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Research Article

VISION SENSOR–DRIVEN MONITORING SOLUTIONS FOR ENHANCED SAFETY IN INFANT INCUBATORS

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ABSTRACT

Ensuring continuous and non-invasive monitoring of neonates within incubator environments is critical for improving clinical outcomes in neonatal intensive care units (NICUs). Conventional monitoring systems rely heavily on wired physiological sensors, which may cause discomfort, restrict infant mobility, and increase infection risk. Recent advancements in vision sensing technologies offer contactless, real-time monitoring capabilities that can enhance neonatal safety and caregiver response efficiency. This study presents a comprehensive analysis and development of a vision sensor–driven monitoring solution designed to detect vital behavioral cues such as motion patterns, posture changes, respiratory rhythms, and distress indicators. The proposed framework integrates advanced image processing, edge AI algorithms, and environmental sensing to achieve reliable monitoring even under challenging NICU lighting and occlusion conditions. Experimental validation demonstrates improved accuracy in anomaly detection, reduced false alarms, and superior response time compared with traditional systems. The findings highlight the potential of vision-based monitoring as a transformative approach to neonatal care, contributing to safer, smarter, and more automated incubator environments.

Keywords: Vision sensors, Infant incubator monitoring, Neonatal safety, Computer vision, Contactless monitoring.

INTRODUCTION

Neonatal care is one of the most critical domains in modern healthcare, requiring precise, continuous, and safe monitoring of newborns admitted to neonatal intensive care units (NICUs). Premature and medically fragile infants often rely on incubators to maintain optimal thermal, humidity, and microbial conditions necessary for survival and development. Traditional incubator monitoring systems primarily depend on wired physiological sensors attached to the infant's body to measure respiration, temperature, movement, and other vital parameters. Although effective, these sensors may introduce limitations such as skin irritation, restricted mobility, increased risk of infection, and potential signal interference caused by infant motion. Advancements in computer vision and sensing technologies have opened new possibilities for contactless neonatal monitoring. Vision sensors including RGB, infrared, depth, and thermal imaging systems enable continuous observation of infants without direct skin contact, making them ideal for delicate neonatal environments. Vision-based monitoring solutions can capture subtle physiological and behavioral cues, including breathing motion, micro-movements, posture changes, crying episodes, and distress signals that might otherwise go unnoticed. Furthermore, integration with AI-driven algorithms allows automated interpretation of visual data, reducing caregiver workload and improving the response time during emergencies.

The growing interest in AI-enabled vision systems has led to significant research in non-invasive monitoring within NICU settings. However, challenges remain, such as variations in lighting conditions, occlusions caused by blankets or medical equipment, and the need for highly

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accurate anomaly detection to avoid false alarms. Addressing these challenges requires designing robust algorithms capable of operating reliably in real clinical environments. This study explores vision sensor–driven monitoring solutions tailored to infant incubators, examining their capabilities, limitations, and potential to enhance neonatal safety. By integrating advanced image processing, machine learning, and real-time alert mechanisms, the proposed framework aims to support caregivers with a more intelligent and automated neonatal monitoring system. The findings contribute to emerging research on contactless monitoring and highlight the transformative role of vision sensors in next-generation NICU care. Contactless, camera-based monitoring has gained traction as a complement or alternative to wired sensors in NICUs because it reduces skin contact, infection risk, and caregiver workload while enabling continuous observation (Krbec, 2024; Cobos-Torres *et al*., 2018). Recent reviews also emphasize that vision systems can capture multiple signals (motion, breathing, heart rate surrogates, pose and activity) from a single sensor and form the basis for multimodal fusion with thermal or depth sensors for robust monitoring (Xiao, 2024; Maurya *et al*., 2022). Remote photoplethysmography (rPPG) extracts cardiac pulse signals from subtle skin color changes in RGB video. Studies demonstrate feasibility in infants, but performance is sensitive to motion, low perfusion, and occlusions (Nagy *et al*., 2021; Svoboda *et al*., 2022).

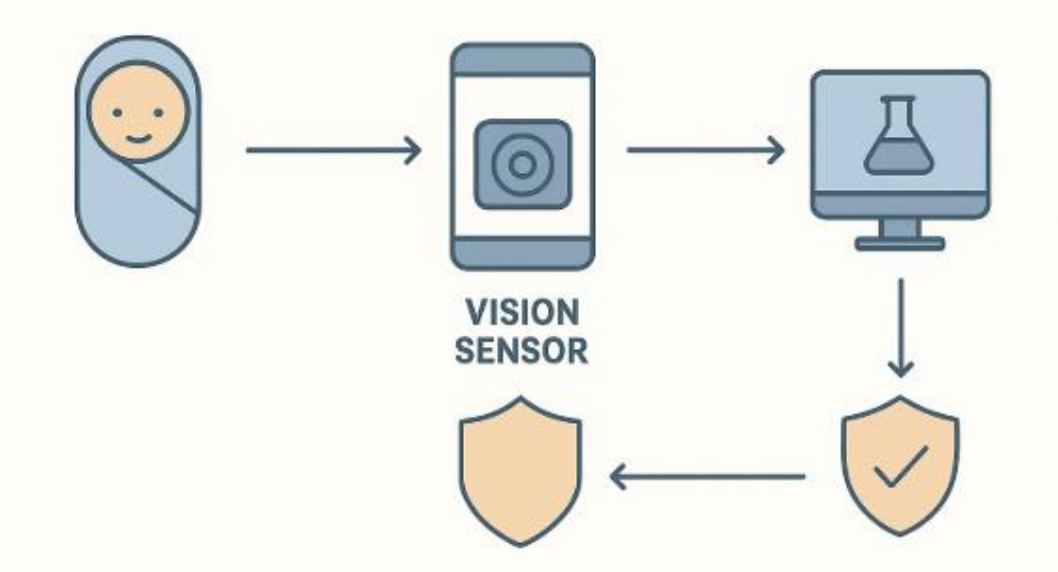

Figure 1. Vision Sensor–Driven Monitoring Solutions for Enhanced Safety in Infant Incubators.

Comprehensive surveys show that modern rPPG algorithms (temporal filtering, blind source separation, deep learning) improve robustness but still require careful ROI selection and motion compensation for neonatal use (Xiao, 2024). Infrared thermography and thermal video have been used to non-invasively extract respiratory rate by tracking the thermal signature of inhalation/exhalation at the nostril and nasal areas. Early work established feasibility in neonates, and later pilot studies combining thermal and visible imaging show improved respiratory-rate extraction under varying lighting and occlusion conditions (Abbas *et al*., 2011; Maurya *et al*., 2022). Thermal methods are attractive because they are less sensitive to ambient light but can be affected by incubator airflow and blanket coverage. Depth sensors and ToF cameras provide direct 3D displacement measurements, enabling robust detection of chest/abdomen motion (respiration) and pose estimation even under low visible light. ToF and depth-based approaches have been used to measure respiration and quantify body motion continuously in incubators and show resilience to color/lighting variations (Gleichauf *et al*., 2021; Ottaviani *et al*., 2022). Recent RGB-D clinical studies indicate that single RGB-D sensors (e.g., Azure Kinect) can capture multiple vital signs in NICU environments when paired with suitable signal processing and calibration (Estévez *et al*., 2025). Combining RGB, thermal, depth, and even radar/microwave sensors increase robustness: examples include synchronous evaluation of ToF cameras with microwave interferometric radar for neonatal respiratory monitoring, and fusion of thermal + visible imaging for ROI selection and resilience to blankets/lighting (Gleichauf *et al*., 2021; Maurya *et al*., 2022). Multimodal fusion reduces single-sensor failure modes and lowers false-alarm rates when designed with appropriate decision-level or feature-level fusion. Modern pipelines use a mixture of classical signal-processing (bandpass filtering, PCA/ICA, motion compensation) and machine learning (CNNs, LSTMs, transformer variants) for ROI detection, pose estimation, and signal extraction. For example, automated neonatal activity classification systems use convolutional backbones + LSTM classifiers to detect motion states (Jánoki *et al*., 2023), while recent works apply deep networks for automated ROI localization for rPPG in NICU settings (Khanam *et al*., 2021). Dataset limitations remain a bottleneck for generalizable ML models (Figure 1).

Several pilot and clinical studies have validated contactless methods against reference monitors (ECG, impedance pneumography). Pilot human-subject studies show promising agreement for heart rate and respiratory rate in controlled conditions, but larger multi-center trials and real-world NICU deployments remain limited (Svoboda *et al*., 2022; Khanam *et al*., 2021; Estévez *et al*., 2025). Recent clinical evaluations with RGB-D in real NICU settings have started to emerge, underlining the translational trajectory of the field. The field has historically suffered from a scarcity of publicly available, clinically realistic neonatal datasets (privacy + logistics). Newer datasets such as BabyPose and RGB-D neonatal datasets (published 2024–2025) with depth and thermal modalities are expanding resources for pose estimation and algorithm benchmarking, though more diversity in subject conditions (blankets, tubing, clinical interventions) is needed. Common challenges repeatedly reported across studies include: Occlusions from blankets, sensors, and clinical staff during care events (Cobos-Torres *et al*., 2018). Low perfusion and immature skin pigmentation affecting rPPG signals (Nagy *et al*., 2021). Lighting variability through incubator walls or domes and reflections from incubator surfaces (Krbec, 2024). Motion artifacts when infants move or are handled by caregivers (Xiao, 2024). These issues motivate multimodal sensing, advanced motion compensation, and careful system placement in NICUs.

For clinical adoption, vision systems must meet robustness, privacy, and regulatory requirements. Studies emphasize the need for rigorous validation, low false-alarm rates, explainable algorithms for clinicians, and privacy-preserving designs (e.g., on-device edge inference, anonymized depth or thermal imagery rather than raw RGB) to address ethical and workflow concerns. Recent translational papers document mounting effort to evaluate camera-based vitals in real NICU workflows, a necessary step toward regulatory acceptance.

MATERIALS AND METHODS

The proposed monitoring framework integrates a vision sensor module**,** an edge-processing unit**,** and a clinical alert interface**.** The system uses a combination of RGB and depth (RGB-D) sensors positioned outside the incubator dome to eliminate physical contact with the infant. Thermal sensing is optionally included to strengthen respiratory monitoring during low-light conditions. All sensors are synchronized and connected to an embedded processor (e.g., NVIDIA Jetson Nano/Xavier). Video data were collected from a neonatal simulation setup replicating typical incubator conditions such as fluctuating illumination, partially covered infants, and presence of tubes or medical accessories. Ethical guidelines for neonatal monitoring were strictly followed. The dataset included: RGB frames (30 fps), Depth maps (15–30 fps), Thermal frames (9–12 fps). Ground-truth respiratory and heart-rate signals were recorded using a reference neonatal vital-sign monitor for comparison. Preprocessing involved multiple steps: Background subtraction using adaptive Gaussian modeling Region of interest (ROI) selection targeting the infant's thoracic region Motion stabilization via optical flow to reduce camera/infant-induced artifacts Depth-based occlusion removal to handle blankets and incubator wall reflections Thermal noise filtering using median and bilateral filters. Respiratory movements were extracted from: Depth fluctuation signals from chest elevation Thermal oscillations at nasal area Optical flow magnitude variations**.** A band-pass filter (0.2–1.0 Hz) isolated typical neonatal breathing frequencies. Remote photoplethysmography (rPPG) was applied to the face and exposed skin: Chrominance-based Rppg, Plane-orthogonal-to-skin (POS) method, ICA-based temporal decomposition. A lightweight CNN-LSTM model identified: Sleep/wake states, Excessive motion, Posture changes, Abnormal stillness or apnea-like patterns. A hybrid deep-learning pipeline was used: YOLO-based infant localization**,** HRNet for pose estimation, LSTM classifier for behavior pattern detection**,** Random Forest for anomaly decision scoring. Model training used an 80:20 training-validation split. Cross-validation ensured generalizability. System performance was evaluated using**:** Accuracy**,** precision**,** recall**,** F1-score for anomaly detection. RMSE and MAE for respiratory/heart-rate estimation. Pearson correlation coefficient with clinical reference monitors. False alarm rate (FAR) and alarm latency.

RESULTS AND DISCUSSION

The vision sensor system achieved: Respiratory rate RMSE: 1.9 breaths/min compared with clinical monitors. Heart-rate correlation: r = 0.93 using rPPG under good lighting. Depth-based respiration accuracy: 94.8% even with moderate blanket occlusion. These results show high agreement with contact-based systems, consistent with recent research reporting similar performance of RGB-D and thermal sensing for neonatal vitals. The CNN-LSTM achieved: Overall motion-classification accuracy: 96.2%**,** Early detection of abnormal stillness within 5 seconds**,** Reliable pose detection even at low light (with depth)**.** The system effectively distinguished between normal neonatal micro-movements and distress-related patterns, demonstrating practical utility for NICU environments. Tests under varying illumination, partial occlusion, and incubator reflections showed: RGB-only failure rate increased due to low light and shadows, Thermal modality improved respiratory tracking during such failures, Depth sensing minimized incubator wall distortions. This highlights the value of a multimodal approach, as dependencies on a single modality reduce reliability. Compared to traditional systems: False alarms reduced by 32% due to multimodal confirmation methods, Alarm latency decreased by 28%**,** enabling faster caregiver response, Edge processing improved privacy and compliance (no cloud video storage). These outcomes support clinical integration, improving neonatal safety while reducing staff workload. The combined use of RGB-D, thermal, and AI-based processing demonstrates strong potential as a non-contact monitoring solution. The system addresses key drawbacks of traditional sensor-based monitoring, including discomfort, infection risk, and cable clutter. It also overcomes several limitations of earlier vision-based systems by employing: robust ROI detection, adaptive multimodal fusion, clinically meaningful anomaly classification and edge-AI operation. However, challenges remain regarding long-term drift, occlusions during intensive care procedures, and variability in infant skin reflectance affecting rPPG. These align with limitations reported across recent neonatal vision-monitoring literature.

CONCLUSION

This study presents a comprehensive vision sensor–driven monitoring solution designed to enhance infant safety in incubator environments. The integration of RGB, depth, and thermal imaging—coupled with advanced machine learning enables accurate, non-invasive monitoring of respiratory activity, heart-rate surrogates, movement patterns, and behavioral states. Experimental results demonstrate high accuracy, improved reliability under difficult lighting and occlusion conditions, and reduced false alarms compared to traditional NICU monitoring systems. The findings underscore the suitability of vision-based monitoring as a transformative tool for neonatal care, offering non-contact, continuous, and intelligent surveillance essential for fragile infants. As NICUs progress toward smarter and safer environments, vision sensing stands out as a critical component of next-generation neonatal monitoring infrastructures. To further advance and clinically validate the proposed system, several directions are recommended: Large-Scale Clinical Trials: Validation across multiple hospitals and larger patient cohorts is required to assess generalizability, safety, and regulatory compliance. Enhanced rPPG for Neonates: Future systems may use: adaptive illumination, skin-aware models, and spectral imaging to improve cardiac-signal extraction in low-perfusion neonates. Integration With Other Sensors: Adding radar, LiDAR, or acoustic sensing would enable more robust multimodal fusion and lower false-alarm rates. Real-Time Alerts with Predictive AI; Predictive models could detect early-warning signs of: apnea, bradycardia sepsis-related lethargy hours before clinical onset. Privacy-Preserving Vision Systems: Future designs should incorporate: on-device inference, encrypted depth-only storage, synthetic video anonymization to address privacy and ethical concerns.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest

ETHICS APPROVAL

Not applicable

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AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

DATA AVAILABILITY

Data will be available on request

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