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# Performance of artificial intelligence models in estimating blood glucose level among diabetic patients using non-invasive wearable device data

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ABSTRACT

*Introduction:* Diabetes Mellitus (DM) is characterized by impaired ability to metabolize glucose for use in cells for energy, resulting in high blood sugar (hyperglycemia). DM impacted 463 million individuals worldwide in 2019, with over four million fatalities documented. Blood glucose levels (BGL) are usually measured, as standard protocols, through invasive procedures. Recently, Artificial Intelligence (AI) based techniques have demonstrated the potential to estimate BGL using data collected by non-invasive Wearable Devices (WDs), thereby, facilitating monitoring and management of diabetics. One of the key aspects of WDs with machine learning (ML) algorithms is to find specific data signatures, called Digital biomarkers, that can be used in classification or gaging the extent of the underlying condition. The use of such biomarkers to monitor glycemic events represents a major shift in technology for self-monitoring and developing digital biomarkers using non-invasive WDs. To do this, it is necessary to investigate the correlations between characteristics acquired from non-invasive WDs and indicators of glycemic health; furthermore, much work is needed to validate accuracy.
*Research Design & Methods:* The study aimed to investigate performance of AI models in estimating BGL among diabetic patients using non-invasive wearable devices data An open-source dataset was used which provided BGL readings, diabetic status (Diabetic or non-diabetic), heart rate, Blood oxygen level (SPO2), Diastolic Blood pressure, Systolic Blood Pressure, Body temperature, Sweating, and Shivering for 13 participants by age group taken from WDs. Our experimental design included Data Collection, Feature Engineering, ML model selection/ development, and reporting evaluation of metrics.
*Results:* We were able to estimate with high accuracy (RMSE range: 0.099 to 0.197) the relationship between glycemic metrics and features that can be derived from non-invasive WDs when utilizing AI models.
*Conclusion:* We provide further evidence of the feasibility of using commercially available WDs for the purpose of BGL estimation amongst diabetics.

## Introduction

### *Background*

Diabetes Mellitus (DM), a metabolic condition characterized mostly by the impaired ability of the body to utilize glucose for cellular energy and hence high blood glucose (BG) levels, affected 463 million individuals worldwide in the year 2019 (reference?). It is forecasted that 10.2% of the global population will be suffering from the disorder by the year 2030 and expected to increase to 700 million by 2045 [1]. Maintaining a normal range of blood glucose is important as consistently high levels can be a cause of major complications for diabetic patients such as heart attacks, stroke, kidney failures, vision loss, and nerve damage.

BG monitoring techniques have come a long way, it is now common amongst diabetes to self-monitor using electronic glucose meters, but these are invasive devices requiring users to self prick their fingertips in order to draw blood. As this is a recurrent procedure, it can cause stress and suffering not least due to the risk of infections [2].

Smartphones and other smart gadgets have further improved accessibility to monitoring devices. Continuous glucose monitoring (CGM) devices are readily available along with a handheld monitoring screen or via an app, but these normally still require the use of an

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external attachable sensor. Furthermore, such sensors are often semi-invasive, requiring connectivity range via Wi-Fi or Bluetooth to an external device or smartphone app [3,4].

For AI techniques to be effective the correct algorithm for the data in question needs to be applied. Only then it is possible to give advanced and clinically useful analytics to digest important data from the vast volumes of continuous data provided by WDs. Machine learning (ML) is technically a subset of AI, it is sometimes used interchangeably with AI. Briefly, the term AI is used when computers are made smarter, and ML is a collection of AI algorithms that discover patterns from data while having the capacity to self-learn so that it grows smarter over time without human involvement. There are two categories of classifications for ML algorithms: classical and modern. Classical methods demand less training data and computing resources for pattern recognition than modern approaches. Traditional techniques, on the other hand, frequently outperform modern approaches. Deep learning (DL) is a subset of AI, DL is a modern ML methodology in which algorithms mimic the brain's neural networks to train with or without supervision; nevertheless, unlike classic ML approaches, which are easier to understand, DL approaches can be "black box".

Wearable Devices (WDs) are an emerging technology, due to their non-invasive nature using biosensors requiring no input from users other than the wearing of devices such as smartwatches and wristbands, with the additional advantage of being considered stylish and fashionable, has meant high rates of user acceptance. Although in its infancy, studies have reported on the efficacy of sensors combined with Artificial Intelligence (AI) algorithms in commercially available WDs for the purpose of diabetes monitoring [5,6]. Near-infrared (NIR) accelerometer sensors, Galvanic skin response (GSR), electrocardiogram (ECG), and photoplethysmography (PPG) sensors are already incorporated into WDs. Because WDs are in close proximity to the user, they have an advantage over external sensor-driven devices when it comes to monitoring physiological indications like skin temperature and heart rate. This is especially useful for anticipating and monitoring diabetes-related metrics. The ability to generate digital biomarkers to monitor glycemic events represents a major shift in technology for self-monitoring and developing digital biomarkers using non-invasive WDs. To do this, it is necessary to investigate the correlations between characteristics acquired from non-invasive WDs and indicators of glycemic health.

This study sought to examine the performance of AI algorithms in estimating BG levels among diabetic patients using WD generated data. We investigated the relationship between glycemic metrics (blood glucose level) in terms of their performance, and features that can be derived from non-invasive WDs.

When it comes to the application of AI to biosensor data for the purpose of diabetes, there is literature applying ML and DL techniques for the purpose of blood glucose estimation (prediction or forecasting) [5–15], diagnostics solutions [15–19], glucose level monitoring [14, 20-26], Self-Administration and monitoring [27–30], prevention [31, 32] and classification [33–36]. Unfortunately, the number of peer-reviewed studies is still low as WDs are yet in their infancy. There is tremendous potential to enhance the quality of life for diabetic patients by utilizing ML and DL algorithms from the emerging field of AI and appropriately organizing and processing massive volumes of non-invasive WD data. By conducting the analytics within this study, we hope to further encourage research in this field by reporting on the accuracy of ML and DL techniques. Our goal in this study is to highlight the accuracy of each chosen ML model, furthermore, running a combination of ML and DL techniques on the same datasets, collected each through invasive/ non-invasive wearables respectively, delivers a clearer picture on how each model performs in terms of accuracy of BG level estimation.

### *Related work*

Previous studies have highlighted the need for studies to validate the ML approaches on clinical data from WDs [37]. Several previous studies report BG levels from WD data and the application of AI algorithms for estimation purposes (including forecasting/prediction, as these terms are often used interchangeably) [38]. Classical ML approaches were previously deployed in six studies [7-10,20,31], most of which used ensemble boosted trees, namely Random Forest (RF) [5,7-10,20]. From the studies that applied Modern approaches, Artificial Neural Networks type Convolutional Neural Network (CNN) was used [11,21,39]. The best models identified among some previous studies from classical models were RF [8–10] and CNN in Modern [11,21,39]. Clarke grid error (CGE) [7,8,10,11,21,39,40] and Root mean square error (RMSE) [7-9,27,33] were the most commonly used evaluation metrics in many of these studies. These studies reported RMSE values ranging from 0.357–25.621 and CGE from 56.52% to 95%. Outlining that in general high accuracy is achievable using WD sensors.

## Methods

### *Experimental design*

Given previous studies that have looked at glucose levels using AI models for determining blood glucose values [38], we hypothesized that we could report levels of accuracy for two ML and two DL models, further validating the usability and accuracy of data acquired through WDs, especially under the consideration that traditionally, the data provided for the training of these models was only acquired by using invasive methods such as CGMs or finger prick methods. The proposed predictive analysis system for BG level estimation is illustrated in Fig. 1 and described in the sections that follow. The system comprised of a detailed diabetes dataset, collected through wearable CGM and Smart Band, was used for the Predictive Analysis of DM after being run through various Feature Engineering Steps. The prediction results were validated using RMSE and MAE error calculation metrics.

### *Data collection*

For this study, an open-source dataset was used, titled *Dataset for People for their Blood Glucose Level with their Superficial body feature readings*, available on IEEE [41] . The dataset provides Blood Glucose level readings, diabetic status (Diabetic or non-diabetic), heart rate, Blood oxygen level (SPO2), Diastolic Blood pressure, Systolic Blood Pressure, Body temperature, Sweating, and Shivering for 13 participants by age group generated by two different WDs. Blood glucose readings were gathered through a continuous glucose monitoring kit named Freestyle LibrePro [42]. While the rest of the parameters were collected through a smart band named Riversong Wave O2 Colored. The duration for data collection was one year from June 2020 to December 2021; each patient wore the devices for approximately 3 months. The Freestyle LibrePro [42] (CGM) patch was updated every 14 days. The data was transferred directly from devices to the PC through cable without the intervention of any gateway devices. For the non-diabetic patients, only the average blood glucose levels over 5 days were reported. Further demographics of data including identity were not disclosed in the interest of data privacy and ethics. The dataset collected was already pre-processed by the authors, so no further pre-processing was carried out.

### *Sample size*

The dataset contained a sample size of 13 participants of which 8 males (3 non-diabetics and 5 diabetics), and 5 females (2 non-diabetics and 3 diabetics). The ratio of diabetic to non-diabetic within genders was 60% to 40%. The age of participants ranged from 9 years to 77 years. A total of 16,800 data points were available in this dataset.

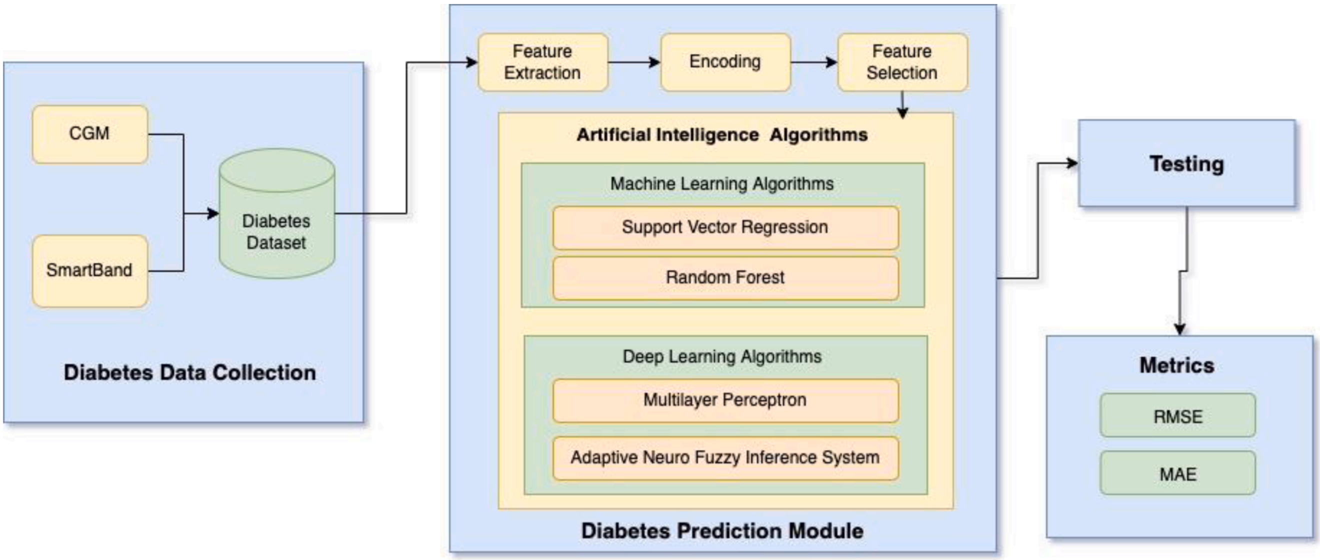


**Fig. 1.** The proposed predictive Analysis System illustrates the proposed predictive analysis system for BG level estimation. The system comprised of a detailed diabetes dataset, collected through wearable CGM and Smart Band, and used for the Predictive Analysis of DM after being run through various Feature Engineering Steps. The prediction results were validated using RMSE and MAE error calculation metrics.

*Feature engineering*

*Feature extraction*

In order to classify by "Age", we created a new feature called "Age group". The age groups were divided into two categories: Young and Adult. Ages under and equal to 18 were designated as young, and those above 18 as adults (Fig. 2). Age grouping was critical in identifying various patterns and trends among different individuals since different physiological circumstances of the body alter with age.

*Encoding*

Encoding data on categorical characteristics was done to improve model calculations. Label encoding was employed as the encoding technique. 'Diabetic/Non-Diabetic' and 'Age group' were the category characteristics for this dataset.

*Feature selection*

To properly deploy the predictive model, feature selection, or more particularly dimension reduction, was performed. A categorization model developed using the whole set of data characteristics may produce inconsistent results; hence, it is better to select the most relevant set of features that may help achieve a higher degree of true positive rate whilst minimizing the false positive rate. There is a variety of feature selection approaches used to determine the most useful characteristics; these approaches are classified as embedding methods, filter methods, and wrapper methods [41]. For this study, the filter strategy was applied to identify the most relevant characteristics. The dataset is first subjected to a filter-based feature selection approach known as Correlation-Based Feature Selection (CFS), which looks for feature subsets based on the degree of feature redundancy. The assessment procedure seeks for subsets of characteristics that are substantially associated with the target class separately but have minimal inter-correlation. The relevance of a collection of features increases as

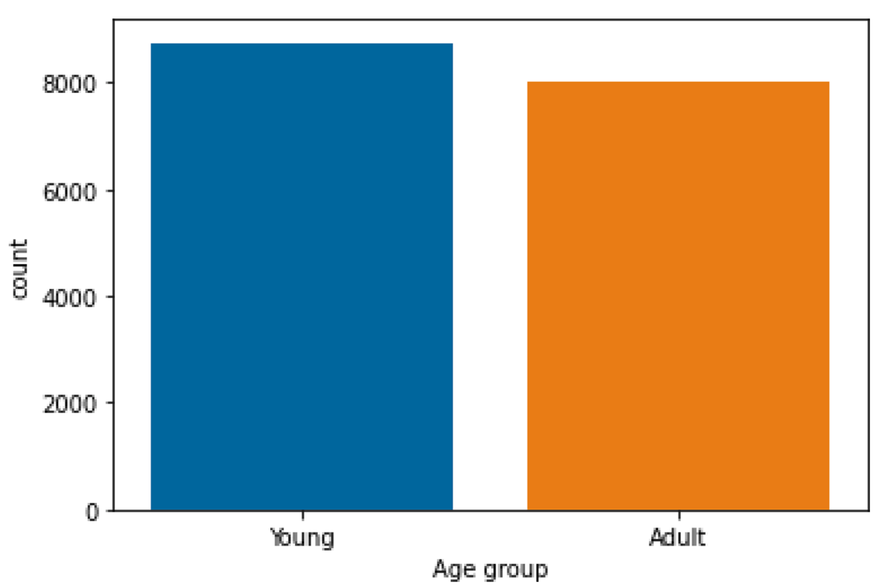


**Fig. 2.** Age group division.

the correlation between features and target class develops and reduces as the inter-correlation grows.

*Artificial intelligence (AI) algorithms*

*Model selection/development*

We applied four different models: 2 ML models (RF and SVR) and 2 DL models (MLP and Fuzzy Logic). All training and testing were being performed on each subset accordingly. The dataset was divided into training and testing with a ratio of 80:20. To develop personalized models for the age groups. For all models, the root RMSE and MAE were calculated to assess performance.

*Traditional machine learning (ML) algorithms*

*Support vector regression (SVR).* SVR is a supervised machine learning approach for dealing with regression issues and allows for the estimate of a real-valued function (e.g., continuous score on a clinical scale). SVR is based on the fundamental concept of SVM, which is a sparse kernel machine that conducts classification using a hyperplane specified by a few support vectors. SVR performs well when dealing with high-dimensional data.

*Random forest (RF).* RF is a supervised classification technique. RF, also known as random decision forests, is an ensemble learning approach for classification and regression that works by generating a multi-node decision tree network during training and predicting the mode of the classes or mean prediction of the individual trees.

*Deep learning (DL) algorithms*

*Multi-layer perceptron (MLP).* It is one of the most popular, simple, and commonly used neural networks. Its network is made up of a collection of sensory components that constitute the input layer, one or more hidden layers of processing elements, and a set of processing elements that create the output layer. The ANN learns the patterns in the input data through back propagation technique and can predict both continuous and discrete data. Based on the neural organization of the brain, the ANN Algorithm represents each cluster by a neuron. Each link is assigned a weight that is determined adaptively during learning. We employed the ANN Multilayer Perceptron method in this paper.

*Adaptive neuro fuzzy inference system (ANFIS).* ANFIS is an AI technique that combines the neural networks with fuzzy rule-base and rule-implication procedures from fuzzy set theory. ANFIS creates mapping based on both human knowledge (in the form of fuzzy if-then rules) and a hybrid learning algorithm using specified input/output data values. The ANFIS technique is used in modeling and simulation of nonlinear functions, regulates one of the most essential parameters of an inference machines and estimates a chaotic time series, all of which results in more effective, faster reaction or settling times.

*Evaluation metrics*

The models were built utilizing the Python programming language, using Python version 3.7.13 with packages including NumPy, pandas, skLearn (Scikit-learn), seaborn, and Matplotlib. The tests were executed on a computer running the MacOS Monterey operating system with Intel (R) Xeon(R) CPU @ 2.20 GHz and 12 GB RAM.

The quality of the results obtained by various ML algorithms was tested in terms of regression error rate measurement, namely root mean squared error (RMSE) and mean absolute error (MAE). RMSE is defined as the residuals' standard deviation (prediction errors). Residuals are a measure of how far away data points are from the regression line; RMSE is a measure of how spread out these residuals are. In other words, it indicates how concentrated the data is around the best fit line.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

MAE is defined as the summation of all absolute errors. The discrepancy between the measured and "actual" value is known as absolute error.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

## Results

*Pre-processing/feature engineering*

The confusion matrix of the correlation (Fig. 3) presents the results after feature normalization and additional features extracted. The quantitative analysis demonstrates the correlation between the attributes and target outcomes. It could be observed that some of the features are not highly correlated with the target outcome (BG levels), amongst these features that could be observed are Age, Diabetic, Nondiabetic, and Age group. Thus, we dropped these columns improve model accuracy. Likewise, it could be observed that sweating and shivering are highly correlated with each other, therefore, we selected one of them to remove feature duplication and redundancy. Whilst other independent features are correlated with BG levels (dependent variable) both positively and negatively contributing to impact of occurrence.

*Blood glucose estimation models*

Fig. 4 demonstrates the quantitative results for selecting the best performing preprocessing and ML model, with the RMSE and MAE presented for comparison. Providing an overview of each model's capacity to achieve the lowest error rate from the suggested pipeline, along with the best preprocessing and attribute selection algorithms and the number of selected attributes. The examination of Fig. 4 shows evidence of improved outcomes from several models when appropriate preprocessing is used.

All regressors show their best results for the selected features, with not much variation in predictions between classical and current models. The tree-based regressor, and the RF model, outperformed the other models in both the young and adult population datasets.

As shown in Table 1, RMSE values ranged from 0.189 to 0.197 in the young group and from 0.183 to 0.193 in the adult group. MAE values varied between 0.097 and 0.112 in the young group and between 0.099 and 0.108 in the adult group. While the best model was RF in both groups according to RMSE, the best model is ANFIS in both groups according to MAE.

## Discussion

*Principal findings*

Although the application of ML and DL models to this dataset gave promising results for BG level estimation using WD data, considering previous studies reported RMSE values of 0.357–25.621 [7-9,27,33], we report RMSE values of 0.099 to 0.197. Nonetheless, these values should be treated with caution due to the low number of participants in the dataset (13).

*Strengths and limitations*

We use a blend of traditional and deep learning ML models (a combination of ensemble (tree based), inference (ANFIS), and linear (SVM)) to further validate the performance of blood glucose level

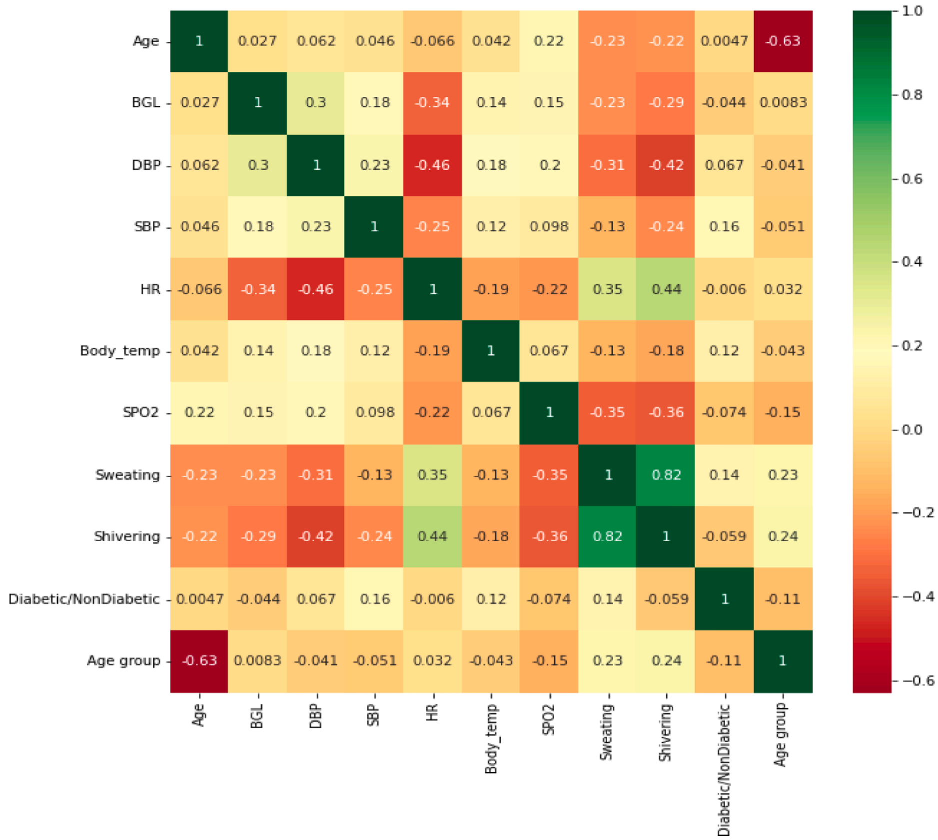


**Fig. 3.** Confusion matrix of attributes correlation presents the results after feature normalization and additional features extracted. It shows the correlation between the attributes and target outcomes. For example sweating and shivering are highly correlated whereas age is not.

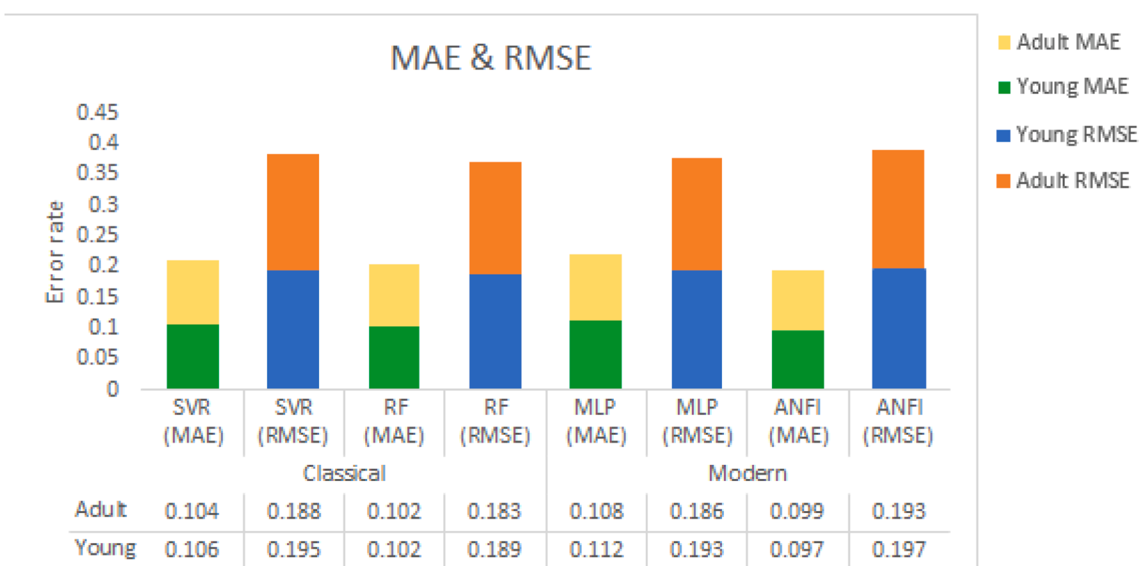


**Fig. 4.** RMSE and MAE plot shows the best model was RF in both groups according to RMSE. RMSE values ranged from 0.189 to 0.197 in the young group and from 0.183 to 0.193 in the adult group. For MAE the best model is ANFIS in both groups according to MAE. MAE values varied between 0.097 and 0.112 in the young group and between 0.099 and 0.108 in the adult group.

estimation using WD data. To the best of our knowledge, no previous study reports this combination of models on the WD diabetes dataset. A major limitation is the number of participants in the study, however we still have a large number of data points, which satisfies the data requirements for building ML models. It is also difficult to have a true comparison with previous studies as there are many varying factors such as device manufacturer, age range of participants, models applied and level of optimization of each model, individual device manufacturer's methods of calculating metrics etc.

**Table 1**
Performance of the models for each group.

| | RMSE | MAE |
|---|---|---|
| **Young Model** | | |
| SVR | 0.195 | 0.106 |
| RF | 0.189 | 0.102 |
| MLP | 0.193 | 0.112 |
| ANFIS | 0.197 | 0.097 |
| **Adult Model** | | |
| SVR | 0.188 | 0.104 |
| RF | 0.183 | 0.102 |
| MLP | 0.186 | 0.108 |
| ANFIS | 0.193 | 0.099 |

### *Practical and research implications*

#### *Practical implications*

BG level estimation using non-invasive WDs is a much welcome advancement and the accuracy levels reported provide much welcomed confidence in the commercially available bio-signals that can be collected with such devices. Although the models applied in this study performed well, in particular ANFIS, which is known to be faster than other AI models, could provide greater benefits once larger studies are conducted to validate its performance. This would lead to the possibility of offline WDs having algorithms run directly on the devices with an often-limited processing power; hence most devices currently use gateway or host devices such as smartphones or cloud spaces for any AI calculations. As the technology progresses, we would expect to see more applications of AI directly on the WD.

#### *Research implications*

We have further reported the accuracy of glucose estimation when comparing glycemic metrics and features from WDs when AI models are applied. Optimizations on larger datasets are needed to further validate this finding. More data needs to be made publicly available by researchers and manufacturers need to generate more raw data such as PPG values and make it available so that researchers can optimize and develop more accurate metrics such as BG values.

In general, the usefulness of such an intelligent system has to be understood in the application scenarios. A person with diabetes can rely now on the WDs data rather than having to get their finger pricked every now and then. On the one hand, this reduces the physical and psychological stress on them. On the other hand, such a non-invasive system can provide the BG values with appreciable accuracy at any time. This feature can help the patients to fine-tune their diet, lifestyle, or exercise patterns according to the readings and predictions from the AI-based system, being used. It is a well-known fact in diabetes management that prevention is better than intervention. The regular readings can steer the management patterns of diabetes and will help the patients improve their quality of life.

## Conclusion

This study provides further support to the feasibility of using commercially available WDs for the purpose of BG level estimation using noninvasive WDs amongst diabetic patients. We were able to estimate with high accuracy (RMSE range: 0.099 to 0.197) the relationship between glycemic metrics, and features that can be derived from non-invasive WDs when utilizing AI models. The findings from this study should encourage the development of future studies examining the use of digital biomarkers for BG level estimation. Due to their commercially available and fashionable nature and high user acceptance, WDs could represent a major advance in clinical care for diabetic patients.

## Declaration of Competing Interest

The authors have no competing interests to declare.

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