Aswan University Journal of Science and Technology Volume 5, issue 2, June 2025

Review paper

A Comprehensive Study for Blood Glucose Level Monitoring Using Photoplethysmography

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Abstract

Abnormal blood glucose levels pose a significant risk to patient health, as they can cause severe complications and potentially become life-threatening if not promptly identified and managed. Given the importance of early detection, there has been a growing focus on the development of effective, non-invasive techniques for monitoring blood glucose. One such promising approach involves the use of photoplethysmography (PPG) signals, which have attracted considerable attention within both the medical and engineering communities. Over the past decade, researchers have leveraged advancements in artificial intelligence (AI) and machine learning to refine methods for estimating blood glucose levels using PPG-based data. These efforts span a wide range of algorithms and modelling techniques, including deep learning architectures, signal processing methods, and feature extraction strategies. This survey aims to provide a comprehensive overview of the latest contributions to this field, examining how various approaches address challenges such as measurement accuracy, individual variability, and real-time feasibility. By critically evaluating these AI-driven techniques, we shed light on the current state of PPG-based blood glucose measurement and outline potential directions for future research and clinical application.

Keywords: digital medicine; blood glucose; non-invasive; photoplethysmography; deep learning; continuous glucose monitoring.

1. Introduction

Diabetes is a long-term global health issue, contributing to 1.5 million deaths. It ranks among the most significant contributors to mortality [1]. Prolonged hyperglycemia can lead to serious complications, including cardiovascular disease, kidney failure, and neuropathy. As the diagnosis of diabetes is imbalanced blood sugar levels (BGL) [2]. This marks Regular monitoring of BGL indispensable for preventing or delaying these adverse outcomes. Traditionally, finger-pricking using handheld glucometers is the most common technique for measuring BGL. Although this method offers a reliable reading. Repeated skin penetration often causes physical discomfort and emotional distress, which can result in poor adherence to the recommended monitoring frequency. Implantable microneedles offer a more continuous alternative, yet still carry the burden of invasiveness and potential patient unease. These limitations underscore the need for more user-friendly solutions that reduce pain and inconvenience while still ensuring accurate glucose measurements.

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Received January 09, 2025, received in revised form, February 02, 2025, accepted February 02, 2025.

(ASWJST 2021/ printed ISSN: 2735-3087 and on-line ISSN: 2735-3095) https://journals.aswu.edu.eg/stjournal

Photoplethysmography (PPG) has emerged as a noteworthy non-invasive modality for BGL estimation. First developed in 1937. PPG measures changes in light absorption or reflection related to blood volume fluctuations in living tissue. Through either transmissive or reflective photoelectric sensors, this technique captures pulsatile blood flow, which is influenced by various physiological parameters. Crucially, PPG relies on minimal hardware, a light source, and a photodetector. This makes PPG highly compatible with modern wearable devices and smartphones. This integration capability offers a practical avenue for continuous, real-time glucose monitoring without the repeated skin penetration demanded by traditional methods.

In recent years, progress in AI techniques for biomedical signal processing has fueled extensive research in PPG-based blood glucose level (BGL) measurement. These developments have empowered researchers to explore innovative methods and contribute to studies, enhancing the accuracy and reliability of BGL monitoring through photoplethysmography (PPG). This progress has paved the way for more accessible, non-invasive monitoring options, offering new possibilities for diabetes management and improving patient outcomes.

A key motivation for this work is the lack of an updated, focused review on PPG-based BGL monitoring. The most recent review [3] In this field, conducted in 2022, combined PPG with electrocardiographic (ECG) methods, making it the only comprehensive resource to date. However, this combined approach does not fully address the unique challenges, advancements, and potential of PPG-based BGL monitoring on its own. Given the rapid development of AI and sensor technologies in recent years, there is a critical need for a dedicated review that evaluates current progress in PPG-based BGL monitoring, highlights recent breakthroughs, and identifies remaining challenges. This work aims to fill that gap by providing a targeted analysis of the field, supporting further research and innovation in non-invasive diabetes management.

2. Methods

2.1 Eligibility Criteria

The eligibility criteria for selecting articles in this systematic review are as follows:

- **Language**: Only articles written in English are included.
- **Scope**: Studies must focus on blood glucose level (BGL) estimation.
- **Methods**: The use of traditional, machine learning, or deep learning methodologies is required.
- **Signal Type**: Studies must specifically involve PPG signals for diabetes monitoring only.
- **Full Text**: Papers not available in full text or limited to conference abstracts are excluded.

No publication year restrictions are applied to ensure comprehensive coverage.

2.2 Data Sources and Search Strategy

The following electronic databases are searched for relevant studies: IEEE Xplore and Google Scholar. The search strategy included combinations of keywords related to PPG signals and diabetes estimation, such as:

- **General terms**: "PPG signal," "BGL," and "blood glucose estimation."

- **Advanced combinations**:
  - "PPG signal AND BGL"
  - "PPG signal AND blood glucose estimation AND machine learning"
  - "PPG signal AND blood glucose estimation AND deep learning"

This strategy ensured that studies using machine learning or deep learning for PPG signal-based blood glucose monitoring were captured. References were organized using Mendeley, where duplicates were removed, and three-step filtering (title, abstract, and full-text evaluation) was employed to finalize the selection.

2.3 Classification of Existing Methods

After applying the Eligibility Criteria (Section 2.1) and Search Strategy (Section 2.2), the included studies can be systematically classified based on:

1. Data Characteristics
   - Number of Subjects (small-scale vs. large-scale studies)
   - Blood Glucose Levels (BGL) Range (e.g., normal to hyperglycemic, varying severity)
   - PPG DEVICE
   - Sampling Frequency
   - Population Details (gender split, age ranges, or any specific clinical condition)

Table 1: Study Details and Dataset, and PPG Device Specifications.

Reference	Subjects	Samples	Gender	BGL Range (mg/dL)	PPG Device	Frequency (Hz)
Monte-Moreno [4]	410	4500	213/197	49–393	Oximeter	75
Zhang et al. [5]	18	251	NA	<200	Oximeter	100
Chowdhury et al. [6]	18	88	NA	<150	Smartphone Camera	30
Habbu et al. [7]	611	611	344/267	70–450	Custom Microcontroller	100
Hina et al. [8]	200	200	NA	<160	FPGA System	100
Manurung et al. [9]	89	51	50/39	<80, >130, Mid-range	Arduino	50
Gupta et al. [10]	NA	NA	NA	NA	Arduino	35
Salamea et al. [11]	217	7740	NA	58.6–390.7	Wristband	64
Hina et al. [12]	200	NA	112/88	80–400	SoC	128
Guzman et al. [13]	5	100	3/2	NA	Oximeter	60
Islam et al. [14]	52	52	38/14	68–211	Fingertip Videos	30
Prabha et al. [15]	217	7263	90/127	58.6–390.7	Wristband	64
Reguig et al. [16]	10	10	10/0	NA	Arduino	60
Alghlayini et al. [17]	52	198	NA	68–211	Smartphone Camera	30
Shama Satter et al. [18]	34	34	17/17	80–200	Custom Oximeter	24
Adigüzel et al. [19]	217	7263	90/127	58.6–390.7	Wristband	64
Liao et al. [20]	15	NA	NA	84–221	Procomp5 Infiniti	256
Gupta et al. [21]	26	NA	NA	84–199	SFH7050 Module	NA

2. Methodology
    - Machine Learning (ML)-Based Methods
      Classic machine learning algorithms (e.g., Support Vector Machines, Random Forests) require feature extraction and often manual feature engineering.
    - Deep Learning (DL)-Based Methods
      Neural network-based approaches (e.g., CNNs, RNNs/LSTMs, Transformers) capable of end-to-end learning, often requiring less manual feature engineering but larger datasets. But they require substantial data, higher computational resources, and may lack interpretability compared to simpler methods.
3. Model Training
    - Training Window (length of data used for training, real-time vs. retrospective)
4. Performance Evaluation
    - Evaluation Metrics (MAE, RMSE, MARD, accuracy, sensitivity, specificity, Clarke error grid, etc.)

2.4 Data Extraction

For each study visited, the coming information was also involved: (i) study objective, (ii) number of subjects, (iii) number of signals, (iv) gender split (male/female), (v) blood glucose levels (BGL) range, (vi) sampling frequency, (vii) extracted features, (viii) AI approach, (ix) AI algorithm, (x) training window, and (xi) Evaluation Metrics. The results were analyzed to highlight the advantages and disadvantages of each approach, along with potential future improvements.

3. Challenges and future extensions

3.1. The Effect of the dataset

While generating datasets for PPG-based BGL models, diversity and representativeness are critical considerations. A representative dataset includes various demographic information such as gender, age, skin tones, weight, and height, along with varied BGL distributions. BGL distributions should contain the following ranges: hypoglycemic (<70 mg/dL), normal (70–140 mg/dL), and hyperglycemic (>140 mg/dL). This ensures the model generalizes well and performs accurately across different populations and conditions. Conversely, non-representative datasets are typically homogeneous, reflecting a single demographic or BGL distribution. Such datasets produce models that fail to generalize to practical, real-world scenarios, as they perform well only within their narrow training confines. This lack of representativeness undermines the model's applicability and reliability.

The proposed survey involves studies with volunteer numbers ranging from five to 611. Moreover, eight out of eighteen studies have their whole blood glucose level (BGL) readings below 250 mg/dL, as mentioned or deduced from Clarke's error grid - while three studies did not report this information, as shown in figure 1. This means that more than half of the studies do not adequately represent an important segment of readings. Besides the insufficient number of participants, eleven studies have fewer than 150 participants, as shown in figure 2. Consequently, these datasets conditions are insufficient for effectively training machine learning (ML) or deep learning (DL) models as they are data-driven. Therefore, it is critical to have a larger and more diverse dataset to ensure that the trained models are generalized, accurate, and capable of capturing the complexity and the variability of real-world scenarios.

Table 2: Methodology, Features, and Evaluation Metrics.

Reference	Method	Algorithm	Features	Window Size	Metrics
Monte-Moreno [4]	Machine Learning	Random Forest (RF)	33	5 s	r = 0.9; CEG: [87.7% A, 10.3% B, 1.9% D]
Zhang et al. [5]	Machine Learning	SVR + Genetic Algorithm (GA)	22	2 s	R^2 = 0.97; RMSE = 1.58 mg/dL; MAPE = 6.04%; CEG: [100% A]
Chowdhury et al. [6]	Machine Learning	Principal Component Regression (PCR)	5	60 s	SEP = 18.31 mg/dL; CEG: [82.6% A, 17.4% B]
Habbu et al. [7]	Deep Learning	Neural Network (NN)	Time/Freq. + SPA	60 s	R^2 = 0.91; r = 0.95; CEG: [83% A, 17% B]
Hina et al. [8]	Machine Learning	Fine Gaussian SVR (FGSVR)	10	10 s	MARD = 8.97%
Manurung et al. [9]	Deep Learning	Neural Network (NN)	7	24 s	MAE = 5.855 mg/dL
Gupta et al. [10]	Machine Learning	Random Forest (RF)	22	28.5 s	R^2 = 0.62–0.91
Salamea et al. [11]	Machine Learning	Random Forest (RF)	33	5 s	MSE = 202.6 mg/dL; MAE = 8.59 mg/dL; r = 0.88
Hina et al. [12]	Machine Learning	Fine Gaussian SVR (FGSVR)	6	1 s	R^2 = 0.937; MARD = 7.62%
Guzman et al. [13]	Machine Learning	SVM + Lasso + Elastic Net Ensemble	20	10 min	MAE = 16.24 mg/dL; RMSE = 18.63 mg/dL
Islam et al. [14]	Deep Learning	Partial Least Squares Regression (PLS)	5	50–60 s	SEP = 17.02 mg/dL
Prabha et al. [15]	Machine Learning	Extreme Gradient Boost Regression (XGBR)	5	150 s	MAE = 5.21 mg/dL; SEP = 5.53 mg/dL; R^2 = 0.99; CEG: [98.97% A]
Reguig et al. [16]	Machine Learning	Linear Regression	2	NA	R^2 = 0.89–0.97
Alghlayini et al. [17]	Deep Learning	Bayesian Optimization-Based CNN	Raw PPG Signal	20 s	RMSE = 25.88 mg/dL; MAE = 16.91 mg/dL; CEG: [92.85% A]
Shama Satter et al. [18]	Machine Learning	CatBoost	50	30 s	r = 0.96; RMSE = 10.94 mg/dL; R^2 = 0.92; MAE = 8.01 mg/dL
Adigüzel et al. [19]	Machine Learning	CatBoost	51	150 s	R^2 = 0.71; RMSE = 39.13 mg/dL; MAE = 25.21 mg/dL
Liao et al. [20]	Deep Learning	Hybrid CNN + LSTM	Raw PPG Signal	1 s	MAE = 4.7 mg/dL; RMSE = 11.146 mg/dL
Gupta et al. [21]	Machine Learning	Extreme Gradient Boost Regression (XGBR)	30	3 s	CEG: [96.15% A, 3.85% B]

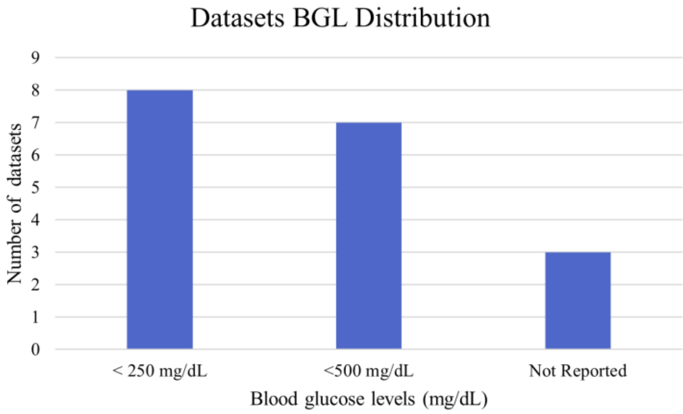

Figure 1: Datasets BGL Distribution

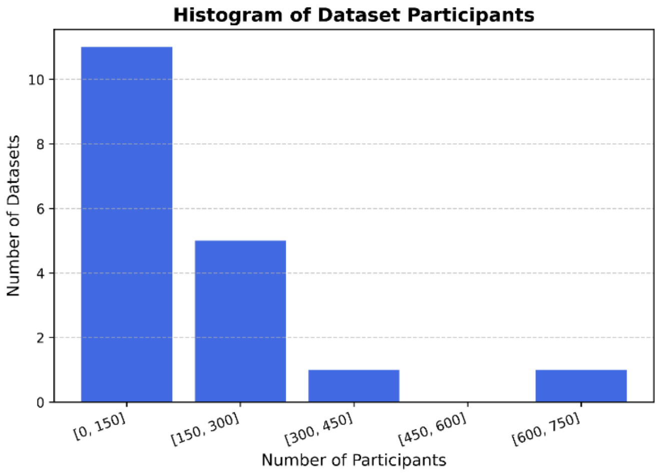

Figure 2: Histogram of datasets participants.

3.3. Sampling Frequency

As shown in section 3.2, portability is one of the essential goals of the PPG-capturing technique. Therefore, sampling frequency should be considered due to its vital role in battery life and computational complexity. Higher sampling frequencies consume more power and require greater computational resources. This is evident in most studies, as eleven employed sampling frequencies lower than 64 Hz, along with four employed sampling frequencies between 64 and 144, while only one used a higher sampling frequency, as shown in Figure 4.

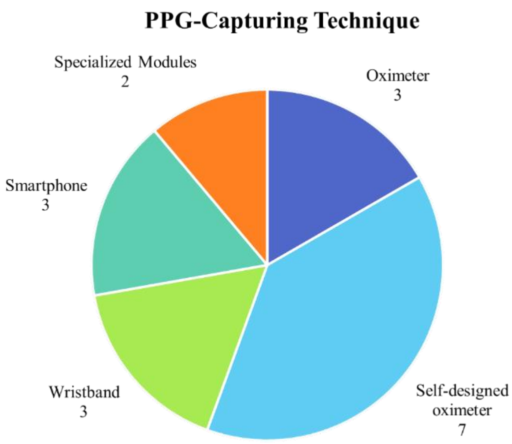

Figure 3: Pie chart of PPG capturing devices.

Table 3: PPG capturing devices.

PPG-Capturing Technique	Number of Studies	Description
Oximeter	3	The most conventional method for capturing PPG signals.
Self-designed oximeter	7	Involves custom-built devices using microcontrollers like Arduino, FPGA, or a system-on-chip
Wristband	3	Utilizes wristbands with integrated PPG sensors
Smart phone	3	Captures PPG signals using videos of fingertips recorded by smartphones.
Specialized Modules	2	Uses specialized hardware modules to capture PPG signals, such as Procomp5 Infiniti and the SFH 7050 module.

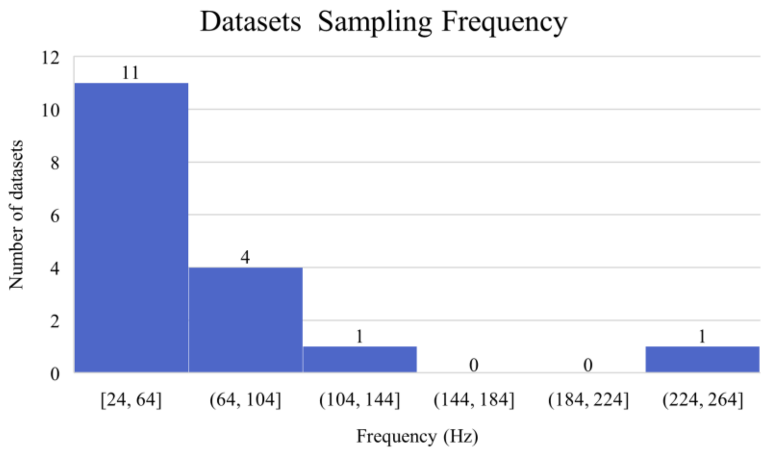

Figure 4: Histogram of datasets sampling frequencies.

3.4. Feature Extraction

Feature extraction is vital for estimating BGL from raw PPG signals. Feature extraction spans a wide spectrum from basic morphological and timing features to sophisticated nonlinear and deep learning-based representations. While traditional hand-crafted features offer interpretability and can be extracted with relatively small datasets, modern data-driven methods can discover latent patterns strongly linked to glucose variations.

Therefore, existing approaches can generally be categorized into three classes:

1. Machine learning with feature extraction: Traditional ML algorithms combine physiological information. Such as time-domain features -like peak amplitudes, pulse widths, and intervals- capture fundamental waveform morphology and timing. Besides, in the frequency domain, techniques such as the Fourier Transform quantify power distribution and dominant frequencies. They can reveal periodic changes in autonomic regulation that may correlate with BGL. These metrics can reflect vascular changes potentially linked to glucose fluctuations. And require relatively small datasets. However, they rely on an explicit feature extraction step before training.
2. Deep learning with feature extraction: These methods incorporate DL components but still depend on handcrafted features, limiting the potential for fully automated learning.
3. Deep learning from raw PPG signals: This approach exploits DL's ability to autonomously learn features directly from the raw data, thus maximizing the potential of deep architectures.

Before DL became a trend, physiological signals were primarily processed using ML. ML methods can be trained effectively with smaller datasets. In contrast, DL methods usually require larger datasets but can learn complex feature representations on their own. Studies [15, 16, 18, 19] demonstrate that feature selection significantly impacts accuracy. And they proved that redundant or poorly chosen features can mislead the training process and introduce errors during calculation. Consequently, future research should consider adopting the third approach to fully harness DL's capacity for automatic feature extraction from raw PPG signals.

3.5. The Applied Models

Recent advancements in artificial intelligence have emphasized the complementary strengths and limitations of machine learning (ML) and deep learning (DL) techniques in analyzing photoplethysmography (PPG) data for monitoring blood glucose levels (BGL), as in table 3.

Various machine learning and deep learning models have been applied, including random forest (RF), fine gaussian support vector regression (FGSVR), Support vector regression (SVR) with genetic algorithm (GA), principal component regression (PCR), extreme gradient boost regression (XGBR), categorical boosting (CatBoost), neural network (NN), ensemble (SVM, Lasso, Elastic net) model, partial least square regression (PLS), linear regression, Bayesian optimization-based convolutional neural network (CNN), and hybrid CNN and long short-term memory (LSTM).

The most utilized models are random forest and gaussian support vector regression, each applied in three studies, as random forest (RF) combines multiple decision trees to capture complex, non-linear relationships in data and is relatively robust to outliers, even when handling a large number of features, thus reducing the risk of overfitting. It also offers some interpretability through feature importance scores, which can be valuable in applications that demand transparency. Furthermore, RF is well-suited for small to medium-sized datasets with moderate dimensionality, striking an effective balance between performance and interpretability. In scenarios where rapid experimentation and reasonable accuracy are prioritized over exhaustive hyperparameter tuning, RF frequently serves as a strong and practical baseline choice.

While support vector regression (SVR) is recognized for its robust theoretical framework and capacity to manage complex, high-dimensional data, especially when kernel functions (e.g., Gaussian) are applied. This approach often generalizes well even from relatively small training sets, making it particularly attractive in scenarios where data collection is costly or limited, such as in biomedical applications. However, SVR can become computationally expensive as the dataset grows, necessitating careful consideration of resource constraints. When accuracy and reliability are paramount, and the dataset is not exceedingly large, SVR remains a compelling and effective modeling option. After RF and SVR come principal component regression, extreme gradient boost regression, and categorical boosting, as shown in figure 5. Therefore, there are many areas to be discovered in applying various DL models.

3.6. Window size

In the reviewed works, various window sizes of PPG signals were employed before feeding them into machine learning or deep learning models, ranging from one second to several minutes. The choice of window size for the PPG signal varied significantly, reflecting its critical role in preparing input data for machine learning or deep learning models. The window size, which defines the duration of the PPG signal segment analyzed by the model, directly influences the temporal resolution of the features extracted. Across the studies, window sizes ranged from a second to several minutes, with shorter windows (e.g., 1-30 seconds) capturing rapid changes but potentially introducing more noise, while longer windows (e.g., 30-600 seconds) provide smoother signals at the expense of losing finer details. Shorter windows were typically favored for real-time monitoring applications where computational efficiency and responsiveness are crucial, whereas longer windows were used in scenarios requiring more comprehensive analysis of PPG trends.

Moreover, methods for determining the optimal window size varied across studies, ranging from empirical tuning based on domain knowledge to systematic evaluations on validation datasets. Despite this diversity, challenges persist, such as the absence of universally accepted guidelines and the need to balance performance and efficiency for PPG-based BGL estimation. Advancing this area could involve exploring adaptive window sizing approaches or establishing standardized practices tailored to PPG-based BL estimation, further enhancing the overall reliability, generalizability, and adaptability of machine learning models in this field.

Table 3: Comparison of Machine Learning (ML) and Deep Learning (DL) for PPG-Based BGL Monitoring.

Aspect	Machine Learning (ML)	Deep Learning (DL)
Data Requirements	Requires smaller datasets; suitable for limited data scenarios.	Data-intensive; performs better with large and diverse datasets.
Feature Engineering	Relies on manual feature extraction, requiring domain expertise.	Automatically extracts features from raw PPG signals, eliminating manual intervention.
Computational Cost	Computationally efficient; feasible for low-power devices like wearables.	High computational cost, requiring substantial resources for training and deployment.
Model Interpretability	Results are more interpretable, making them easier to trust in clinical settings.	Acts as a "black box," reducing interpretability and limiting clinical acceptance.
Noise and Artifacts	Performance is more sensitive to noise due to reliance on pre-processed features.	Robust to noise and artifacts, as raw data handling is a strength of DL approaches.
Scalability	Limited scalability for highly complex or large datasets.	Scales well for complex, non-linear relationships in large datasets.
Real-Time Feasibility	Suitable for real-time applications due to low latency.	Requires optimization (e.g., lightweight models) for real-time deployment.
Advantages	- Easier to implement and computationally cheaper.	- Excels at capturing non-linear relationships.
	- Suitable for resource-constrained applications.	- Eliminates the need for manual feature selection.
Limitations	- Dependent on the quality of manual feature extraction.	- High resource demands and overfitting risks for small datasets.
Proposed Enhancements	- Hybrid approaches combining ML for feature extraction with DL for refinement.	- Lightweight models (e.g., MobileNet), synthetic data generation, and transfer learning.

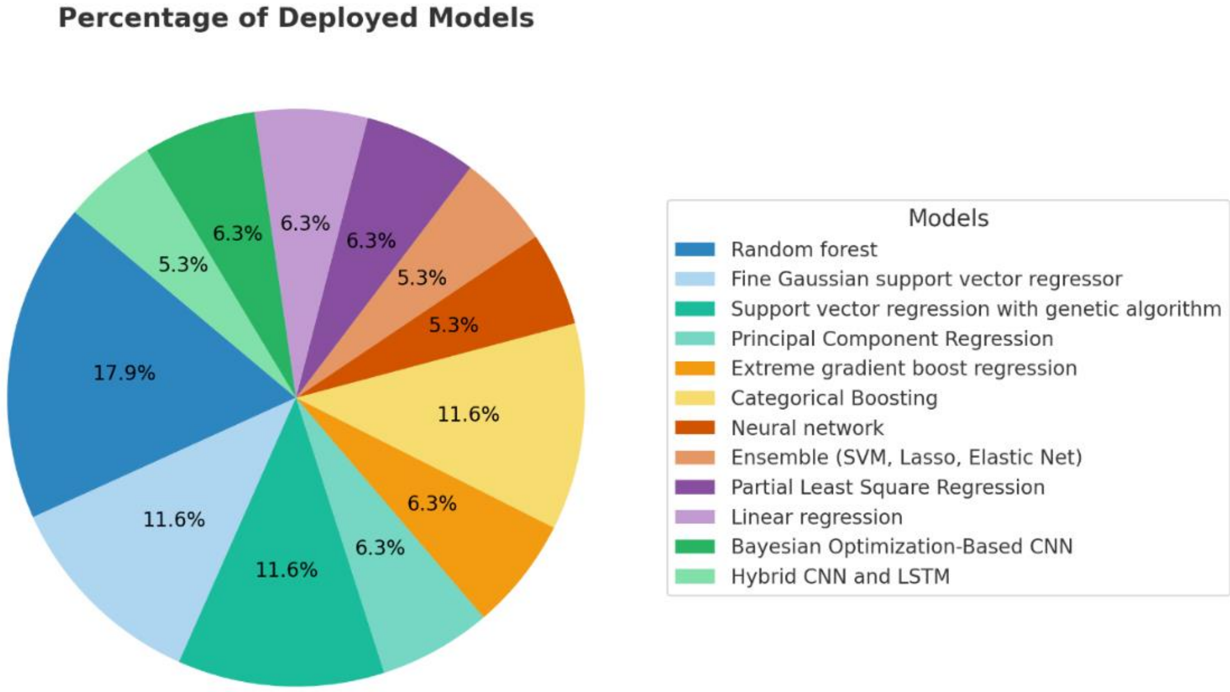

Figure 5*:* Percentage of applied models.

3.7. Evaluating Metrics

Performance metrics varied across the surveyed studies. Their usage frequencies were as follows: **mean absolute error (MAE)** was employed in eight studies, making it one of the most common metrics for evaluating the overall accuracy of predictions by calculating the average absolute difference between predicted and actual values. Similarly, the **coefficient of determination (R^2)** was also reported in eight studies, providing valuable insight into how much of the variance in the target variable, with higher R^2 values indicating stronger model performance. **Root mean square error (RMSE)**, reported in six studies, was another frequently applied metric, highlighting larger prediction errors by squaring differences between predicted and actual values, penalizing significant deviations. **Pearson's correlation coefficient (r)**, reported in five studies, measured the strength and direction of the linear relationship between predicted and actual values, capturing the model's ability to outline trends. **Standard error of prediction (SEP)**, reported in four studies, provided insights into the variability of predictions compared to actual values, reflecting precision. Less frequently used were the **mean absolute relative difference (MARD)** and **mean absolute percentage error (MAPE)**, both appearing in two studies. These metrics offered ways to assess errors in relation to actual values, with MARD focusing on relative errors and MAPE providing percentage-based evaluation, making it easier to compare across datasets of different scales. **Mean square error (MSE)** and **relative error (RE)** were reported in only one study using each. MSE, like RMSE, measures the average of the squared differences but without taking the square root, while RE expresses the error as a proportion of the actual value.

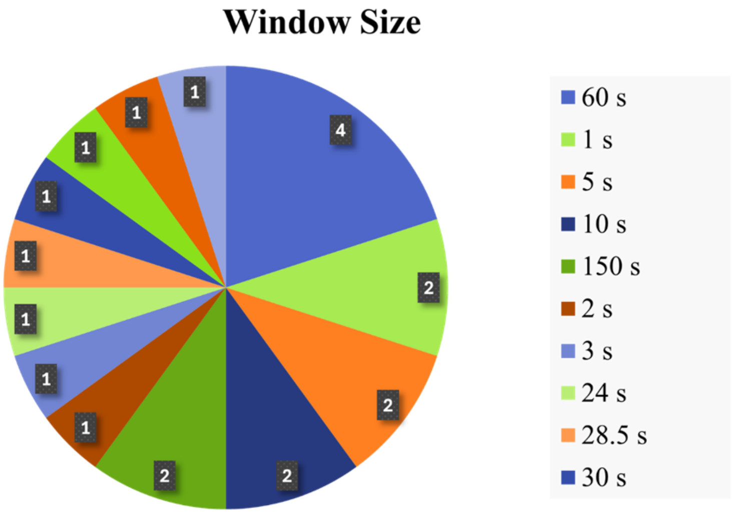

Figure 6: Pie chart of applied window sizes.

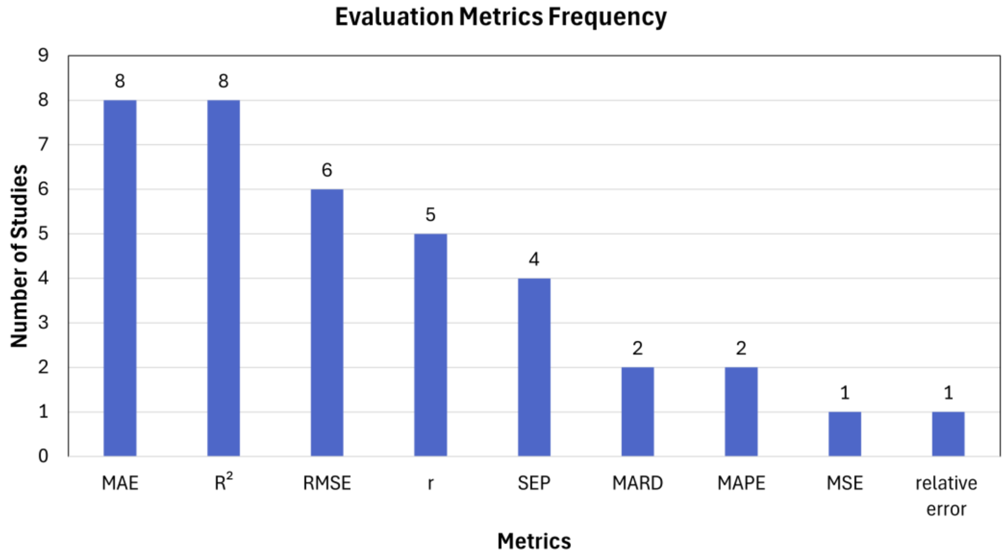

Figure 7: Evaluation metrics frequency.

4. Conclusion

This paper provides a comprehensive review of the current advancements in non-invasive blood glucose level (BGL) monitoring using photoplethysmography (PPG) signals. With the increasing prevalence of diabetes and the need for more patient-friendly diagnostic tools, PPG-based BGL estimation has emerged as a promising alternative to invasive methods. Through the systematic evaluation of methodologies, including machine learning, deep learning approaches, and feature extraction techniques, we identified key trends, challenges, and opportunities in this field.

Although noteworthy progress has been made, challenges such as ensuring dataset representativeness, standardizing PPG capturing techniques, and optimizing machine learning models continue to hinder clinical adoption. Importantly, the use of deep learning models that process raw PPG signals has demonstrated exciting potential by eliminating the need for feature engineering and improving accuracy. However, issues like dataset variability, optimization of sampling frequency, and window sizing remain critical obstacles to enhancing model generalizability.

This study emphasizes the urgent need for larger and more diverse datasets, as well as adaptive frameworks, to address these challenges. Future research should prioritize the integration of PPG technology into everyday wearable devices and the development of innovative AI-driven solutions to enable continuous, real-time glucose monitoring. Tackling these issues could establish PPG-based BGL monitoring systems as accessible, non-invasive, and reliable tools for diabetes management, advancing patient outcomes and quality of life.

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