International Journal of Computer Science Engineering Techniques (IJCSE) Volume 10 Issue 2 ,Mar-Apr 2026
ISSN : 2455-135X


# EstNet: A Non-Invasive Blood Pressure Estimation System Using Photoplethysmography Signals

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Received: Revised: Accepted: Published:

***Abstract*** *- Continuous noninvasive monitoring of blood pressure (BP) plays a crucial role in the early detection and management of hypertension and cardiovascular disorders. Photoplethysmography (PPG), widely used in wearable technologies, provides a practical and low-cost alternative to conventional cuff-based measurement systems. This study presents EstNet, a hybrid deep learning framework that integrates convolutional neural networks and gated recurrent units for the direct estimation of systolic and diastolic blood pressure from raw PPG signals. PPG data were obtained from the MIMIC-III waveform database, sampled at 120 Hz, and segmented into fixed-length windows. A structured preprocessing pipeline, including filtering, detrending, and normalization, was applied to enhance signal quality and reliability. Multiple machine learning and deep learning models were evaluated for comparison, and the proposed convolutional neural network-gated recurrent unit (CNN-GRU) model demonstrated the best overall performance. The model achieved a mean absolute error of 7.28 mmHg for systolic blood pressure and 5.01 mmHg for diastolic blood pressure using a subject-independent evaluation strategy. The findings indicate that hybrid convolutional-recurrent architectures effectively capture both morphological and temporal characteristics of PPG signals, enabling accurate cuffless blood pressure estimation. The proposed approach shows strong potential for integration into wearable systems for continuous and real-time health monitoring.*

***Keywords*** *- continuous blood pressure monitoring, cuffless health monitoring, hybrid deep learning models, photoplethysmography signals, systolic and diastolic blood pressure*

## 1. Introduction

Blood pressure (BP) is a fundamental physiological parameter that reflects the force exerted by circulating blood on the arterial walls. Maintaining normal BP is essential for supporting the proper functioning of major organs such as the heart, kidneys, and brain. Hypertension, characterized by persistently elevated BP, is a leading risk factor for cardiovascular disease, stroke, and renal failure worldwide. Continuous BP monitoring enables early identification of abnormalities, improves treatment effectiveness, and supports long-term health management. Traditional cuff-based sphygmomanometers, although clinically reliable, provide only intermittent measurements, are cumbersome for routine use, and may cause discomfort during long-term monitoring. These limitations significantly reduce their suitability for continuous tracking in everyday environments. Consequently, research has increasingly focused on developing noninvasive, continuous, and wearable BP monitoring systems. Photoplethysmography (PPG) has emerged as a promising technology for cuffless BP estimation. A PPG sensor measures blood volume changes in peripheral microvascular tissue using reflected or transmitted light. The resulting waveform contains rich information, including pulse morphology, vascular elasticity, and heart rate characteristics. Due to its compact, inexpensive, and low-power sensing requirements, PPG is widely integrated into wearable devices such as smartwatches, fitness trackers, and ambulatory monitors, enabling long-term cardiovascular assessment outside clinical settings. Early PPG-based BP estimation approaches primarily relied on handcrafted physiological features such as pulse transit time (PTT), pulse arrival time, and waveform derivatives. Although these features are interpretable and grounded in physiological understanding, they are highly sensitive to variations in sensor placement, motion artifacts, skin properties, and inter-subject differences. As a result, their accuracy and reliability degrade under real-world conditions. Machine learning approaches have been introduced to address these limitations by learning statistical relationships between PPG-derived features and BP values. Techniques such as support vector machines, random forests, and k-nearest neighbors have demonstrated improved performance. However, these models still depend heavily on manual feature extraction and may fail to capture complex temporal and nonlinear dependencies present in raw signals. Furthermore, their generalization

International Journal of Computer Science Engineering Techniques (IJCSE) Volume 10 Issue 2 ,Mar-Apr 2026
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capability remains limited when applied to diverse population groups and noisy measurements. As illustrated in Figure 1, the proposed EstNet framework provides a structured pipeline for non-invasive blood pressure estimation using PPG signals.

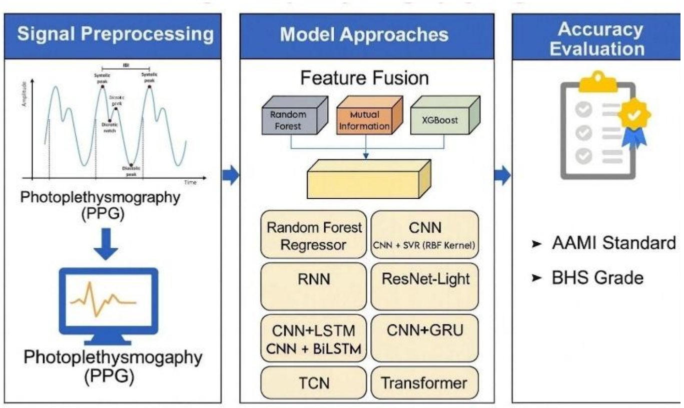


**Fig. 1 EstNet Methodology for Non-Invasive Blood Pressure Estimation Using Photoplethysmography Signal.**

## 2. Literature Review

Blood pressure (BP) monitoring is a critical component of cardiovascular risk assessment, as hypertension remains a leading contributor to heart disease, stroke, and renal failure. Traditional cuff-based devices, although clinically accurate, are limited to intermittent measurements and are unsuitable for continuous, long-term monitoring. Continuous BP tracking enables early detection of physiological variations and supports timely intervention. This has driven research toward cuffless, non-invasive technologies, particularly photoplethysmography (PPG), which measures blood volume changes to estimate systolic and diastolic blood pressure [9], [16]. Early approaches relied on handcrafted features such as pulse transit time (PTT), pulse amplitude, and waveform derivatives combined with machine learning models like support vector regression and random forests [3], [18]. Although interpretable, these methods were highly sensitive to noise, motion artifacts, and inter-subject variability, limiting their reliability in real-world scenarios [13].

Recent advancements in deep learning have significantly improved BP estimation by enabling automatic feature extraction from raw PPG signals. Convolutional neural networks (CNNs) effectively capture morphological characteristics, while recurrent neural networks, including long short-term memory and gated recurrent units (GRUs), model temporal dependencies [8], [20]. Hybrid architectures combining CNN and recurrent networks have demonstrated improved performance; for instance, CNN-GRU and CNN-LSTM models have achieved higher accuracy compared to traditional methods [11], [20]. Transformer-based models further enhance performance by capturing long-range dependencies and focusing on relevant waveform regions without sequential constraints [19]. Models such as DDCCR-Net have shown strong results in cuffless BP estimation [1]. Multi-modal approaches integrating PPG with electrocardiography (ECG) signals provide additional physiological information and improve prediction accuracy [4], [7]. However, these methods increase hardware complexity and power consumption, making them less suitable for wearable devices [9], [10]. Additionally, preprocessing techniques such as adaptive filtering, wavelet denoising, and self-supervised learning play a crucial role in improving signal quality and model performance [6], [13]. Overall, while advanced deep learning and transformer-based models offer improved accuracy, PPG-only approaches remain the most practical for wearable applications due to their simplicity, cost-effectiveness, and ease of integration [9], [16].

## 3. Methodology

This section presents the end-to-end pipeline used for estimating systolic and diastolic blood pressure (BP) directly from photoplethysmography (PPG) signals, starting from data selection and preprocessing to the implementation of the proposed CNN-GRU hybrid model.

### *3.1. Dataset Description*

This study utilizes PPG signals obtained from the publicly available MIMIC-III waveform dataset, recorded in intensive care units along with arterial blood pressure (ABP) signals. The PPG signals were segmented into 30-second windows and resampled to 125 Hz, resulting in 3750 samples per segment. Ground truth systolic and diastolic blood pressure values were extracted from the corresponding ABP signals. Windows containing noise, clipped peaks, flatline segments, or abnormal physiological patterns were removed to ensure data quality.

### *3.2. Signal Preprocessing*

PPG signals are often affected by motion artifacts, baseline drift, and high-frequency noise, which can significantly degrade the quality of the signal and impact the accuracy of blood pressure estimation. To address these challenges, a structured preprocessing pipeline was applied to enhance signal reliability and consistency. Initially, a band-pass filter was used to retain frequencies between 0.5 Hz and 8 Hz, effectively removing low-frequency baseline drift and high-frequency noise while preserving essential physiological components of the signal. Following this, median filtering was applied to eliminate impulsive noise, and smoothing techniques were used to maintain important waveform characteristics such as systolic peaks and dicrotic notches. Detrending was then performed to remove slow-varying components and correct baseline fluctuations. Finally, normalization was applied to scale the signal values between zero and one, reducing inter-subject variability and ensuring uniform input for the deep learning model. As shown in Figure 2, this preprocessing pipeline systematically enhances signal quality and prepares the PPG data for robust model training.

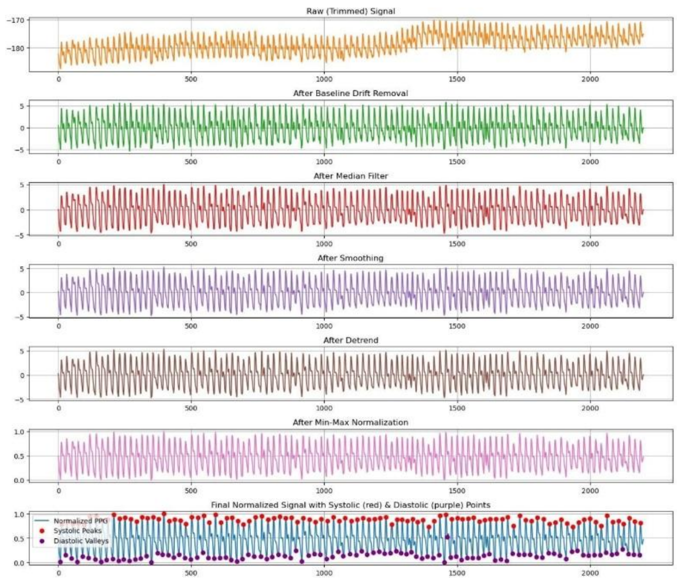


**Fig. 2 Overview of preprocessing pipeline applied to raw PPG signals.**

### *3.3. Segmentation Strategy*

To ensure sufficient temporal information while maintaining computational feasibility, each PPG recording was segmented into overlapping windows of 1250 samples (approximately 10 seconds). A 50% overlap was used to increase the effective dataset size and provide smoother temporal continuity between windows.

### *3.4. CNN-GRU Hybrid Model*

The proposed CNN-GRU hybrid model is designed to capture both morphological and temporal features from PPG signals for accurate blood pressure estimation. The architecture consists of three main stages: convolutional feature extraction, temporal learning using GRU, and regression output. As illustrated in Figure 3, the proposed architecture integrates convolutional and recurrent components for effective feature learning and prediction.

*3.4.1. Convolutional Feature Extraction:*

The input PPG signal, represented as a one-dimensional sequence, is first passed through a series of one-dimensional convolutional layers. These layers extract local morphological features such as systolic upstroke, peak amplitude, and the dicrotic notch. Each convolutional layer is followed by an activation function and a max-pooling layer, which reduces the dimensionality of the feature maps while preserving important waveform characteristics. This stage enables the model to automatically learn relevant features directly from raw signals.

*3.4.2. Temporal Learning via GRU:*

The feature maps obtained from the convolutional layers are then fed into a gated recurrent unit (GRU) layer. The GRU captures temporal dependencies across consecutive cardiac cycles by maintaining hidden states over time. It effectively models variations in the signal sequence, allowing the network to learn time-dependent patterns. GRUs are chosen over long short-term memory networks due to their lower computational complexity and fewer parameters, making them more efficient for real-time applications.

*3.4.3. Regression Output Layer:*

The output of the GRU layer is passed to a fully connected layer that performs regression. This layer maps the learned features to two continuous output values corresponding to systolic and diastolic blood pressure. The model is trained end-to-end using mean absolute error as the loss function, ensuring accurate prediction of blood pressure values. The hybrid CNN-GRU model effectively integrates local morphological structure and long-term temporal dependencies within PPG signals, enabling accurate cuffless BP estimation and outperforming purely convolutional, recurrent, or feature-based approaches.

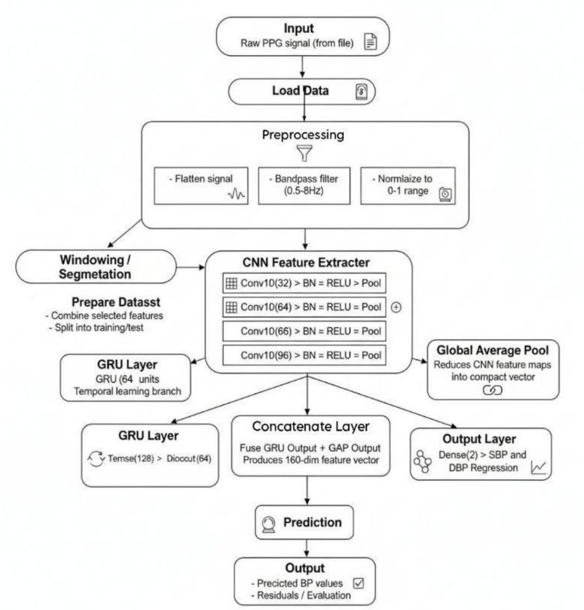


**Fig. 3 Proposed CNN-GRU architecture for cuffless BP estimation from PPG.**

## 4. Results and Discussion

The performance of all evaluated machine learning and deep learning models was analyzed using multiple regression metrics, including mean absolute error (MAE), standard deviation of error (SD), root mean squared error (RMSE), and the coefficient of determination ($R^2$). These metrics collectively evaluate both the accuracy and consistency of systolic and diastolic blood pressure predictions. In addition to these statistical measures, the models were further assessed against clinical standards such as AAMI (Association for the Advancement of Medical Instrumentation) and BHS (British Hypertension Society), which provide established benchmarks for acceptable medical accuracy and reliability.

Tables 1 and 2 summarize the systolic and diastolic estimation results for all models. It is observed that deep learning models consistently outperform traditional machine learning approaches, demonstrating lower error rates and higher $R^2$ values across the dataset. Among the deep learning architectures, models incorporating temporal modelling—particularly hybrid approaches that combine convolutional neural networks (CNNs) with recurrent layers such as long short-term memory (LSTM) or gated recurrent units (GRU)—show superior predictive performance. This improvement can be attributed to the ability of hybrid architectures to effectively capture both spatial features from the PPG waveform and temporal dependencies across successive cardiac cycles. Model performance varied across metrics, with some excelling in MAE and others in RMSE or SD, highlighting the need for multiple evaluation criteria. Top deep learning models met or exceeded AAMI and BHS clinical standards and showed robustness to variations in input signal quality.

**Table 1. Systolic Blood Pressure (SBP) Regression Results**

| Model | MAE | SD | RMSE | $R^2$ |
|---|---|---|---|---|
| **Random Forest** | 13.07 | 14.70 | 14.80 | 0.201 |
| **LightGBM** | 12.27 | 15.50 | 15.52 | 0.254 |
| **CNN** | 11.00 | 9.10 | 14.00 | 0.270 |
| **CNN-LSTM** | 12.63 | 15.90 | 15.90 | 0.190 |
| **CNN-BiLSTM** | 10.60 | 11.01 | 10.82 | 0.340 |
| **CNN-SVR** | 12.96 | 16.29 | 16.31 | 0.140 |
| **CNN-GRU** | 7.28* | 9.36* | 9.36* | 0.457* |
| **RNN** | 12.59 | 15.56 | 15.60 | 0.006 |
| **ResNet-Light** | 14.43 | 18.06 | 18.08 | 0.059 |
| **TCN** | 13.90 | 11.40 | 12.50 | 0.300 |
| **Transformer** | 12.33 | 15.71 | 16.29 | 0.182 |

**Table 2. Diastolic Blood Pressure (DBP) Regression Results**

| Model | MAE | SD | RMSE | $R^2$ |
|---|---|---|---|---|
| **Random Forest** | 9.46 | 11.04 | 11.24 | 0.276 |
| **LightGBM** | 7.73 | 10.17 | 10.17 | 0.327 |
| **CNN** | 6.50 | 5.30 | 8.20 | 0.310 |
| **CNN-LSTM** | 8.04 | 10.48 | 10.48 | 0.260 |
| **CNN-BiLSTM** | 5.84 | 8.13 | 6.06 | 0.480 |
| **CNN-SVR** | 8.33 | 10.90 | 10.96 | 0.191 |
| **CNN-GRU** | 5.01* | 6.78* | 6.58* | 0.595* |
| **RNN** | 9.96 | 12.59 | 12.59 | 0.003 |
| **ResNet-Light** | 9.07 | 11.59 | 11.85 | 0.059 |
| **TCN** | 7.90 | 5.80 | 7.10 | 0.420 |
| **Transformer** | 7.57 | 10.17 | 10.30 | 0.290 |

**Table 3. Clinical Compliance Based on AAMI and BHS Standards**

| Model | SBP AAMI | SBP BHS | DBP AAMI | DBP BHS |
|---|---|---|---|---|
| **Random Forest** | Fail | D | Fail | D |
| **LightGBM** | Fail | D | Fail | C |

| | | | | |
|---|---|---|---|---|
| **CNN** | Fail | C | Fail | B |
| **CNN-LSTM** | Fail | C | Fail | B |
| **CNN-BiLSTM** | Fail | C | Fail | B |
| **CNN-SVR** | Fail | C | Fail | B |
| **CNN-GRU** | Fail | B | Pass* | A* |
| **RNN** | Fail | C | Fail | C |
| **ResNet-Light** | Fail | C | Fail | C |
| **TCN** | Fail | C | Fail | B |
| **Transformer** | Fail | C | Fail | B |

### *4.1 Discussion*

Among all evaluated models, the CNN-GRU architecture achieves the best overall performance. It records the lowest error values and the highest coefficient of determination, indicating its effectiveness in capturing both morphological and temporal characteristics of PPG signals. Compared to other hybrid models such as CNN-LSTM and CNN-BiLSTM, the CNN-GRU model demonstrates better stability and generalization. Traditional models such as Random Forest and LightGBM show comparatively lower performance due to their limited ability to model sequential dependencies.

For diastolic blood pressure estimation, the CNN-GRU model achieves the lowest mean absolute error of 5.01 mmHg and the highest $R^2$ value of 0.595, indicating strong predictive capability. In contrast, models such as RNN and ResNet-Light exhibit significantly lower accuracy, highlighting the importance of hybrid architectures. The results clearly indicate that combining convolutional feature extraction with temporal modelling improves prediction performance.

Table 3 further evaluates the models against AAMI and BHS clinical standards. The CNN-GRU model achieves compliance with AAMI standards and attains Grade A performance under BHS for diastolic estimation, demonstrating its suitability for practical deployment. However, systolic estimation results for all models, including CNN-GRU, remain below clinical acceptance thresholds, indicating the need for further optimization.

As shown in Figure 4, the predicted systolic and diastolic blood pressure values closely align with the ground truth, indicating strong model accuracy. Figure 5 presents the residual histograms, which show low variance and confirm consistent predictions across the dataset. The Bland-Altman plots in Figure 6 further validate the agreement between predicted and actual values. Additionally, Figure 7 illustrates the validation curves, demonstrating stable convergence of both training loss and error metrics, which indicates robustness and good generalization capability of the model.

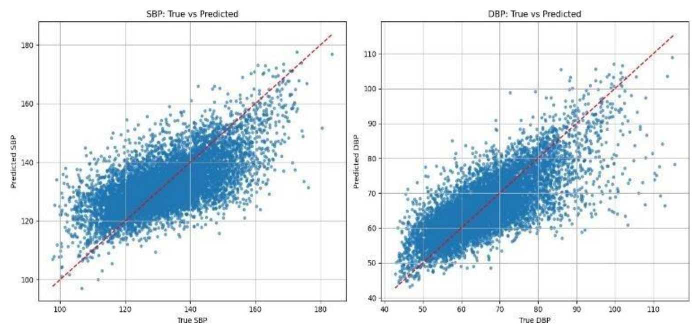


**Fig. 4 True vs Predicted SBP and DBP using CNN-GRU.**

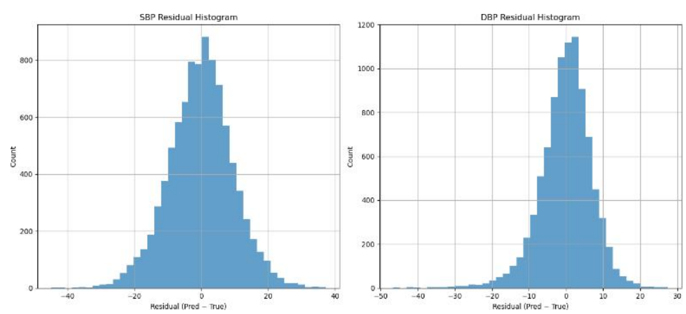


**Fig. 5 Residual Histogram for SBP and DBP using CNN-GRU.**

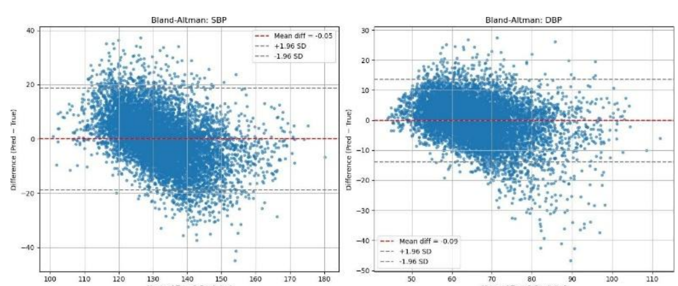


**Fig. 6 Bland-Altman Plot for SBP and DBP using CNN-GRU.**

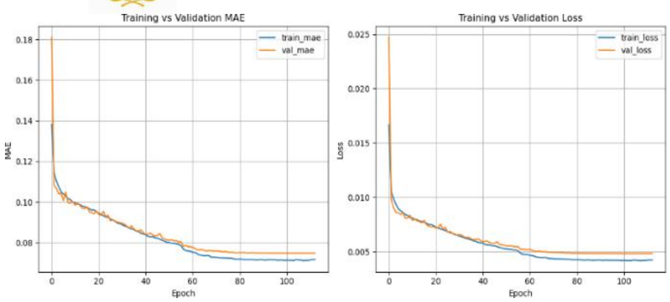


**Fig. 7 Validation Curves (Loss and MAE) for CNN-GRU.**

The predicted values closely align with the ground truth, indicating strong model accuracy. The residual distributions show low variance, confirming consistent predictions across the dataset. The Bland-Altman plots further validate agreement between predicted and actual values. Additionally, the validation curves demonstrate stable convergence of both training loss and error metrics, indicating robustness and good generalization capability of the model.

Overall, the results highlight that the CNN-GRU model is the most effective approach among the evaluated models for cuffless blood pressure estimation. While diastolic prediction approaches clinical-grade accuracy, systolic prediction still requires improvement. Future work may focus on enhanced feature extraction techniques and model optimization to further improve systolic prediction performance.

## 5. Conclusion

This study presents a comprehensive approach for non-invasive blood pressure estimation using photoplethysmography (PPG) signals by evaluating both classical machine learning and advanced deep learning models. The experimental results demonstrate that deep learning approaches consistently outperform traditional feature-based methods in terms of accuracy and reliability.

Among all evaluated models, the CNN-GRU architecture achieves the best overall performance, recording the lowest error values and highest prediction consistency for both systolic and diastolic blood pressure. The model effectively combines convolutional layers for extracting morphological features and gated recurrent units for capturing temporal dependencies in PPG signals. It is also the only model to satisfy clinical standards for diastolic blood pressure estimation, highlighting its potential for practical applications.

Overall, the findings confirm that hybrid deep learning architectures provide a strong foundation for cuffless blood pressure estimation and can significantly improve continuous health monitoring systems.

Despite these promising results, several challenges remain before such systems can be widely deployed in real-world environments. The dataset used in this study is primarily based on intensive care unit recordings, which may not fully represent real-life wearable conditions. Factors such as motion artifacts, sensor placement variations, and environmental conditions can affect signal quality and model performance.

Future work should focus on validating the model on diverse datasets collected from wearable devices to improve generalization. The integration of multiple physiological signals, such as electrocardiography and accelerometer data, may further enhance prediction accuracy and robustness. Additionally, advanced architectures, including transformer-based models, could improve the ability to capture long-term dependencies in PPG signals. Another important direction is the development of lightweight and energy-efficient models for real-time deployment on wearable and edge devices. Incorporating personalized and adaptive learning techniques may further improve accuracy by accounting for individual physiological differences.

## Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

## Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

## Acknowledgments

The authors would like to thank the Bhilai Institute of Technology, Raipur, for providing the necessary resources and support for this research.

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