

Deep Neural Networks for Noninvasive Hemodynamic Monitoring under Physical Activity

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Abstract

Noninvasive hemodynamic monitoring under physical activity presents a challenging intersection of wearable sensing, physiological modeling, and robust machine learning. Photoplethysmography and related opto-physiological signals enable continuous observation of cardiovascular variables without invasive catheters, but ambulation, exercise, and postural changes introduce severe motion artifacts, sensor displacement, and nonstationary physiological dynamics that degrade conventional estimation pipelines. Deep neural networks offer the capacity to learn hierarchical representations that can disentangle motion corruption from genuine hemodynamic change, yet their deployment in real-world systems requires attention to architecture, data infrastructure, robustness, sustainability, fairness, and governance. This paper provides a system-level examination of deep learning for noninvasive hemodynamic monitoring during physical activity. It discusses the structural trade-offs among recurrent, convolutional, and attention-based architectures, the design of multimodal data acquisition and preprocessing infrastructure, and the challenges of motion artifact mitigation. The analysis further addresses edge computing, federated learning, energy consumption, regulatory accountability, algorithmic fairness, and explainability. Rather than focusing narrowly on model accuracy, the paper emphasizes how sensing, learning, and deployment infrastructures must be co-designed to support safe, equitable, and sustainable monitoring across heterogeneous populations and activity intensities. The discussion integrates cross-domain perspectives from biomedical signal processing, distributed systems, and technology policy to provide forward-looking insights into next-generation noninvasive hemodynamic monitoring systems.

Keywords

deep neural networks; noninvasive hemodynamic monitoring; physical activity; photoplethysmography; motion artifacts; edge computing; fairness; governance.

1. Introduction

Deep learning has reshaped the analysis of complex physiological signals by enabling hierarchical feature extraction from raw or minimally processed data [1]. In cardiovascular

monitoring, photoplethysmography has become a central noninvasive modality because it captures pulsatile blood volume changes through optical sensors and can be embedded in compact wearable devices [2]. Wearable photoplethysmography platforms now support continuous observation outside clinical settings, creating opportunities for early detection, ambulatory management, and personalized prevention [3]. At the same time, cuffless blood pressure estimation algorithms have emerged as a promising alternative to intermittent cuff-based measurement, with machine learning methods capable of extracting vascular dynamics from pulse waveforms [4]. However, physical activity introduces substantial measurement complexity because motion artifacts, tissue deformation, and rapidly changing autonomic state compromise the assumptions underlying many estimation models [5].

Hemodynamic monitoring extends beyond blood pressure to include variables such as cardiac output, systemic vascular resistance, stroke volume variation, and pulse pressure dynamics. These variables are not directly observed by a single sensor but must be inferred from multimodal physiological signals and contextual motion information. During physical activity, hemodynamic variables change in ways that are both clinically meaningful and technically difficult to separate from noise. A walking or running individual may produce pulse waveform distortions that resemble pathological patterns, and sensor attachment may degrade in unpredictable ways. Deep neural networks can learn to use accelerometer, gyroscope, and multiple wavelength optical data to reduce ambiguity, but this capability does not automatically translate into trustworthy field operation. The design of such systems requires a holistic perspective that links sensor front-end characteristics, preprocessing pipelines, network architectures, training data diversity, inference infrastructure, and regulatory oversight.

This paper adopts a systems-oriented perspective rather than a purely algorithmic one. It examines the structural trade-offs involved in building deep neural networks for noninvasive hemodynamic monitoring under physical activity, with emphasis on architecture, data governance, deployment sustainability, robustness, fairness, and policy implications. The goal is to clarify how technical and institutional components interact and to provide a conceptually grounded discussion of future research directions.

2. Background and Related Work

Temporal modeling has been central to physiological signal analysis because hemodynamic variables evolve over multiple time scales. Recurrent architectures such as long short-term memory networks introduced gated mechanisms for maintaining state across long sequences and have been used widely for temporal regression tasks [6]. More recently, attention-based models have provided an alternative by allowing the network to weight relevant time points across a signal without sequential processing [7]. Attention mechanisms are particularly attractive for hemodynamic monitoring because they can focus on specific cardiac cycles or waveform segments while suppressing irrelevant periods. However, attention increases memory requirements and can be less interpretable when many heads attend to diffuse regions.

Convolutional architectures have also been foundational in physiological deep learning. Residual networks introduced identity mappings that improve gradient flow and make it possible to train deeper architectures for complex representation learning [8]. Batch normalization supports stable optimization by standardizing intermediate activations, while adaptive optimization methods such as Adam provide practical training efficiency across noisy loss landscapes [9], [10]. These methods, originally developed for computer vision and natural language processing, have been transferred to photoplethysmography and

hemodynamic estimation. Existing systems for cuffless blood pressure estimation have used multistage deep networks that separate signal enhancement from regression, improving robustness to artifact-contaminated inputs [11]. Multimodal fusion between electrocardiogram and photoplethysmography signals has also been explored to exploit complementary information about electrical and mechanical cardiac activity [12].

Beyond wearable optical sensing, smartphone-based oscillometric approaches have demonstrated that noninvasive blood pressure estimation can be embedded into widely available consumer hardware, suggesting a broader ecosystem in which monitoring does not depend exclusively on specialized medical wearables [13]. At the same time, detailed analysis of photoplethysmogram morphology remains relevant because features such as systolic peak, diastolic notch, and reflection index contain physiological information that may guide hybrid models and support clinical interpretation [14]. Together, these lines of work establish a rich technical foundation, but they also reveal persistent gaps in system-level reliability under real-world physical activity.

3. System Architecture for Noninvasive Hemodynamic Monitoring under Physical Activity

A robust noninvasive hemodynamic monitoring system should be organized as a layered architecture that separates sensing, signal conditioning, representation learning, inference, and decision support. This separation is not merely a software engineering convenience; it enables independent validation, targeted updates, and better failure analysis. The sensing layer typically includes optical photoplethysmography channels, inertial measurement units, and sometimes electrocardiogram or temperature sensors. The conditioning layer performs synchronization, artifact detection, normalization, and segmentation. The representation learning layer maps conditioned input windows into features that are meaningful for hemodynamic inference. The inference layer produces estimates of blood pressure or related variables, and the decision support layer integrates uncertainty, quality indicators, and contextual information. Such an architecture allows the system to degrade gracefully when certain sensors fail or when activity intensity exceeds the expected envelope.

The choice between an end-to-end network and a cascaded system is a major architectural trade-off. End-to-end approaches can be attractive because they remove handcrafted stages and allow the network to optimize all components jointly. Deep learning principles concerning capacity, regularization, and generalization suggest that end-to-end models may perform well when large representative datasets and sufficient computational resources are available [15]. However, end-to-end models can be difficult to audit, and their failure modes may be opaque. Cascaded systems, in which separate modules handle activity recognition, motion artifact suppression, vital sign extraction, and hemodynamic mapping, offer more interpretable intermediate outputs. They enable clinicians and engineers to inspect where a pipeline fails, but they also introduce error propagation across stages. In physical activity monitoring, a cascaded design may be preferable when safety demands intermediate quality checks, while an end-to-end model may be advantageous for latency-constrained edge devices.

Temporal architecture selection also shapes system behavior. Recurrent models such as long short-term memory networks are well suited for sequential processing but can be computationally expensive on long windows [6]. Attention-based transformers can process long sequences in parallel and capture global dependencies, but they may require substantial memory and careful positional encoding for variable-length physiological segments [7]. Convolutional front-ends reduce high-frequency noise and extract local waveform features,

while residual connections and normalization stabilize training [8], [9]. In practice, many contemporary designs use hybrid convolutional and attention modules to balance local detail and global context. The inference hardware must be considered during architecture selection because a model with high theoretical accuracy may be impractical for continuous wearable use if it cannot run within battery and thermal constraints.

Output formulation also has structural implications. Hemodynamic variables such as beat-to-beat blood pressure or pulse wave transit time are often noisy and personalized. A system that outputs point estimates without uncertainty may encourage overconfident clinical interpretation. Modern architectures should therefore include uncertainty estimation, quality flags, and calibration layers. These additions impose training and evaluation costs but substantially improve the trustworthiness of noninvasive monitoring under dynamic physical activity.

4. Data Acquisition and Preprocessing Infrastructure

Data quality is the limiting factor in many noninvasive hemodynamic monitoring efforts. Wearable photoplethysmography signals recorded during physical activity are affected by ambient light, skin perfusion changes, sensor pressure variation, and repetitive motion artifacts. Accelerometer and gyroscope data can serve as references for motion, but synchronization error can introduce spurious correlations. Therefore, the data acquisition layer must be designed with precise timestamping, calibrated gains, and multimodal alignment. Multi-wavelength optical sensors can improve robustness because different wavelengths respond differently to tissue and motion, but they also increase power consumption and sensor complexity.

Preprocessing infrastructure must balance artifact suppression against information preservation. Aggressive bandpass filtering can remove motion components but may also eliminate slow hemodynamic fluctuations or rapid waveform features. Adaptive filtering that uses motion references can help, but it requires careful validation because filter adaptation can inadvertently distort physiologically meaningful signals. Windowing and segmentation should account for heart rate changes, irregular rhythms, and activity transitions. A rapid vital sign extraction approach for real-time opto-physiological monitoring under varying physical activity intensity levels demonstrates that low-latency processing and robustness to changing activity states are simultaneously achievable through carefully designed pipelines [16]. This highlights the importance of treating preprocessing as a system component rather than a fixed pre-step.

The data infrastructure must also support continuous learning and domain adaptation. Training datasets should include diverse activity protocols, such as walking, running, cycling, and postural transitions, as well as resting baselines. Ground truth hemodynamic measurements are costly and often invasive, so transfer learning and weak supervision are valuable. Data augmentation via motion simulation, sensor misalignment simulation, and synthetic waveform blending can increase robustness without requiring proportional increases in labeled physiological data. However, augmentation must preserve physiological plausibility; otherwise the model may learn artifacts of the simulation.

Privacy and data governance are especially important because physiological data are sensitive and can reveal health status, identity-related patterns, and behavioral information. Distributed data storage, access control, and de-identification procedures should be integrated into the acquisition infrastructure from the outset. A well-designed data infrastructure enables model

updates, auditability, and compliance with health data regulations while also supporting the large-scale collection necessary for deep learning.

5. Deep Neural Network Design and Structural Trade-offs

Designing a deep neural network for noninvasive hemodynamic monitoring involves navigating multiple structural trade-offs. Capacity must be sufficient to learn complex waveform-to-hemodynamic mappings, but excessive capacity increases overfitting and inference cost. Convolutional layers are efficient at extracting local waveform patterns such as systolic upstrokes and dicrotic notches [14]. However, they alone may not capture long-range temporal dependencies that emerge during gradual changes in vascular tone or prolonged exercise. Recurrent layers introduce temporal memory but may be difficult to parallelize and can suffer from vanishing gradients over long sequences [6]. Attention mechanisms provide global receptive fields and dynamic weighting, yet they can be computationally heavy and may require large datasets to learn meaningful attention patterns [7].

Residual connections allow deeper networks by alleviating optimization difficulties, which is useful when modeling complex physiological variability [8]. Batch normalization helps stabilize training but can be problematic when batch statistics are contaminated by highly variable motion artifacts or small batch sizes on edge devices [9]. Adaptive optimizers such as Adam are widely used, but their interaction with nonstationary physiological data and domain shift requires careful tuning [10]. Multistage architectures have been proposed to decompose the estimation problem into subproblems such as signal cleaning, feature extraction, and blood pressure regression [11]. Task decomposition improves modularity and can reduce the need for enormous end-to-end datasets, but it requires careful loss balancing and can suffer from cascading errors. Multimodal architectures that fuse electrocardiogram and photoplethysmography signals may improve robustness because they combine electrical and mechanical cardiac information [12]. Yet multimodal fusion increases hardware requirements and synchronization complexity.

Another structural trade-off concerns personalization. Population-level models must generalize across diverse physiological conditions, but hemodynamic relationships are highly individualized. Personalized layers or subject-specific calibration can improve accuracy but demand additional data and complicate deployment. Federated personalization offers a potential middle path, but it raises new systems challenges [18]. The optimal architecture is therefore not universal; it depends on deployment constraints, target population, available sensors, and regulatory requirements. A model intended for clinical decision support may favor interpretable modular designs, while a consumer wellness application may prioritize low-latency end-to-end inference despite lower transparency.

The objective function itself is a structural choice with clinical implications. Hemodynamic estimation often involves multiple correlated outputs, such as systolic, diastolic, and mean arterial pressure, along with pulse rate and cardiac output proxies. Joint learning can exploit correlation but may obscure individually poor performance. Auxiliary tasks, such as activity recognition and signal quality assessment, can regularize the network and provide useful system outputs. However, auxiliary tasks increase annotation burden and can distract the network if not properly weighted. These trade-offs illustrate that deep neural network design for hemodynamic monitoring is not simply a search for the highest accuracy but a process of co-optimizing clinical utility, safety, efficiency, and maintainability.

6. Robustness and Motion Artifact Mitigation

Robustness under physical activity is a defining requirement. Motion artifacts overlap with the frequency range of hemodynamic signals, making linear filtering insufficient and sometimes harmful. A deep network must learn to identify artifact patterns and use motion reference signals to recover the underlying physiological waveform. Multimodal inputs are valuable because accelerometer and gyroscope signals contain information about movement direction and intensity that can be associated with artifact signatures. Attention mechanisms can weight reliable portions of the photoplethysmogram while suppressing corrupted segments. Temporal context is also important because brief artifacts can be inferred from neighboring clean cycles.

Distribution shift is a major source of robustness failure. Training data collected in controlled laboratory protocols may not represent the full range of ambulatory activities, environmental conditions, or sensor attachment variations. Skin tone, sweat, temperature, and sensor pressure alter optical coupling and signal amplitude. A network trained on young healthy subjects may fail on older adults or patients with vascular stiffness. Robustness therefore requires deliberate data diversity, stress testing, and evaluation under protocol shifts that simulate real-world variation [5]. Out-of-distribution detection and uncertainty estimation can flag unreliable predictions rather than silently producing erroneous values. The system should also include fallback strategies, such as asking the user to reduce movement or switching to a more reliable measurement mode when uncertainty exceeds a threshold.

Evaluation protocols for motion robustness should include exercise transitions, treadmill walking and running, cycling, stair climbing, and free-living ambulation. Performance should be assessed not only through aggregate error but also through worst-case error, stability during motion bursts, and recovery time after artifact events. The rapid vital sign extraction system described for varying physical activity intensity levels highlights the importance of real-time operation under changing activity states [16]. Its emphasis on low latency and dynamic adaptation is relevant to broader hemodynamic monitoring because delayed or stale estimates can be clinically misleading during rapidly changing physiological states.

Robustness also implies resilience to adversarial or accidental input perturbations. Sensor dropout, battery voltage changes, and firmware updates can alter signal statistics. Periodic monitoring of input drift and model performance in deployment is necessary. Continuous validation against reference devices in calibration studies can help, but it is costly. A practical system may combine on-device quality monitoring with cloud-based anomaly detection to identify systematic drift. Robustness is therefore an operational property of the entire system, not a fixed characteristic of the trained model.

7. Deployment, Edge Computing, and Sustainability

Deployment choices determine whether a deep learning model can function continuously within wearable and mobile ecosystems. Cloud-only inference offers abundant computational resources but introduces communication latency, increases privacy risk, and depends on network availability. Edge inference enables real-time processing and local data control, but edge devices have limited memory, energy, and thermal budgets. Model compression through quantization, pruning, and knowledge distillation can reduce resource use but may degrade accuracy or robustness if not carefully validated. A hybrid architecture may run lightweight signal quality checks and preliminary estimation on the edge while delegating heavy retrospective analysis to the cloud.

Federated learning has emerged as a promising paradigm for training across decentralized devices without centralizing raw physiological data. Communication-efficient federated methods reduce bandwidth demands by compressing model updates and performing local optimization [17]. However, federated systems face significant challenges, including heterogeneity of devices, non-independent data distributions, personalization, security, and evaluation complexity [18]. In hemodynamic monitoring, federated learning is appealing because it can incorporate diverse activity patterns and sensor configurations without pooling sensitive health data. Yet heterogeneity in ground truth labels, device quality, and population characteristics can make model convergence unstable. Personalization strategies, such as fine-tuning global models on local data or maintaining local adaptation layers, can mitigate some of these challenges but introduce added complexity.

Sustainability is an important but often overlooked dimension. Training large deep networks consumes substantial energy and contributes to carbon emissions. In continuous monitoring, inference energy is also nontrivial because wearables may process signals for many hours each day. Efficient architectures, quantization, and selective inference can reduce energy demand. From a lifecycle perspective, the environmental cost of manufacturing sensors, edge hardware, and cloud infrastructure should be considered. A sustainable monitoring system should avoid unnecessary model updates, use renewable energy where possible, and design for hardware longevity through over-the-air updates rather than premature replacement. Sustainability also intersects with accessibility because energy-hungry systems may not be viable in low-resource settings.

8. Governance, Fairness, and Policy Implications

Noninvasive hemodynamic monitoring can influence clinical decisions, lifestyle recommendations, and patient safety. It therefore requires governance mechanisms that go beyond technical validation. Interpretability is a central concern because clinicians and patients may need to understand why a model produced a particular estimate. Some researchers argue that high-stakes domains should prefer inherently interpretable models over post hoc explanations for black-box systems [19]. In healthcare, explainability must be grounded in the needs of clinicians, patients, and regulators, and it should not be reduced to saliency maps alone [20]. A hemodynamic monitoring system might provide contextual explanations such as which sensor channels contributed most, whether motion artifacts were present, and how confidence changed over time. Such explanations support accountability but require careful design to avoid misleading users.

Fairness is another critical issue. Optical sensors and deep models may perform differently across skin tones, body compositions, ages, fitness levels, and disease states. Bias can arise from unrepresentative training data, from measurement physics, or from evaluation metrics that hide subgroup disparities. A broad survey of bias and fairness in machine learning identifies multiple sources of harm and mitigation strategies, including fairness constraints and subgroup auditing [21]. However, fairness is not simply a technical optimization problem. Algorithmic fairness interventions can conflict with other values, and they must be situated within social and institutional context [22]. For hemodynamic monitoring, fairness requires diverse data collection, transparent subgroup performance reporting, and participatory design with affected communities. A model that performs well on average but poorly for a particular skin tone may be unacceptable for clinical use.

Regulatory governance must address the software as a medical device lifecycle. Pre-market validation should include stress testing under physical activity, subgroup analyses, and post-

market surveillance for drift and adverse events. Data protection regulation affects how physiological data can be collected, stored, and shared. Cross-border data flows and cloud processing raise jurisdictional questions. Algorithmic accountability mechanisms, such as model cards, datasheets, and audit logs, can support transparency. Liability frameworks must clarify responsibility when a model error contributes to a missed hypertensive episode or false alarm. Policy should also promote interoperability so that monitoring systems can exchange data with electronic health records and other health platforms.

9. Future Directions

Future systems will likely integrate more diverse physiological modalities and contextual information. Advances in wearable sensing may enable continuous tracking of cardiac output proxies, vascular compliance, and fluid responsiveness without invasive lines. Foundation models for physiological signals may learn from large-scale multimodal datasets and adapt to downstream hemodynamic tasks with limited labels. However, these models will raise unresolved questions about data ownership, consent, and generalization. Causal inference and physics-informed learning may help separate motion artifacts from genuine hemodynamic change by encoding known physiological relationships into the network. Digital twin approaches may simulate individual cardiovascular responses to physical activity and guide personalized monitoring.

System-level research should also address adaptive deployment, where models update safely in the field without catastrophic forgetting. On-device learning and federated personalization will need robust evaluation across heterogeneous devices and regulatory boundaries. Sustainability must become a first-class design objective, with quantifiable trade-offs among accuracy, energy, latency, and hardware lifecycle. Finally, fairness and governance research should move beyond aggregate metrics to examine how monitoring systems affect different communities and how patients experience algorithmic surveillance in everyday life. These directions require interdisciplinary collaboration among machine learning researchers, clinicians, sensor engineers, regulators, and social scientists.

10. Conclusion

Deep neural networks offer substantial promise for noninvasive hemodynamic monitoring under physical activity, but realizing that promise requires more than architectural innovation. This paper has argued that sensing, data infrastructure, model design, robustness engineering, deployment, sustainability, fairness, and governance must be treated as interconnected system components. Physical activity introduces motion artifacts and physiological nonstationarity that challenge naive estimation pipelines. Hybrid temporal architectures, multimodal fusion, cascaded modular designs, and uncertainty-aware outputs can improve robustness, but they also create trade-offs in interpretability, resource use, and maintainability. Edge computing and federated learning can support privacy and scalability, while raising challenges of heterogeneity and energy consumption. Governance and fairness require deliberate attention to diverse populations, transparent evaluation, and regulatory accountability. A durable noninvasive hemodynamic monitoring system will be one that aligns technical performance with clinical usefulness, equity, and environmental responsibility.

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