Healthcare Transformation with Informatics and Artificial Intelligence
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Estimating Blood Glucose Levels Using Machine Learning Models with Non-Invasive Wearable Device Data

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Abstract. In 2019 alone, Diabetes Mellitus impacted 463 million individuals worldwide. Blood glucose levels (BGL) are often monitored via invasive techniques as part of routine protocols. Recently, AI-based approaches have shown the ability to predict BGL using data acquired by non-invasive Wearable Devices (WDs), therefore improving diabetes monitoring and treatment. It is crucial to study the relationships between non-invasive WD features and markers of glycemic health. Therefore, this study aimed to investigate accuracy of linear and non-linear models in estimating BGL. A dataset containing digital metrics as well as diabetic status collected using traditional means was used. Data consisted of 13 participants data collected from WDs, these participants were divided in two groups young, and Adult Our experimental design included Data Collection, Feature Engineering, ML model selection/development, and reporting evaluation of metrics. The study showed that linear and non-linear models both have high accuracy in estimating BGL using WD data (RMSE range: 0.181 to 0.271, MAE range: 0.093 to 0.142). We provide further evidence of the feasibility of using commercially available WDs for the purpose of BGL estimation amongst diabetics when using Machine learning approaches.

Keywords. Blood glucose level, Deep learning, Machine learning, Artificial Intelligence, Diabetes, Wearable devices

1. Introduction

Diabetes Mellitus (DM) affected 463 million people globally in 2019 [1]. Blood glucose levels are typically monitored through invasive techniques. However, AI-based approaches using non-invasive Wearable Devices (WDs) have shown promise in predicting BGL, thereby, improving diabetes monitoring. Previous studies were conducted to estimate BGL from WD data [2], they mainly applied non-linear models as opposed to linear models. Among the non-linear models the most popular were Deep learning (DL) methods. These deep models are computationally expensive and need a lot of data for training, whereas generally non-linear models may need more data and be more challenging to interpret. The best models identified for glucose estimation in some

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previous studies from non-linear ML models were RF [3-5] and CNN [6-8] which was the only model used mostly by studies that deployed deep learning methods. These studies reported RMSE values ranging from 0.357-25.621 and Clarke grid error (CGE) from 56.52% to 95%. Outlining that in general high accuracy is achievable using WD sensors.

Earlier AI studies estimated blood glucose levels primarily utilizing wearable sensor data from prototype WDs. By presenting accuracy levels using ML models, our aim was to validate the accuracy of data gathered from commercially accessible WDs for glucose estimation. We looked at the performance variations between ML algorithms that were linear and non-linear in nature and attempted to draw attention to the key differences. Our findings encourage more study in this area by revealing information about how accurate ML approaches are in estimating BGL.

2. Materials and Methods

We used a comprehensive diabetes dataset collected from wearable CGM and Smart Band, and after performing feature engineering steps, we analyzed DM Predictive Analysis. The prediction results were verified using RMSE and MAE error calculation metrics.

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 [9]. The dataset includes BGL, heart rate, blood oxygen level, diastolic blood pressure, systolic blood pressure, body temperature, sweating, and shivering data for 13 participants by age group. The data was collected by two different WDs and also includes diabetic status. Blood glucose readings were collected using Freestyle LibrePro [13], a continuous glucose monitoring kit. The remainder of parameters were collected using Riversong Wave O2 Colored smart band. Data collection lasted a year (June 2020 - December 2021), with patients wearing the devices for about 3 months. The CGM patch was updated every 14 days, and data was transferred directly to a computer via cable. Non-diabetic patients' data only reported average blood glucose levels over 5 days. The dataset was pre-processed by the authors and required no additional processing. The dataset had 13 participants (8 males and 5 females) with a 60:40 diabetic to non-diabetic ratio. Participant ages ranged from 9 to 77 years, and the dataset had 16,800 data points. Feature engineering involved extraction, encoding, selection, and model selection.

Linear and non-linear models were applied to the dataset, which was divided into two subcategories based on age: young (ages under or equal to 18) and adult (ages above 18). Training and testing were performed on each subset, using a ratio of 80:20. To develop personalized models for the age groups, linear regression, Elastic-Net, and Lasso were used from linear models, while decision trees, Gradient Boosting Machine, and Adaptive Neuro Fuzzy Inference System were used for non-linear models. The models were built using Python and evaluated using root mean squared error (RMSE) and mean absolute error (MAE).

3. Results

Figure 1 and 2 shows the RMSE and MAE values for each model in each age group, respectively. All regressors performed well on the chosen features, with minimal differences between linear and non-linear models. However, in both datasets (young and adult populations), the decision tree-based regressor performed worse than other models, which could be attributed to the low number of participants which led to inability to learn patterns and generalize well, unlike GBM and ANFIS which are more adaptable.

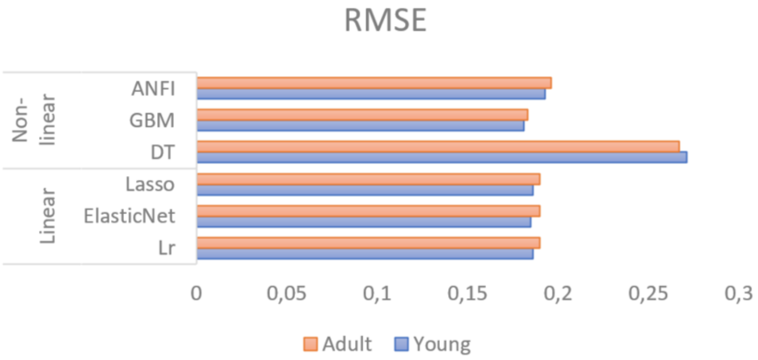

Figure 1. RMSE values for adult and young population for each model

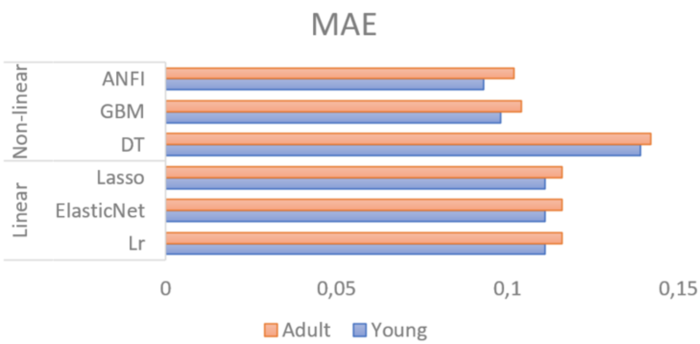

Figure 2. MAE values for adult and young population for each model

4. Discussion

Although the application of ML models to this dataset gave promising results for BGL estimation using WD data (RMSE 0.186 to 0.271, MAE: 0.093 to 0.142), considering previous studies reported RMSE values of 0.357-25.621, mainly using non-linear ML approaches in similar problems [3-8], we report RMSE values of 0.186 to 0.271 using simpler linear models which outperformed more complex models in previous studies. Nonetheless, these values should be treated with caution due to the low number of participants in the dataset. Since both linear and non-linear models performed equally well, they can be a reliable and efficient option in many situations, especially when the dataset is small, computational resources are scarce, and interpretability is a top priority. Although the models used in this study performed well, larger studies are needed to validate the performance of ANFIS, which some studies report as being faster than other deep AI models and requiring minimal computational resources [10]. The claim made in the study needs to be further verified, but if it is, algorithms could be run directly on lowpower WDs, making offline execution possible. Technology advancements could result in an increase in AI applications on WDs currently in use, improving diabetes management and patient quality of life. The results need to be supported by additional research using larger sample sizes and other commercially available devices.

5. Conclusion

This study demonstrates the viability of non-invasive blood glucose level estimation in diabetic patients using commercially available wearable devices. To accurately estimate the relationship between glycemic metrics, features from the devices were derived using linear and non-linear models. The clinical care provided to diabetic patients may significantly improve thanks to wearable technology, which has a high user acceptance rate.

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