PPG Signal Quality Assessment Using a Compact CNN Module

R. TRIVENI[1], N.S. IFFATH MUSKAN[2], B. LAKSHMI PRASANNA[3], R. BHAVANI[4], P. ANJUM REHABAR[5], C. NAVYA[6]

[1 2,3,4,5,6]Department of Electronics and Communication Engineering
Aditya College of Engineering, Madanapalle – 517 325, Andhra Pradesh, India.

Abstract: Photoplethysmography (PPG) signals are widely used in healthcare applications to monitor heart rate and assess cardiovascular conditions. However, these signals are highly sensitive to motion artifacts and noise during acquisition, which can significantly affect their quality and reliability. Ensuring good signal quality is therefore essential for accurate analysis and diagnosis. In this paper, a deep learning-based approach is proposed for automatic PPG signal quality assessment. The method utilizes wavelet-based time–frequency representation to convert PPG signals into scalogram images, which are then used as input to a compact Convolutional Neural Network (CNN) model. A dataset of 5804 PPG signal segments is preprocessed and analyzed to classify signals into good and bad quality categories. The proposed model achieves an accuracy of 98.3%, with high sensitivity and specificity, demonstrating its effectiveness in identifying poor-quality signals. The results also show a significant reduction in heart rate estimation error after filtering noisy signals. Overall, the proposed approach provides a reliable and efficient solution for PPG signal quality assessment and can be applied in real-time healthcare monitoring systems.

Index Terms: Photoplethysmography (PPG), Signal Quality Assessment, Convolutional Neural Network (CNN), Wavelet Transform, Deep Learning.

I. INTRODUCTION

Photoplethysmography (PPG) is a simple and non-invasive optical technique that is widely used to monitor physiological parameters such as heart rate, blood oxygen saturation, and overall cardiovascular health. Due to its low cost and ease of implementation, PPG has become an essential component in wearable devices and modern healthcare monitoring systems. With the increasing demand for continuous health monitoring, the reliability of PPG signals has gained significant importance in both clinical and real-time applications.

However, one of the major challenges associated with PPG signals is their susceptibility to noise and motion artifacts. Body movements, poor sensor contact, and environmental disturbances can significantly degrade signal quality. Low-quality PPG signals can lead to inaccurate analysis and unreliable health information, which may affect critical medical decisions. Therefore, it is necessary to assess the quality of PPG signals before using them for further processing and diagnosis. Several traditional methods have been developed to evaluate PPG signal quality, including statistical and rule-based approaches. However, these methods often require manual feature extraction and may not perform well under varying conditions. In recent years, deep learning techniques have shown promising results in automatically learning complex patterns from biomedical signals, offering a more efficient and accurate solution.

In this paper, a deep learning-based approach is proposed for automatic PPG signal quality assessment. The method utilizes wavelet transform to convert PPG signals into time–frequency representations, which are then processed using a compact Convolutional Neural Network (CNN) model for classification. The objective of this work is to accurately classify PPG signals into good and bad quality categories, thereby improving the reliability of subsequent analysis. The rest of the paper is organized as follows. Section II presents the related work in the field of PPG signal quality assessment. Section III describes the existing methods. Section IV presents the proposed methodology, including data preprocessing and model design. Section V discusses the experimental results and performance evaluation. Finally, Section VI concludes the paper and outlines future research directions.

II. RELATED WORK

Photoplethysmography (PPG) is a non-invasive optical sensing technique widely used for monitoring physiological parameters such as heart rate and blood oxygen levels. Temko (2017) demonstrated the effectiveness of PPG signals for accurate heart rate monitoring during physical activities. Similarly, Chung et al. (2008) proposed a wearable healthcare monitoring system integrating ECG, accelerometer, and SpO_2 sensors, emphasizing the importance of reliable physiological signal acquisition. Recent advancements have focused on applying deep learning techniques to PPG signal analysis. Panwar et al. (2020) introduced PP-Net, a deep learning framework for estimating heart rate and blood pressure from PPG signals, showing improved estimation accuracy through automatic feature learning.

Signal quality assessment has gained significant attention due to the impact of noise and motion artifacts on PPG signals. Qi et al. (2023) proposed a method combining multi-class features with multi-scale temporal information for improved classification performance. Similarly, Rodrigues (2023) developed a hybrid rule-based and machine learning approach for evaluating PPG signal quality, achieving better reliability in detecting poor-quality signals.

Deep learning approaches have also been applied in related areas. A hybrid ResNet and Bi-LSTM model (2023) was proposed for cardiovascular disease detection using PPG signals, combining spatial and temporal feature extraction. Asgharnezhad et al. (2023) introduced a multi-stage machine learning framework to enhance classification reliability, while recent studies (2023) explored deep learning models for hypertension detection using PPG signals. Noise removal is another critical aspect of PPG signal processing. Ahmed et al. (2023) proposed a hybrid deep learning and wavelet transform-based approach for denoising PPG signals, significantly improving signal quality. Manikandan and Boppu (2022) developed a CNN-based model for PPG signal quality assessment in IoMT devices, demonstrating the effectiveness of deep learning in automatic feature extraction.

Traditional signal processing methods have also been widely used. Sukor et al. (2011) introduced waveform morphology-based quality measures, while Li and Clifford (2012) applied dynamic time warping and machine learning techniques for signal quality assessment. Couceiro et al. (2014) proposed methods for detecting motion artifacts using time and frequency domain analysis, and Cherif et al. (2016) developed a random distortion testing approach for artifact detection. More recent studies have focused on deep learning-based artifact detection. Goh et al. (2020) proposed a one-dimensional CNN model for detecting motion artifacts in wearable PPG devices, achieving high classification accuracy. Liu et al. (2020) applied supervised learning methods to evaluate signal quality in wearable pulse oximeters. In addition, PPG signals have been used for extracting various physiological parameters. Sharma (2019) demonstrated respiration extraction from PPG signals, while Rozi et al. (2012) analyzed vascular aging using second derivatives of PPG signals. Charlton et al. (2018) provided a comprehensive review of breathing rate estimation using ECG and PPG signals. Biswas et al. (2019) proposed a deep learning framework for heart rate estimation and biometric identification.

Although numerous methods have been proposed for PPG signal analysis, accurately distinguishing between good-quality and poor-quality signals remains a challenging task due to motion artifacts and noise. Therefore, this work proposes a compact CNN-based approach combined with wavelet-based time–frequency representation to achieve efficient and accurate PPG signal quality assessment.

III. Existing Method

Several studies have been conducted for PPG signal quality assessment using traditional signal processing and machine learning techniques. Methods such as SQI-based analysis, SVM, and neural networks have been used, but they often depend on manual feature extraction and may not perform well under noisy conditions. Therefore, more advanced approaches are required for accurate and reliable classification.

IV. Proposed Methodology

The proposed system focuses on developing an efficient deep learning-based approach for assessing the quality of photoplethysmography (PPG) signals. The overall methodology consists of signal preprocessing, feature extraction using wavelet transform, and classification using a compact Convolutional Neural Network (CNN) model.

A. Dataset Description

The dataset used in this study is obtained from the MIMIC Perform dataset, which is publicly available through PhysioNet and related repositories such as Zenodo. This dataset contains physiological signals collected from critically ill patients during clinical care, including photoplethysmography (PPG) signals used in this work.

A total of 5804 PPG signal segments, each of 10 seconds duration, are considered for analysis. The dataset includes signals recorded under various conditions, representing both good-quality signals and poor-quality signals affected by motion artifacts and noise.

The raw signals are preprocessed to remove noise and ensure consistency. The segmented signals are then transformed into time–frequency representations using Continuous Wavelet Transform (CWT). These wavelet-based scalogram images are used as input to the proposed CNN model for classification.

This dataset provides a reliable and diverse set of signals for training and evaluating the performance of the proposed PPG signal quality assessment system.

B. Proposed System Workflow

The workflow of the proposed system is illustrated in Fig. 1. Initially, raw PPG signals are collected from the dataset. The proposed system begins with data preprocessing of raw PPG signals, followed by splitting the dataset into training and testing sets. The training data is used to train a deep learning model, while the testing data is used for evaluation. The model generates predictions, and its performance is assessed using metrics such as loss and accuracy.

The preprocessed PPG signals are then segmented into fixed-length windows of 10 seconds. Each segment is transformed into a time–frequency representation using Continuous Wavelet Transform (CWT). This transformation converts the one-dimensional signal into a two-dimensional scalogram image, capturing both temporal and frequency information effectively.

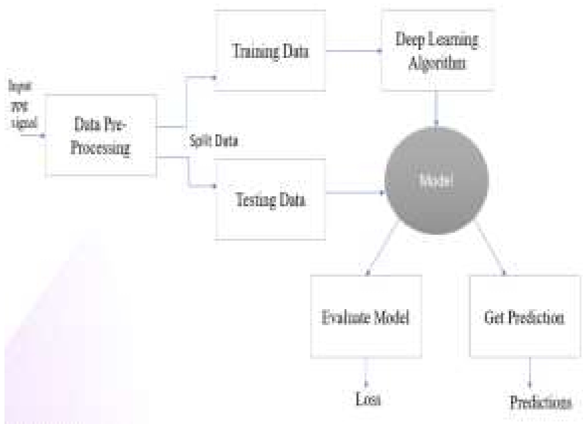

Figure 1: Block diagram of the proposed PPG signal quality assessment system

C. Wavelet Scalogram Representation

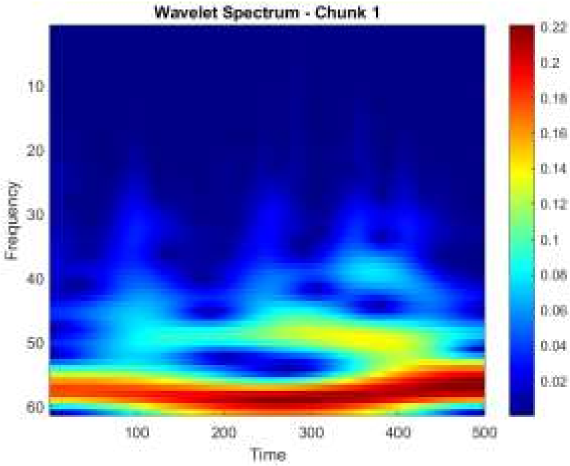

Figure 2: Wavelet scalogram of a good-quality PPG signal

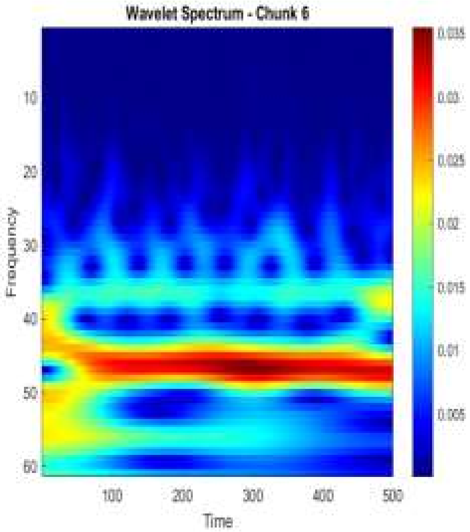

Figure 3: Wavelet scalogram of a poor-quality PPG signal

The wavelet scalograms of PPG signals provide a clear distinction between good and poor-quality signals. As shown in Fig. 2, good-quality signals exhibit smooth and consistent patterns in both time and frequency domains. In contrast, Fig. 3 shows distorted and irregular patterns in poor-quality signals due to motion artifacts and noise. These visual differences help the CNN model to effectively learn and classify signal quality. The generated scalogram images are used as input to the compact CNN model.

The compact CNN architecture is designed with multiple convolutional and pooling layers to automatically extract meaningful features from the input images.

D. Compact CNN Architecture

The architecture of the proposed Compact Convolutional Neural Network (CNN) is shown in Fig. 4. The model takes grayscale scalogram images of size 20 × 500 as input, generated from PPG signals using wavelet transform. The input is processed through convolutional layers with 7 × 7 filters to extract important features from the signal representation. A Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity, followed by max pooling layers of size 2 × 2 to reduce spatial dimensions and computational complexity.

Additional convolution and pooling layers are used to capture deeper features from the input data. The extracted features are then flattened into a one-dimensional vector and passed through fully connected layers for classification. A dropout layer with a rate of 0.5 is used to prevent overfitting and improve generalization. Finally, a sigmoid activation function is applied in the output layer to classify the input signal as either good quality or poor quality.

The model classifies each PPG signal segment into two categories: good quality and poor quality. By filtering out low-quality signals, the proposed system improves the reliability of further physiological analysis such as heart rate estimation. The overall approach is computationally efficient and suitable for real-time healthcare monitoring applications, especially in wearable devices.

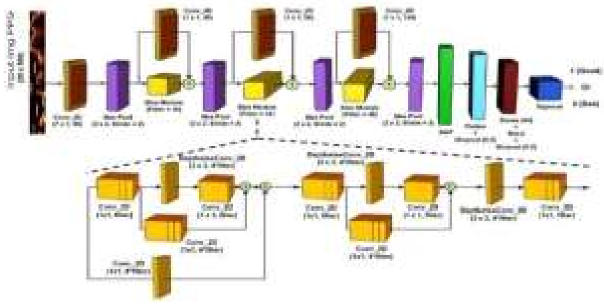

Figure 4: Compact CNN architecture for PPG signal classification

E. Performance Metrics

The performance of the proposed CNN model is evaluated using standard classification metrics. Accuracy measures the overall correctness of the model. Specificity measures the ability of the model to correctly identify poor-quality signals. Sensitivity (recall) indicates the model's ability to correctly identify good-quality signals, while specificity measures the correct detection of poor-quality signals. The F1-score provides a balance between precision and recall, making it suitable for classification tasks.

A confusion matrix is used to visualize the model performance, showing true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The performance metrics are computed using the formulas shown in Fig. 5.

$$Accuracy\ (ACC) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

$$Sensitivity\ (Se) = \frac{TP}{TP + FN} \times 100$$

$$Specificity\ (Sp) = \frac{TN}{FP + TN} \times 100$$

$$F1\ Score\ (F1) = \frac{2TP}{2TP + FP + FN} \times 100$$

Figure 5: Performance metrics formulas

- True Positive (TP): instances that are correctly classified as positive.

- True Negative (TN): instances that are correctly classified as negative.
- False Positive (FP): instances that are incorrectly classified as positive.
- False Negative (FN): instances that are incorrectly classified as negative.

F. Advantages

- Automatically classifies PPG signals as good or poor quality.
- Reduces manual feature extraction effort.
- Handles noise and motion artifacts effectively.
- Wavelet transform captures both time and frequency information.
- Compact CNN is computationally efficient for real-time use.
- Improves reliability of heart rate and physiological parameter estimation.

G. Applications

- Used in wearable devices for continuous health monitoring.
- Helps in accurate heart rate and cardiovascular analysis.
- Useful in remote patient monitoring and telemedicine.
- Improves reliability of fitness and smart health trackers.
- Can be applied in hospitals for real-time patient observation.
- Assists in early detection of abnormal physiological conditions.

V. RESULTS

A. Training and Validation Performance

The performance of the proposed Compact CNN model is evaluated using the prepared PPG dataset. The model is trained and tested on wavelet-based scalogram images to classify signals into good and poor quality.

The training and validation accuracy of the model are shown in Fig. 6. It can be observed that the model achieves high accuracy with stable convergence during training. Similarly, the loss curve indicates a steady decrease in loss, demonstrating effective learning without overfitting.

The model shows consistent performance across both training and validation phases. This indicates that the model is well generalized and does not suffer from overfitting. The use of wavelet-based scalogram images helps in capturing important signal patterns effectively, and the CNN model is able to learn meaningful features from the input data.

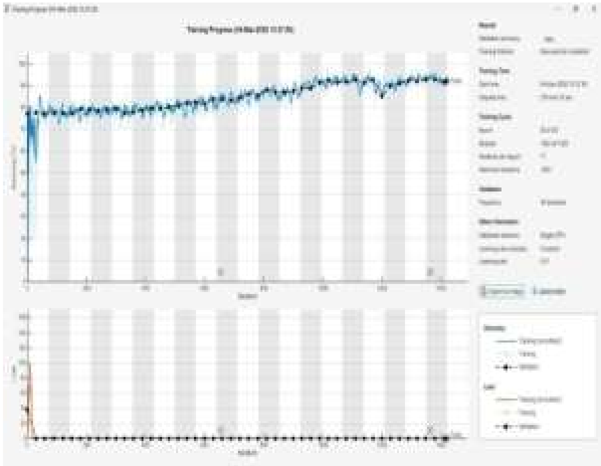

Figure 6: Training and validation accuracy and loss of the proposed model

B. Confusion Matrix and Model Performance

The confusion matrix of the classification results is presented in Fig. 7. The confusion matrix is used to evaluate the performance of the classification model by comparing predicted and actual classes. It displays true positives, true negatives, false positives, and false negatives, which helps in understanding how effectively the model distinguishes between good and poor-quality PPG signals.

The matrix indicates that most of the signals are correctly classified, with very few misclassifications, demonstrating the effectiveness of the model in accurately distinguishing between clean and noisy signals. As shown, 3584 good signals are correctly classified while 46 are misclassified as bad, and 2307 bad signals are correctly classified while 63 are misclassified as good.

The proposed model achieves an overall accuracy of 98.3%, with a sensitivity of 98.9% and specificity of 96.7%. The F1-score of 98.8% further confirms the balanced performance of the model in classifying both good and poor-quality signals. These results demonstrate that the proposed wavelet-based CNN approach is highly effective in distinguishing between clean and noisy PPG signals.

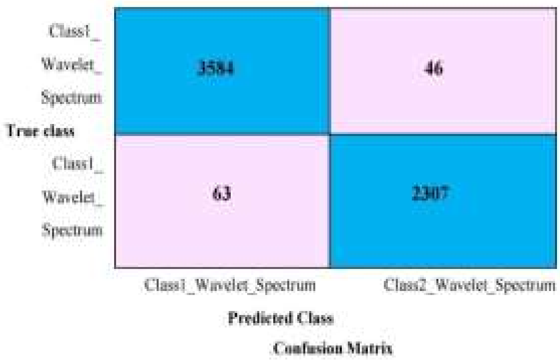

Figure 7: Confusion matrix of PPG signal classification

C. Comparison with Baseline Models

A comparative analysis is carried out to evaluate the performance of the proposed model against existing baseline methods. The evaluation is based on standard metrics such as accuracy, sensitivity, specificity, and F1-score, providing a clear understanding of the model's classification capability. The confusion matrix and ROC curve are used to further analyse the performance. The model achieves an AUC score of 0.992, indicating excellent discrimination between good and poor-quality signals. Out of the total evaluated signal segments, the majority are correctly classified, demonstrating the robustness of the proposed approach.

To validate the effectiveness of the model, it is compared with traditional and deep learning-based baseline methods such as SVM with multiple signal quality indices, HOG combined with MLP, and 1D CNN. As summarized in Table 1, the proposed Compact CNN model outperforms these methods in terms of accuracy and reliability. This improvement is mainly due to the use of wavelet-based scalogram images, which capture both time and frequency characteristics of the PPG signals.

TABLE 1: COMPARISON OF BASELINE MODELS AND THE COMPACT CNN

Methods	**Se (%)**	**Sp (%)**	**F1-score (%)**	**ACC (%)**
SQIs + SVM	90.6	59.5	90.3	84.4
1D-CNN	97.7	88.4	97.4	95.8
MLP + HOG	95.7	44.1	91.0	85.0
Proposed Compact CNN	98.9	96.7	98.8	98.3

D. Comparison with Existing Works

Further comparison with existing works, presented in Table 2, also indicates that the proposed model achieves superior performance across different evaluation metrics. The use of a larger and more diverse dataset improves the generalization capability of the model. Additionally, the proposed approach effectively handles noise and motion artifacts, making it more suitable for real-world healthcare applications. Overall, the proposed method demonstrates higher accuracy, better robustness, and improved scalability compared to existing techniques for PPG signal quality assessment. From Table 2, it is clearly observed that the proposed model outperforms existing methods in terms of accuracy, sensitivity, and specificity, confirming the effectiveness and reliability of the proposed approach for PPG signal quality assessment.

TABLE 2: PERFORMANCE COMPARISON WITH DIFFERENT WORKS

Author	**Dataset**	**Subjects**	**Se (%)**	**Sp (%)**	**ACC (%)**
Sukor, 2011 [14]	104, 60s	13	89	77	83
Li, 2012 [15]	1055, 6s	104	99	80.6	95.2
Couceiro, 2014 [16]	—	15	84.3	91.5	88.5
Cherif, 2016 [17]	104, 6s	—	84	83	83
Goh, 2020 [18]	—	—	91.8	87.3	89.9
Liu, 2020 [19]	12876, 7s	20	91.8	87.3	89.9
Proposed	28366, 5s	32	99.3	94.5	98.3

VI. CONCLUSION

In this paper, a deep learning-based approach for photoplethysmography (PPG) signal quality assessment is presented. The proposed method utilizes wavelet-based time–frequency representations along with a Compact Convolutional Neural Network (CNN) to effectively classify PPG signals into good and poor-quality categories.

The experimental results demonstrate that the proposed model achieves high classification accuracy, along with strong sensitivity and specificity. The use of wavelet scalogram images enables the model to capture both temporal and frequency features, improving its ability to distinguish between clean and noisy signals.

Compared to traditional machine learning and existing deep learning approaches, the proposed method shows improved performance and robustness. It also reduces the need for manual feature extraction, making the system more efficient and suitable for real-time applications. Overall, the proposed approach provides a reliable and effective solution for PPG signal quality assessment, which can be beneficial for wearable healthcare systems and remote patient monitoring applications.

REFERENCES

1. Temko, "Accurate Heart Rate Monitoring during Physical Exercises Using PPG," IEEE Trans. Biomed. Eng., vol. 64, no. 9, pp. 2016–2024, 2017.
2. Wan-Young Chung, Young-Dong Lee, and Sang-Joong Jung, "A Wireless Sensor Network Compatible Wearable U-healthcare Monitoring System Using Integrated ECG, Accelerometer and SpO2," in Proc. 2008 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., pp. 1529–1532, 2008.
3. M. Panwar, A. Gautam, D. Biswas, and A. Acharyya, "PP-Net: A Deep Learning Framework for PPG-Based Blood Pressure and Heart Rate Estimation," IEEE Sens. J., vol. 20, no. 17, pp. 10000–10011, 2020.
4. Yusheng Qi, Ai Rong Zhang, Yurun Ma, Huidong Wang, and Jiaqi Li, "A Method for Photoplethysmography Signal Quality Assessment Fusing Multi-Class Features with Multi-Scale Series Information," J. Biomed. Eng. (Shengwu Yixue Gongchengxue Zazhi), 2023, doi: 10.7507/1001-5515.202211054.
5. Paula G. Rodrigues, "Signal Quality Assessment of Photoplethysmogram Signals Using Hybrid Rule- and Learning-Based Models," J. Health Informatics, vol. 15, 2023, doi: 10.59681/2175-4411.v15.iespecial.2023.1080.
6. "Hybrid ResNet and Bidirectional LSTM-Based Deep Learning Model for Cardiovascular Disease Detection Using PPG Signals," J. Machine and Computing, 2023, doi: 10.53759/7669/jmc202303030.
7. Hamzeh Asgharnezhad, Afshar Shamsi Jokandan, Ivan Bakhshayeshi, Roohallah Alizadehsani, Somayyeh Chamaani, and Hamid Alinejad-Rokny, "Improving PPG Signal Classification with Machine Learning: The Power of a Second Opinion," 2023, doi: 10.1109/DSP58604.2023.10167869.
8. "PPG Signals for Hypertension Diagnosis: A Novel Method Using Deep Learning Models," 2023, doi: 10.48550/arXiv.2304.06952.

9. Rabia Ahmed, Ahsan Mehmood, Muhammad Mahboob Ur Rahman, and Octavia A. Dobre, "A Deep Learning and Fast Wavelet Transform-Based Hybrid Approach for Denoising of PPG Signals," IEEE Sensors Lett., 2023, doi: 10.1109/LSENS.2023.3285135.
10. M. Sabarimalai Manikandan and Srinivas Boppu, "CNN-Based PPG Signal Quality Assessment Using Raw PPG Signal for Energy-Efficient PPG Analysis Devices in Internet of Medical Things," 2022, doi: 10.1109/ICAIoT57170.2022.10121884.