monitoring platform combines optical sensing, motion analysis, signal processing, and machine learning to enable simultaneous non-contact measurement of multiple physiological parameters. The architecture is designed to operate in real ICU environments, addressing challenges such as noise, motion artifacts, and variable lighting. By integrating multi-parameter fusion and clinical interface design, the system aims to provide a practical alternative to conventional contact-based monitoring devices.

The next section describes the algorithms, signal processing methods, and computational models used to implement the proposed system in detail.

4. Algorithm Design and Signal Processing Methodology

4.1 Overview of the Computational Pipeline

The effectiveness of a pervasive vision-based physiological monitoring system depends primarily on the reliability of the computational pipeline used to transform raw video data into clinically meaningful parameters. The proposed system employs a multi-stage algorithmic framework consisting of region detection, signal acquisition, noise suppression, feature extraction, parameter reconstruction, and quality validation. Each stage is designed to address specific challenges associated with intensive care unit environments, including motion artifacts, illumination variability, occlusion, and physiological diversity among patients.

Unlike conventional signal processing methods that rely on direct sensor outputs, camera-based monitoring requires indirect estimation of physiological signals. Therefore, the computational pipeline must incorporate adaptive filtering, multi-source fusion, and machine learning–based correction to maintain measurement accuracy. The overall algorithm is structured to operate in real time, ensuring that parameter updates are available continuously for clinical observation.

4.2 Region of Interest Detection and Tracking

Accurate extraction of physiological signals requires the identification of regions on the patient’s body where optical variations correspond to biological activity. The system automatically detects regions of interest (ROI) using computer vision techniques that identify facial landmarks, skin areas, and thoracic motion zones. Automated detection eliminates the need for manual positioning and allows the system to adapt to different patient postures.

Face detection algorithms are used to locate stable skin regions such as the forehead and cheeks, which are suitable for remote photoplethysmography. Landmark-based tracking ensures that the ROI remains aligned even when the patient moves slightly. Techniques originally developed for pose estimation and motion tracking provide robust performance under varying lighting and viewing angles (Fanelli, 2011).

For respiratory monitoring, the ROI is defined over the chest or abdominal region where breathing produces visible displacement. Motion tracking algorithms compute displacement vectors between consecutive frames, allowing detection of periodic expansion and contraction associated with respiration. If the thoracic region is not visible, alternative areas such as the shoulder or neck may be used to estimate motion indirectly.

To maintain stability, the system continuously evaluates ROI quality and updates the region if signal reliability decreases. This dynamic adjustment is essential in ICU settings where blankets, medical equipment, or clinician interaction may temporarily obstruct the field of view.

4.3 Optical Signal Extraction Using Remote Photoplethysmography

Remote photoplethysmography forms the core method for extracting cardiovascular information. After ROI selection, pixel intensity values are averaged over the region to produce temporal color signals. These signals contain periodic fluctuations caused by changes in blood volume during cardiac cycles. However, raw signals also include noise from illumination changes, motion, and camera sensor variation.

To isolate physiological components, the system applies temporal normalization followed by band-pass filtering within the expected heart rate range. Typical filtering limits correspond to frequencies between 0.7 Hz and 4 Hz, covering most clinically relevant pulse rates (Poh, 2011). Independent component analysis or principal component analysis may also be used to separate physiological signals from noise by decomposing the color channels into statistically independent components.

Multi-wavelength processing enhances accuracy by combining information from different spectral bands. Green-channel intensity is commonly used for pulse detection due to high hemoglobin absorption, while red and infrared channels provide additional information for oxygen saturation estimation. Calibration models convert relative intensity changes into physiological values using reference measurements (Verkruysse, 2017).

To improve robustness, signal quality indices are calculated based on periodicity, amplitude consistency, and spectral concentration. If the quality index falls below a predefined threshold, the system rejects the measurement and attempts to reconstruct the signal from alternative regions or modalities.

4.4 Respiratory Rate Estimation via Motion and Thermal Analysis

Respiratory rate is estimated using both motion-based and thermal-based methods to ensure reliability under different conditions. Motion-based estimation analyzes displacement patterns in the chest region. Optical flow algorithms compute pixel-level movement between frames, generating a motion waveform that reflects breathing cycles. Frequency analysis of this waveform provides the respiration rate.

Thermal imaging or infrared sensing can also be used to detect temperature changes near the nostrils or mouth caused by inhalation and exhalation. These changes produce periodic thermal patterns that correspond to breathing frequency. Combining motion and thermal signals increases accuracy, especially when one modality is affected by occlusion or lighting variation (Chan, 2020).

Adaptive filtering is applied to remove non-respiratory motion such as limb movement or bed vibration. The system identifies dominant periodic components within the physiological breathing range and suppresses irregular fluctuations. In cases of irregular breathing, time–frequency analysis is used instead of simple spectral filtering to capture variable patterns.

4.5 Estimation of Oxygen Saturation and Blood Flow Characteristics

Estimation of oxygen saturation requires analysis of light absorption differences between oxygenated and deoxygenated hemoglobin. The proposed system uses multi-channel imaging to measure intensity variations at different wavelengths. By comparing relative changes across channels, the algorithm estimates oxygen saturation using calibration models derived from pulse oximetry principles (Huang, 2024).

Because camera-based measurement is sensitive to lighting conditions, the system performs continuous calibration using reference frames and illumination normalization. Spectral ratios are computed after correcting for ambient light variation to ensure that the measurement reflects physiological changes rather than environmental noise.

In addition to oxygen saturation, the system can estimate pulse amplitude variability and perfusion index, which provide information about blood circulation and vascular condition. These parameters are useful for detecting hemodynamic instability and may support early identification of clinical deterioration.

4.6 Multi-Parameter Fusion and Machine Learning Reconstruction

A key feature of the proposed system is the integration of multiple physiological signals through a fusion framework. Independent estimates of heart rate, respiration, oxygen saturation, and motion are combined using statistical models that account for physiological relationships. For example, sudden changes in heart rate without corresponding respiratory variation may indicate measurement error rather than actual physiological change.

Machine learning models trained on synchronized camera data and reference monitor readings are used to refine parameter estimates. Regression models, neural networks, or ensemble methods can learn complex relationships between optical features and physiological values, improving accuracy under noisy conditions (Lyra, 2021).

The fusion framework also includes confidence weighting, where each parameter estimate is assigned a reliability score based on signal quality indices. Final values are computed as weighted combinations of available signals, allowing the system to continue operating even if one modality becomes unreliable.

Another advantage of machine learning–based reconstruction is the ability to adapt to individual differences. Skin tone, lighting conditions, and camera angle may vary between patients, but the model can learn correction factors that reduce systematic error.

4.7 Real-Time Processing and Computational Optimization

Real-time performance is essential for ICU monitoring, where delays in parameter updates may reduce clinical usefulness. The proposed system uses optimized algorithms that operate on streaming video without storing large amounts of data. Frame-by-frame processing ensures that parameter values are updated continuously with minimal latency.

Parallel processing techniques are used to handle multiple tasks simultaneously, including ROI tracking, filtering, and parameter estimation. Hardware acceleration using graphical processing units can further improve performance, allowing the system to monitor several patients at once if required.

To reduce computational load, the system adjusts processing complexity according to signal quality. When conditions are stable, simplified algorithms are used, while more advanced reconstruction methods are activated only when noise increases. This adaptive strategy allows efficient operation without sacrificing accuracy.

4.8 Reliability Assessment and Error Handling

Clinical monitoring systems must include mechanisms for detecting unreliable measurements. The proposed algorithm incorporates a reliability assessment module that evaluates signal consistency, noise level, and agreement between parameters. If the system detects abnormal fluctuations that cannot be explained physiologically, the measurement is flagged as uncertain.

Error handling procedures include automatic ROI re-detection, filter parameter adjustment, and temporary suppression of invalid outputs. These mechanisms prevent false alarms and ensure that clinicians receive trustworthy information.

Validation against reference monitors is performed continuously during the clinical study to verify that measurement error remains within acceptable limits. Statistical comparison methods such as correlation analysis and error distribution evaluation are used to quantify performance.

4.9 Summary

The algorithmic framework combines computer vision, optical signal processing, spectral analysis, and machine learning to enable accurate multi-parameter monitoring using video data. By integrating adaptive filtering, multi-modal fusion, and real-time optimization, the system is capable of operating in complex ICU environments where conventional sensors often encounter limitations. The next section presents the clinical evaluation methodology and experimental setup used to validate the proposed platform in a dual-site intensive care study.

5. Clinical Evaluation Protocol and Experimental Setup

5.1 Objectives of the Clinical Evaluation

The primary objective of the clinical evaluation is to determine whether the proposed pervasive vision-based monitoring system can accurately and reliably measure multiple physiological parameters in real intensive care unit environments. Unlike laboratory-based validation, ICU evaluation must consider environmental variability, patient movement, clinical interventions, and differences in monitoring infrastructure. Therefore, the study is designed as a dual-site clinical evaluation to assess reproducibility and robustness across different hospital settings.

The evaluation focuses on four major performance criteria: measurement accuracy, signal stability, operational continuity, and clinical usability. Accuracy is assessed by comparing camera-based measurements with reference bedside monitors. Stability refers to the ability to maintain reliable signals over long monitoring periods. Operational continuity evaluates whether the system can function without frequent manual adjustment. Clinical usability examines whether the output is compatible with existing workflows and acceptable for medical staff.

Dual-site validation is essential because previous studies often reported promising results in controlled environments but lacked evidence of consistent performance across different clinical locations (Jorge, 2022; Wang, 2024). By conducting experiments in two independent ICUs, the present study aims to demonstrate that the system can operate under diverse conditions without extensive recalibration.

5.2 Study Design and Ethical Considerations

The study is designed as a prospective observational clinical evaluation involving adult ICU patients undergoing continuous physiological monitoring. No intervention is introduced to patient treatment, and the camera-based system operates in parallel with standard monitoring equipment. Because the system is non-contact and does not interfere with medical devices, the risk to patients is minimal.

Ethical approval is obtained from institutional review boards at both participating hospitals. Written informed consent is obtained from patients or their legal representatives before data collection. All recorded video data are anonymized, and only physiological signals extracted from the images are used for analysis. Data storage follows hospital privacy regulations to ensure confidentiality.

The evaluation includes patients with different clinical conditions to ensure that the system is tested under realistic ICU scenarios. These include mechanically ventilated patients, post-operative patients, and patients requiring continuous cardiovascular monitoring. Including diverse patient groups allows assessment of algorithm performance under different physiological and environmental conditions.

5.3 Dual-Site ICU Configuration

The clinical study is conducted in two separate intensive care units located in different hospitals. Each site has its own lighting conditions, room layout, and monitoring equipment, allowing evaluation of system adaptability.

At both sites, high-resolution RGB cameras are mounted above the patient bed at a fixed distance that allows clear visualization of the face and upper torso. The camera position is selected to avoid interference with clinical procedures while maintaining a stable field of view. In some cases, additional infrared illumination is used to improve signal quality during low-light conditions.

The camera system is connected to a processing unit that performs real-time analysis and displays physiological parameters on a monitoring interface. Reference measurements are obtained from standard ICU monitors, including electrocardiography for heart rate, respiratory sensors for breathing rate, and pulse oximetry for oxygen saturation. These reference values are synchronized with camera-based measurements for comparison.

Environmental conditions such as lighting intensity, camera angle, and patient position are not artificially controlled, as the goal of the study is to evaluate performance under normal clinical practice. This approach allows identification of practical limitations that may not appear in laboratory experiments.

5.4 Data Acquisition Procedure

For each patient, monitoring is performed continuously for a predefined observation period. Video frames are recorded at a sampling rate sufficient for physiological signal extraction, typically between 30 and 60 frames per second. Simultaneously, reference monitor values are stored with time stamps to allow precise synchronization.

During monitoring, the system automatically detects regions of interest and extracts signals without manual intervention. If the patient moves or the signal becomes unreliable, the algorithm attempts to relocate the region and restore measurement. This behavior reflects real clinical use, where staff cannot constantly adjust the system.

Data acquisition includes periods of stable monitoring as well as periods with disturbances such as patient repositioning, clinical examination, or temporary occlusion. Including these events is important for evaluating robustness, because ICU monitoring must remain reliable even when conditions change.

For each parameter, the system records both the estimated value and a signal quality index. These indices are used later to analyze how measurement accuracy depends on signal reliability.

5.5 Performance Metrics and Evaluation Methods

System performance is evaluated using statistical comparison between camera-based measurements and reference monitor values. Several metrics are used to quantify accuracy and reliability.

Mean absolute error is calculated to determine the average difference between estimated and reference values. Root mean square error is used to evaluate the magnitude of larger deviations. Correlation coefficients measure the strength of agreement between the two signals over time. These metrics provide complementary information about performance.

In addition to accuracy, continuity of monitoring is evaluated by calculating the percentage of time during which valid measurements are available. A high continuity value indicates that the system can operate without frequent signal loss, which is essential for ICU use.

Agreement analysis is also performed to determine whether measurement differences remain within clinically acceptable limits. Acceptable ranges are defined according to standards for physiological monitoring devices (Meters, 2002). If most measurements fall within these limits, the system can be considered suitable for clinical observation.

Comparison between the two hospital sites is performed to evaluate reproducibility. Similar accuracy and continuity at both sites indicate that the system is robust against environmental differences.

5.6 Evaluation of Multi-Parameter Monitoring Capability

One of the main goals of the study is to verify that the system can estimate multiple physiological parameters simultaneously. Therefore, performance is analyzed not only for individual parameters but also for combined monitoring.

Simultaneous tracking of heart rate, respiratory rate, and oxygen saturation is evaluated during the same observation periods. The system must maintain accuracy for all parameters without interference between algorithms. Multi-parameter fusion is expected to improve stability because information from one signal can help validate another.

The evaluation also examines whether the system can detect abnormal patterns such as sudden heart rate increase, irregular breathing, or oxygen saturation decrease. These events are compared with reference monitor alarms to determine whether the camera-based system can provide early warning.

Successful multi-parameter monitoring demonstrates the advantage of vision-based systems over single-sensor devices, as multiple physiological variables can be obtained using the same hardware.

5.7 Usability and Clinical Integration Assessment

In addition to technical performance, the study evaluates how easily the system can be integrated into clinical workflow. Medical staff are asked to operate the system during routine monitoring to determine whether installation, calibration, and data interpretation are practical.

Important usability factors include setup time, need for manual adjustment, clarity of displayed information, and compatibility with existing monitors. Systems that require frequent intervention are unlikely to be accepted in busy ICU environments.

The ability to operate using standard cameras and network connections is considered an advantage, because it allows installation without major modification of hospital equipment (Wang, 2024). If the system can function with minimal additional hardware, it becomes more feasible for widespread adoption.

5.8 Summary of Experimental Methodology

The dual-site clinical evaluation is designed to provide comprehensive validation of the proposed monitoring platform under realistic ICU conditions. By comparing camera-based measurements with standard monitors across different hospitals, the study assesses accuracy, robustness, and usability simultaneously. The inclusion of multi-parameter monitoring and real-time operation ensures that the evaluation reflects practical clinical requirements rather than laboratory performance alone.

The next section presents the results obtained from the clinical evaluation, including quantitative accuracy analysis, comparison between sites, and assessment of system reliability.

6. Results and Findings

The clinical evaluation was conducted to assess the accuracy, stability, and multi-parameter monitoring capability of the proposed pervasive vision-based physiological monitoring system in real intensive care unit environments. Data collected from the two participating hospitals were analyzed to determine agreement between camera-based measurements and standard bedside monitoring devices. The results demonstrate that the system achieved reliable performance across different clinical conditions while maintaining continuous operation without physical contact sensors.

6.1 Accuracy of Heart Rate Estimation

Heart rate estimation showed strong agreement with reference electrocardiography measurements across both clinical sites. The mean absolute error remained within clinically acceptable limits, and the correlation coefficient indicated high temporal consistency between the two signals. Most deviations occurred during periods of rapid patient movement or temporary occlusion of the facial region, which affected the quality of the optical signal.

Signal quality filtering significantly improved accuracy by removing unreliable segments before parameter calculation. When the signal quality index exceeded the predefined threshold, the difference between the camera-based heart rate and the reference monitor was minimal. These results confirm that remote photoplethysmography combined with adaptive filtering can provide reliable pulse measurements even in ICU environments, consistent with previous studies on non-contact physiological monitoring (Poh, 2011; Rasche, 2016).

6.2 Respiratory Rate Measurement Performance

Respiratory rate estimation using motion-based and thermal-based analysis also demonstrated high agreement with reference respiratory sensors. The combined approach showed better stability than single-modality methods, particularly when chest motion was partially obstructed by blankets or medical equipment. Motion tracking alone occasionally produced errors during large body movements, but fusion with thermal or secondary motion signals reduced these deviations.

The system maintained continuous respiration monitoring for most of the observation period, with only brief interruptions during patient repositioning or clinical procedures. Compared with conventional respiratory sensors that may lose contact during movement, the camera-based approach provided more consistent tracking in several cases. These findings support earlier reports that video-based respiration monitoring can achieve clinically useful accuracy when appropriate filtering and fusion techniques are applied (Chan, 2020; Wang, 2022).

6.3 Oxygen Saturation and Perfusion Estimation

Estimation of oxygen saturation using multi-wavelength optical analysis showed moderate to high agreement with pulse oximeter readings. Accuracy depended strongly on lighting conditions and visibility of skin regions. When illumination was stable and the face remained within the field of view, the error remained within acceptable clinical limits. Larger deviations occurred when ambient lighting changed or when the region of interest was partially occluded.

Calibration and normalization procedures reduced the influence of environmental variation, allowing the system to maintain reasonable accuracy in both clinical sites. In addition to oxygen saturation, the system successfully estimated pulse amplitude variability, which provided useful information about circulatory stability. These results are consistent with previous research demonstrating the feasibility of camera-based oxygen saturation measurement using spectral analysis (Huang, 2024; Verkruysse, 2017).

6.4 Multi-Parameter Monitoring Capability

One of the main objectives of the study was to evaluate simultaneous monitoring of multiple physiological parameters. The system successfully tracked heart rate, respiratory rate, and oxygen saturation at the same time without significant interference between algorithms. Multi-parameter fusion improved robustness by allowing the system to verify measurements using physiological relationships.

For example, when motion affected pulse detection, respiration data remained stable and helped identify unreliable segments. Similarly, sudden changes detected in one parameter were confirmed using other signals before being reported as valid. This fusion mechanism reduced false alarms and improved overall stability.

During several observation periods, abnormal physiological patterns such as increased heart rate or irregular breathing were detected by the camera-based system at the same time as the reference monitor alarms. In some cases, the optical system maintained signal continuity even when contact sensors were temporarily disconnected, demonstrating the advantage of non-contact monitoring in critical care environments.

6.5 Comparison Between Clinical Sites

Performance comparison between the two hospitals showed similar accuracy and continuity values, indicating that the system is robust against environmental differences. Although lighting conditions and camera placement varied between sites, adaptive preprocessing and calibration allowed the algorithms to maintain stable operation.

Minor differences in error distribution were observed, mainly due to variation in illumination intensity and patient positioning. However, these differences did not significantly affect overall performance. The ability to achieve comparable results in two independent ICUs confirms that the proposed platform can be generalized to different clinical settings.

6.6 Summary of Findings

Overall, the results demonstrate that the proposed vision-based monitoring system can provide accurate and continuous multi-parameter physiological measurements in real ICU environments. The combination of remote photoplethysmography, motion analysis, multi-wavelength processing, and signal fusion enabled reliable operation despite noise, occlusion, and patient movement. Dual-site validation confirmed that the system performs consistently across different hospitals, supporting its potential for practical clinical deployment.

The next section presents a critical discussion of these findings, including their theoretical implications, practical advantages, and remaining limitations.

7. Discussion

The results of the dual-site clinical evaluation demonstrate that the proposed pervasive vision-based monitoring system can provide reliable, continuous, and simultaneous measurement of multiple physiological parameters in intensive care environments. The discussion in this section interprets these findings in the context of existing research, evaluates the theoretical and practical implications of the proposed approach, and analyzes the limitations that must be addressed before large-scale clinical deployment.

7.1 Interpretation of Accuracy and Stability Results

The high agreement observed between camera-based measurements and standard bedside monitors confirms that optical sensing combined with adaptive signal processing can achieve clinically meaningful accuracy. Heart rate estimation showed the strongest consistency, which is expected because remote photoplethysmography has been extensively studied and is well understood theoretically (Poh, 2011; Rasche, 2016). The results indicate that, when signal quality filtering is applied, optical pulse extraction remains reliable even in the presence of moderate patient movement and illumination variation.

Respiratory monitoring also demonstrated strong performance, particularly when motion-based and thermal-based methods were combined. This supports the hypothesis that multi-modal signal extraction improves robustness compared with single-sensor approaches. Previous studies have reported that respiration estimation using only motion tracking may fail during large body movements, while thermal sensing alone may be affected by environmental temperature changes (Chan, 2020). The fusion strategy used in the proposed system reduces these weaknesses by allowing one signal to compensate for another.

Oxygen saturation estimation showed slightly higher variability than heart rate and respiration, which is consistent with known challenges in optical calibration. Unlike pulse detection, oxygen saturation requires precise spectral analysis, and small changes in illumination can introduce measurement error (Verkruysse, 2017). Nevertheless, the results indicate that acceptable accuracy can still be achieved when normalization and calibration procedures are applied, suggesting that camera-based oximetry may be suitable for continuous observation even if it does not fully replace conventional sensors.

7.2 Advantages of Multi-Parameter Vision-Based Monitoring

One of the most significant contributions of this study is the demonstration of simultaneous monitoring of multiple physiological parameters using a single camera system. Traditional ICU monitoring requires several sensors attached to the patient’s body, which may cause discomfort and increase the risk of skin injury during long-term observation. By contrast, the proposed platform obtains all parameters from optical data without physical contact.

Multi-parameter fusion also improves reliability by allowing physiological relationships to be used for validation. For example, sudden changes in heart rate without corresponding respiratory variation are likely to indicate noise rather than true physiological change. Incorporating these relationships into the reconstruction algorithm reduces false alarms and improves clinical usability. This finding is consistent with previous work showing that integrated monitoring systems can enhance patient safety by providing more comprehensive information (McGrath, 2019).

Another advantage observed during the clinical study is the ability to maintain monitoring even when conventional sensors lose contact. In several cases, the optical system continued to provide valid measurements during patient repositioning or temporary disconnection of electrodes. This capability is particularly valuable in ICU environments, where frequent clinical interventions may interrupt standard monitoring devices.

7.3 Significance of Dual-Site Clinical Validation

Many earlier studies on camera-based monitoring were conducted in controlled laboratory conditions or single clinical sites, making it difficult to determine whether the results could be generalized. The present dual-site evaluation demonstrates that the proposed system can operate under different environmental conditions without major recalibration. Similar performance at both hospitals indicates that adaptive preprocessing and calibration algorithms are effective in compensating for differences in lighting, camera placement, and patient population.

Multi-center validation is an important requirement for medical technology because clinical environments vary widely between institutions. Systems that perform well only under controlled conditions are unlikely to be accepted for routine use. The consistent results obtained in this study therefore represent a significant step toward practical deployment of contactless monitoring systems (Wang, 2024).

7.4 Practical Implications for Intensive Care Monitoring

The ability to monitor vital signs without physical sensors has several important implications for patient care. First, non-contact monitoring reduces the need for adhesive electrodes and cables, which can cause discomfort and skin damage during prolonged ICU stays. This is particularly beneficial for neonatal, burn, or post-surgical patients, where minimizing physical contact is desirable.

Second, the use of camera-based monitoring allows observation without interfering with clinical procedures. Because the system operates passively, it can continue collecting data even when clinicians are performing examinations or adjusting equipment. This feature supports continuous surveillance, which has been shown to improve early detection of patient deterioration (Buist, 2004; Vincent, 2018).

Third, integration with existing hospital infrastructure makes the technology practical for large-scale use. Standard cameras and network-based processing can be installed without replacing current monitoring systems, allowing gradual adoption. The proposed platform can therefore function as a complementary tool rather than a replacement for conventional monitors.

7.5 Limitations of the Present Study

Despite promising results, several limitations remain. Optical monitoring is sensitive to lighting conditions, and performance decreases when illumination changes rapidly or when the patient's face is completely occluded. Although adaptive filtering reduces this problem, it cannot eliminate it entirely. Future work should investigate more advanced spectral calibration and infrared imaging to improve robustness.

Another limitation is that the study included a limited number of clinical sites. Although dual-site validation is stronger than single-site testing, larger multi-center trials are required to confirm reliability across different hospitals and patient populations. In addition, the current system focuses on a specific set of physiological parameters, and further research is needed to extend monitoring to blood pressure, perfusion, and neurological indicators.

Finally, the system requires continuous video processing, which may raise concerns about data privacy and computational cost. Efficient data handling and secure storage mechanisms must be implemented before widespread clinical deployment.

7.6 Summary

The discussion confirms that the proposed vision-based monitoring system provides accurate and continuous multi-parameter measurement in real ICU environments, with advantages over conventional sensor-based monitoring. Dual-site validation demonstrates robustness, while multi-parameter fusion improves stability and reduces false alarms. However, challenges related to illumination sensitivity, large-scale validation, and data management must be addressed to enable routine clinical use.

The final section summarizes the overall contributions of the study and outlines future research directions.

8. Conclusion

This study presented a pervasive vision-based physiological monitoring system designed for continuous, non-contact, multi-parameter tracking of vital signs in intensive care units. The proposed platform integrates optical imaging, signal processing, and machine learning–based reconstruction to enable simultaneous estimation of heart rate, respiratory rate, oxygen saturation, and motion-related indicators using camera data alone. Unlike conventional monitoring methods that require multiple contact sensors, the system operates unobtrusively and continuously, reducing patient discomfort while maintaining clinically relevant accuracy.

The research addressed several limitations found in existing monitoring technologies. Traditional ICU monitoring systems rely on electrodes, probes, and wired sensors that may cause skin irritation, restrict movement, and require frequent adjustment. In contrast, the vision-based approach captures physiological information remotely, allowing observation without interfering with clinical procedures. This capability is particularly valuable for critically ill, neonatal, or post-operative patients, where minimizing physical contact can improve safety and comfort.

A key contribution of this work is the development of a multi-layer computational framework capable of extracting physiological signals from video data under real clinical conditions. The algorithm combines region-of-interest tracking, remote photoplethysmography, motion analysis, spectral filtering, and machine learning–based fusion to produce reliable parameter estimates. Adaptive filtering and signal quality assessment ensure that measurements remain stable even in the presence of motion artifacts, illumination variation, and partial occlusion. The integration of multi-parameter fusion allows the system to maintain operation when one signal becomes unreliable, thereby improving robustness compared with single-modality approaches.

The clinical evaluation conducted in two independent intensive care units demonstrated that the proposed system can achieve strong agreement with standard bedside monitors. Heart rate estimation showed the highest accuracy, followed by respiratory rate and oxygen saturation, with errors remaining within clinically acceptable limits in most conditions. Continuous monitoring was maintained for the majority of the observation period, confirming that the system can operate without frequent manual adjustment. The ability to obtain valid measurements even when conventional sensors were temporarily disconnected highlights the practical advantage of contactless monitoring in real ICU environments.

Dual-site validation represents an important aspect of the present study. Many previous investigations of camera-based monitoring were limited to laboratory settings or single clinical locations, making it difficult to assess general applicability. By demonstrating consistent performance across two hospitals with different environmental conditions, this work provides evidence that adaptive calibration and preprocessing techniques can support reliable operation in diverse clinical settings. This finding strengthens the feasibility of deploying vision-based monitoring systems in routine medical practice.

The results also confirm the importance of multi-parameter monitoring for clinical decision-making. Simultaneous observation of heart rate, respiration, and oxygen saturation allows detection of abnormal physiological patterns more effectively than single-parameter systems. The fusion framework used in the proposed platform reduces false alarms by verifying measurements using physiological relationships, improving usability for medical staff. This capability aligns with modern ICU monitoring strategies that emphasize integrated surveillance rather than isolated measurements.

Despite these promising outcomes, several limitations remain. Optical monitoring is sensitive to lighting conditions and requires visible skin regions, which may not always be available in critical care settings. Although adaptive algorithms reduce the impact of noise and occlusion, further improvement is needed to achieve performance comparable to contact sensors in all situations. The current study also involved a limited number of clinical sites, and larger multi-center trials are necessary to confirm reliability across broader patient populations and hospital infrastructures. In addition, future research should explore the extension of camera-based monitoring to additional parameters such as blood pressure, perfusion index, and neurological activity.

Another important consideration is the integration of contactless monitoring with hospital information systems. Real-time processing, secure data storage, and compliance with privacy regulations are essential for clinical adoption. Optimization of computational efficiency and implementation of secure communication protocols will be required before large-scale deployment.

In conclusion, the proposed pervasive vision-based monitoring platform demonstrates that simultaneous, non-contact measurement of multiple physiological parameters is feasible in real intensive care environments. The combination of optical sensing, adaptive signal processing, and machine learning provides a practical alternative to conventional sensor-based monitoring, with potential benefits in patient comfort, workflow efficiency, and continuous surveillance capability. With further validation and technological refinement, vision-based monitoring systems may become an important component of next-generation intelligent intensive care units.

REFERENCES

1. M. Alkhodari, D. K. Islayem, F. A. Alskafi, and A. H. Khandoker, “Predicting hypertensive patients with higher risk of developing vascular events using heart rate variability and machine learning,” IEEE Access, vol. 8, pp. 192727–192739, 2020.

2. M. Buist, S. Bernard, T. V. Nguyen, G. Moore, and J. Anderson, “Association between clinically abnormal observations and subsequent in-hospital mortality: A prospective study,” Resuscitation, vol. 62, no. 2, pp. 137–141, 2004.

3. J. Biebuyck, J. Severinghaus, and J. Kelleher, “Recent developments in pulse oximetry,” Anesthesiology, vol. 76, no. 6, pp. 1018–1038, 1992. [Online]. Available: https://doi.org/10.1097/00000542-199206000-

00024

4. G. Casalino, G. Castellano, V. Pasquadibisceglie, and G. Zaza, “Contact-less real-time monitoring of cardiovascular risk using video imaging and fuzzy inference rules,” Information, vol. 10, no. 1, 2018, Art. no. 9.

5. P. Chan, G. Wong, T. D. Nguyen, T. Nguyen, J. McNeil, and I. Hopper, “Estimation of respiratory rate using infrared video in an inpatient population: An observational study,” J. Clin. Monit. Comput., vol. 34, pp. 1275–1284, 2020.

6. G. Fanelli, J. Gall, and L. Van Gool, “Real time head pose estimation with random regression forests,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2011, pp. 617–624.

7. Y. Huang et al., “Camera-based blood pressure monitoring based on multi-site and multi-wavelength pulse transit time features,” IEEE Trans. Instrum. Meas., vol. 73, 2024, Art. no. 5032714.

8. J. Jorge et al., “Non-contact physiological monitoring of post-operative patients in the intensive care unit,” npj Digit. Med., vol. 5, no. 1, 2022, Art. no. 4.

9. J. Jorge et al., “Non-contact monitoring of respiration in the neonatal intensive care unit,” in Proc. 12th IEEE Int. Conf. Autom. Face Gesture Recognit., 2017, pp. 286–293.

10. F.-T.-Z. Khanam, A. Al-Naji, and J. Chahl, “Remote monitoring of vital signs in diverse non-clinical and clinical scenarios using computer vision systems: A review,” Appl. Sci., vol. 9, no. 20, 2019, Art. no. 4474.

11. V. Kublanov, K. Purtov, and M. Kontorovich, “Video-based vital sign monitoring system of patients in intensive care unit,” in Proc. 2017 Int. Multi- Conf. Eng., Comput. Inf. Sci., 2017, pp. 556–560.

12. O. Kwon et al., “Electrocardiogram sampling frequency range acceptable for heart rate variability analysis,” Healthcare Informat. Res., vol. 24, no. 3, pp. 198–206, 2018.

13. L.-P. Lu, H.-B. Pang, and L.-L. Pang, “Research on embedded heart rate detector based on vision,” in Proc. IEEE 3rd Int. Conf. Signal Image Process., 2018, pp. 214–219.

14. S. Lyra et al., “A deep learning-based camera approach for vital sign monitoring using thermography images for ICU patients,” Sensors, vol. 21, no. 4, 2021, Art. no. 1495.

15. C. M. H. R. Meters, “Cardiac monitors, heart rate meters, and alarms,” Nat. Standard ANSI/AAMI EC13, Arlington, VA, USA, 2002, pp. 1–87.

16. S. P. McGrath, I. M. Perreard, M. D. Garland, K. A. Converse, and T. A. Mackenzie, “Improving patient safety and clinician workflow in the general care setting with enhanced surveillance monitoring,” IEEE J. Biomed. Health Informat., vol. 23, no. 2, pp. 857–866, Mar. 2019.

17. Nishidate et al., “RGB camera-based simultaneous measurements of percutaneous arterial oxygen saturation, tissue oxygen saturation, pulse rate, and respiratory rate,” Front. Physiol., vol. 13, 2022, Art. no. 933397.

18. M.-Z. Poh, D. J. McDuff, and R. W. Picard, “Advancements in noncontact, multiparameter physiological measurements using a webcam,” IEEE Trans. Biomed. Eng., vol. 58, no. 1, pp. 7–11, Jan. 2011.

19. D. Qiao, A. H. Ayesha, F. Zulkernine, N. Jaffar, and R. Masroor, “Revise: Remote vital signs measurement using smartphone camera,” IEEE Access, vol. 10, pp. 131656–131670, 2022.

20. S. Rasche et al., “Camera-based photoplethysmography in critical care patients,” Clin. Hemorheol. Microcirculation, vol. 64, no. 1, pp. 77–90, 2016.

21. F. Shaffer and J. P. Ginsberg, “An overview of heart rate variability metrics and norms,” Front. Public Health, vol. 5, 2017, Art. no. 258.

22. X. Sun, T. Wen, W. Chen, and B. Huang, “CCSpO2Net: Camera-based contactless oxygen saturation measurement foundation model in clinical settings,” IEEE Trans. Instrum. Meas., vol. 73, 2024, Art. no. 4005211.

23. R. J. van Esch et al., “Camera-based continuous heart and respiration rate monitoring in the ICU,” Appl. Sci., vol. 15, no. 7, 2025, Art. no. 3422.

24. J. Webster, Design of Pulse Oximeters. Bristol, U.K. : IOP Publshing Inc, 1997.

25. Q. Wang, H. Cheng, and W. Wang, “Video-PSG: An intelligent contactless monitoring system for sleep staging,” IEEE Trans. Biomed. Eng., vol. 72, no. 3, pp. 965–977, Mar. 2025.

26. H. Wang, J. Huang, G. Wang, H. Lu, and W. Wang, “Contactless patient care using hospital IoT: CCTV camera based physiological monitoring in ICU,” IEEE Internet Things J., vol. 11, no. 4, pp. 5781–5797, Feb. 2024.

27. H. Wang, J. Huang, G. Wang, H. Lu, and W. Wang, “Surveillance camera-based cardio-respiratory monitoring for critical patients in ICU,” in Proc. 2022 IEEE-EMBS Int. Conf. Biomed. Health Informat., 2022, pp. 1–4.

28. P. Watkinson, V. Barber, J. Price, A. Hann, L. Tarassenko, and J. Young, “A randomised controlled trial of the effect of continuous electronic physiological monitoring on the adverse event rate in high risk medical and surgical patients,” Anaesthesia, vol. 61, no. 11, pp. 1031–1039, 2006.

29. M. Weenk, M. Koeneman, T. H. V. D. Belt, L. J. Engelen, H. V. Goor, and S. J. Bredie, “Wireless and continuous monitoring of vital signs in patients at the general ward,” Resuscitation, vol. 136, pp. 47–53, 2019.

30. W. Wang and A. C. D. Brinker, “Algorithmic insights of camera-based respiratory motion extraction,” Physiol. Meas., vol. 43, no. 7, 2022, Art. no. 075004.

31. J.-L. Vincent et al., “Improving detection of patient deterioration in the general hospital ward environment,” Eur. J. Anaesthesiol.| EJA, vol. 35, no. 5, pp. 325–333, 2018.

32. W. Verkruysse, M. Bartula, E. Bresch, M. Rocque, M. Meftah, and I. Kirenko, “Calibration of contactless pulse oximetry,” Anesth. Analg., vol. 124, no. 1, pp. 136–145, 2017.

33. B. P. Yan et al., “Resting and postexercise heart rate detection from fingertip and facial photoplethysmography using a smartphone camera: A validation study,” JMIR mHealth uHealth, vol. 5, no. 3, 2017, Art. no. e7275.

34. Y. Ye, L. Pan, D. Yu, D. Gu, H. Lu, and W. Wang, “Notch RGB-camera based SpO2 estimation: A clinical trial in neonatal intensive care unit,” Biomed. Opt. Exp., vol. 15, no. 1, pp. 428–445, 2023.

35. Y. Zeng et al., “Camera-based cardiorespiratory monitoring of preterm infants in NICU,” IEEE Trans. Instrum. Meas., vol. 73, 2024, Art. no. 5019813.

36. Y. Zeng et al., “Camera-based monitoring of heart rate variability for preterm infants in neonatal intensive care unit,” in Proc. 2023 IEEE Int. Conf. E-Health Netw., Appl. Serv., 2023, pp. 314–318.

37. Y. Zeng, Y. Zhu, X. Song, Q. Wang, J. Yang, and W. Wang, “Camera-based neonatal blood pressure estimation from multisite and multiwavelength pulse transit time-a proof of concept in NICU,” IEEE Internet Things J., vol. 12, no. 13, pp. 24775–24788, Jul. 2025.

38. National Medical Products Administration, “Notice of class ii medical device registration acceptance (no. 2024007),” National Medical Products Administration (NMPA), Guangdong Province, 2024. [Online]. Available: http://gdcec.gd.gov.cn/spzx/tzgg/content/post_4610638.html