AI-Driven μPAD Glucose Analysis via Indoor and Outdoor Smartphone Imaging with Flash Control

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***Abstract*—In this study, an AI-driven approach was implemented for μPAD glucose analysis using smartphone images captured under indoor and outdoor conditions with flash on and off. Prior to app integration, three-zone μPADs were fabricated via a wax printing protocol, whose detection areas were modified with 3,3',5,5'-tetramethylbenzidine (TMB), glucose oxidase (GOx), and horseradish peroxidase (HRP) for glucose detection. Color changes on the μPADs were recorded, and a small dataset was generated by photographing the devices with three different smartphones indoors and outdoors with flash control. MATLAB's Classification Learner was used to analyze the dataset, and the best performing model (accuracy: 0.95) was exported as .mat files. These numerical outputs were then converted into .c and .h functions using MATLAB Coder and integrated into a custom Android application called *"GlucoObserver"*, enabling real-time AI-based glucose classification under practical imaging scenarios.**

Keywords*—*Artificial intelligence, Colorimetry, Glucose, Mobile applications

I. Introduction

Accurate monitoring of glucose levels is critical for individuals as it provides prevention of diabetes-related complications [1]–[3]. While conventional glucose meters provide reliable results, their dependency on electrochemical sensors and specific test strips can make them less sustainable and more costly over time. Moreover, these devices require regular calibration [4] and careful handling to ensure accuracy, which might not always be feasible in resource-limited settings or for individuals seeking quick, low-maintenance alternatives.

Recent advances in biosensors have led to flexible, miniaturized, and highly sensitive platforms for point-of-care diagnostics. Flexible screen-printed MWCNT electrodes offer excellent stability and biocompatibility for non-invasive biomedical use [5], while microfluidic and LSI-based sensor arrays enable real-time, multiplexed detection of biomolecules and cellular activity [6], [7]. In parallel, μPADs have emerged as a revolutionary tool in chemical analysis, particularly in resource-constrained environments. These devices are fabricated from paper, which naturally facilitates the flow of fluids through capillary action [8], eliminating the need for external pumps or power sources. For glucose testing, the μPAD surface is coated with reagents that react with glucose in the sample, producing a color change that corresponds to the glucose concentration. This reaction provides a visual, qualitative indication of glucose levels [9] that can also be quantified through image analysis [10]. Their simplicity, portability, and low production cost make μPADs an attractive option for home monitoring, community health initiatives, and even field diagnostics in remote areas.

Despite their advantages, μPADs face limitations that can impact their effectiveness. One major challenge lies in the interpretation of colorimetric results. Variations in lighting conditions, camera quality, and user perception can lead to inconsistent readings, reducing the reliability of the test. Additionally, subtle differences in color intensity that are critical for precise glucose quantification may be difficult to discern with the naked eye [11], [12]. Artificial intelligence (AI) offers a powerful solution to the challenges of colorimetric analysis in μPADs [13]–[17]. By capturing images of the μPAD's color changes using a smartphone camera, AI algorithms can analyze the images to accurately quantify analyte levels. These algorithms are trained to account for variations in lighting, focus, and other environmental factors, ensuring consistent and reliable results. Furthermore, AI can detect subtle differences in color that may be imperceptible to the human eye, improving the sensitivity and precision of the analysis. This integration transforms μPADs into a smart diagnostic tool that combines the accessibility of traditional colorimetric methods with the analytical power of modern technology. Here, an AI-driven approach was developed for μPAD glucose analysis using smartphone images captured indoors and outdoors, both with and without flash. Laboratory experiments with wax-printed μPADs, modified with TMB, GOx, and HRP, tested six glucose concentrations. Images from three smartphones under varying lighting were used to create a dataset, which was analyzed with MATLAB's Classification Learner. The best performing machine learning (ML) model was then integrated into a custom Android app for real-time AI-based glucose classification

II. Materials and Method

A. Use of μPAD for Glucose Measurement

The μPADs were produced via a wax printing method [18]. The design, featuring three circular detection zones and a separate sample inlet channel, was created in Microsoft PowerPoint and printed on Whatman filter paper using a Xerox ColorQube 8900 wax printer. Hydrophobic channels were formed by heating the printed paper on a hot plate at 180°C for 120 seconds to control fluid flow. Each μPAD contained three measurement zones: the first received 0.5 μL of 10 mM TMB; the second, 0.5 μL of 10 mM TMB with 0.5 μL of 50 U/mL HRP; and the third, 0.5 μL of 10 mM TMB, 0.5 μL of 180 U/mL GOx, and 0.5 μL of 50 U/mL HRP, applied sequentially with drying. For testing, glucose solutions adjusted to pH 7

were prepared at six concentrations: 0, 0.25, 0.5, 1, 2, and 5 mM. The fabricated μPADs were then immersed in these solutions for colorimetric analysis.

B. Image Capturing

To achieve high classification performance, ML models must be trained on a well-curated dataset. Since dataset composition directly affects model accuracy, a dataset was created using images captured with three smartphones: Apple, LG, and Redmi. Images were captured at time points t_0(up to 5 minutes) and t_1 (after 15 minutes) using smartphones both with and without flash, under indoor and outdoor conditions. The dataset was transferred to a computer for processing with MATLAB (R2023b, MathWorks Inc.). By placing circular masks on the detection zones, regions of interest were extracted. The detection zones containing GOx were taken as regions of interest as they were the regions where colorimetric reactions due to the reactions of solutions occurred, and there was no color change in the circular areas with no GOx.

After the isolation of the regions of interest by correctly positioning the circular masks, each data was saved into a text file format. The saved .txt files include the corresponding coordinates (x,y) and the radii of circular masks. These saved .txt files were then converted to .mat files which facilitate generating the regions of interest by automatically placing circular masks on the corresponding coordinates.

C. Feature Extraction

After image processing, color and texture features were extracted to train the classifiers on MATLAB. To analyze the effect on color spaces on concentration level, RGB values of the images were converted to HSV and L*a*b* values. RGB, HSV and L*a*b* channels were then extracted to calculate the mean, skewness and kurtosis values. Along with the color features, texture features such as contrast, correlation, energy, and homogeneity — statistical parameters based on color transition and intensity — were extracted. The entropy and mean intensity values were calculated as well as the color and texture features. To train the classifiers in MATLAB programming language, 30 features were extracted.

After extracting the features, thirty-two ML classifiers were trained and evaluated based on their ability to predict different glucose concentrations from the regions of interest to identify and detect the colorimetric analysis depending on their concentration. Seed number was set to 100 and cross-validation value was set to 10. ML results were obtained in time intervals t_0 and t_1. In order to avoid issues caused by high variance and bias, cross-validation value is set to 10. The classification process was repeated 100 times, and 100 different accuracy values from 32 classifiers were obtained.

D. Smartphone Application: GlucoObserver

For the colorimetric analysis of glucose, a smartphone application, *GlucoObserver*, was developed as shown in Figure 1. The functions automatically generated by MATLAB Classification Learner was incompatible with MATLAB Coder, so new functions were created using the numerical parameters (means, covariances, weights, coefficients, etc.) from the exported .mat models. These functions were then converted into C code (.c) via MATLAB Coder for integration into the app, as .m files cannot be directly implemented in Kotlin. To enable this, a custom user interface was designed in Android Studio, with MATLAB Coder facilitating access to the trained model values through the Java Native Interface (JNI). The final application interface was implemented using Kotlin.

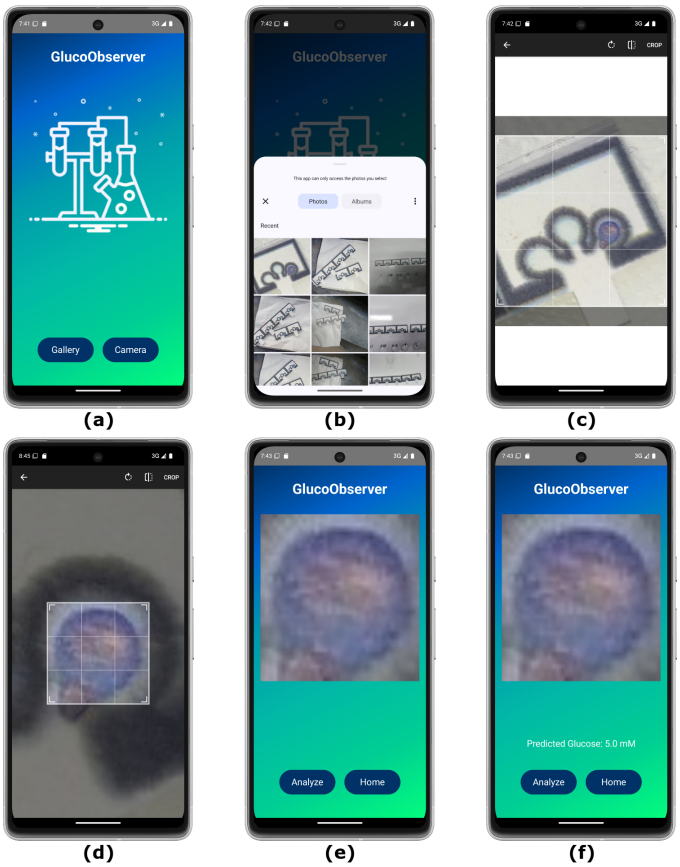

Figure 1: The startup screen is shown in (a) which displays the application logo and the home screen, with two buttons to upload images from the gallery or by taking pictures from the camera. As shown in (b), the user is able to upload an image from the gallery. In (c) and (d), the user can crop the image to detect the region of interest. (e) displays the cropped image with the two new buttons where the user can either analyze the concentration of glucose or go back to the home screen. In (f), the calculated glucose concentration is displayed on the screen.

III. Results and Discussion

To detect glucose in the solutions, a series of different concentrations were prepared. Using wax printing, μPADs with three separate detection zones were fabricated. Each detection zone was then modified with a specific mixture: (i) TMB alone, (ii) TMB + HRP, and (iii) TMB + HRP + GOx. After modification, the μPADs were immersed in glucose solutions of varying concentrations. In the presence of oxygen, GOx catalyzes the oxidation of glucose to produce gluconic acid and hydrogen peroxide (H_2O_2). The generated H_2O_2 then oxidizes TMB in the presence of HRP, forming a blue color. Only the detection zones containing both GOx and HRP exhibited a color change due to H_2O_2-mediated TMB

oxidation. The intensity of the blue color correlated directly with glucose concentration: darker colors indicated higher glucose levels, whereas lighter or absent colors indicated lower concentrations.

All features were extracted from images of the μPADs for training the ML classifiers. Nine color channels (R, G, B, H, S, V, L*, a*, b*) were analyzed, and for each channel, the mean, skewness, and kurtosis were calculated, resulting in 27 features. Additionally, texture features, entropy, and mean intensity values were extracted. These 30 features, along with six response labels [0, 1, 2, 3, 4, 5] corresponding to six glucose concentrations (0, 0.25, 0.5, 1, 2, and 5 mM), were used to train the ML models. Linear discriminant analysis (LDA) as well as medium and narrow neural networks were employed as reference classifiers to evaluate the maximum achievable accuracy for glucose concentration prediction. Classifier performance was assessed using validation accuracy (Eq. 1), precision (Eq. 2), recall (Eq. 3), and F1-score (Eq. 4). As shown in Table 1, the validation accuracy for the medium (Figure 2a) and narrow (Figure 2b) neural networks at the time interval t_0 was 0.73611 at the 24$^{\text{th}}$ and 81$^{\text{st}}$ seed numbers, respectively, while the validation accuracy for LDA at the time interval t_1 was 0.95 at the 76$^{\text{th}}$ seed number (Figure 2c).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$f1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Table I: Performance comparison of ML classifiers on glucose classification.

	t_0 (%)	t_1 (%)
MNN (24$^{\text{th}}$ seed)	**0.73611**	0.90278
NNN (81$^{\text{st}}$ seed)	**0.73611**	0.85416
LDA (76$^{\text{th}}$ seed)	0.65278	**0.95139**

Finally, the trained LDA model was integrated into the custom Android application, *GlucoObserver*, allowing users to perform glucose quantification tests. The app automatically detects the region of interest (ROI) and features a simple, offline-capable interface for uploading images from the camera or gallery. Users can crop the uploaded image on the edit screen, confirm it, and then either analyze the glucose concentration or return to the home screen (Figure 1).

IV. Conclusion

In this study, an AI-driven approach was developed for μPAD glucose analysis by integrating MATLAB-based ML algorithms with a custom Android Studio user interface. Laboratory experiments with wax-printed μPADs, modified

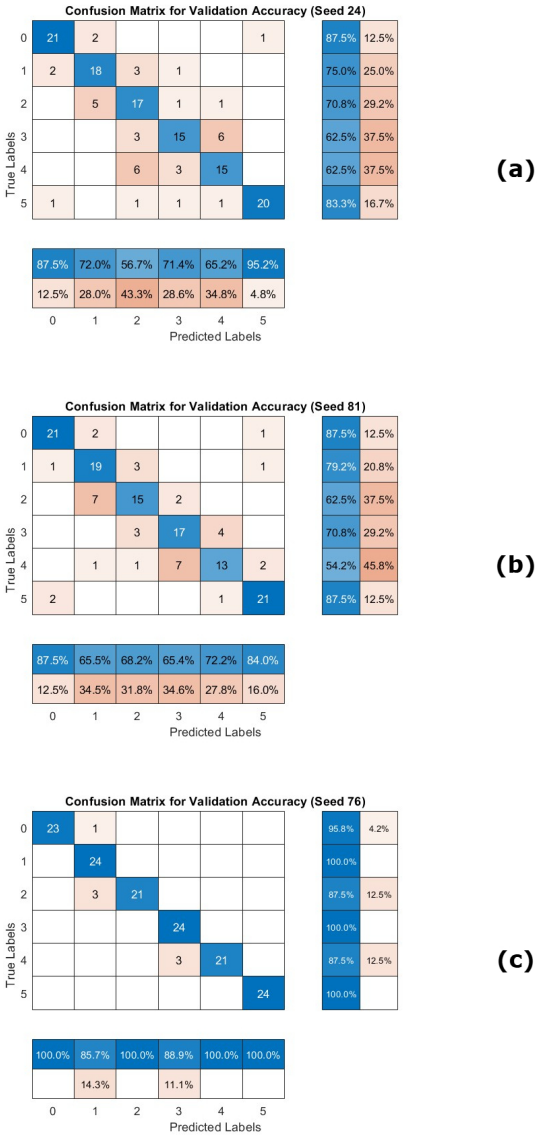

Figure 2: The confusion matrices of the performed artificial intelligence tests are presented in this figure. Panel (a) shows the confusion matrix for the MNN at seed 24, while panel (b) corresponds to the NNN at seed 81; both neural network classifiers were applied to the time interval t_0. Panel (c) displays the confusion matrix for the LDA at seed 76 for the time interval t_1.

with TMB, GOx, and HRP, provided a dataset of images captured under indoor and outdoor conditions with flash on and off. The models, analyzed using MATLAB's Classification Learner and converted into C code via MATLAB Coder, were successfully integrated into the mobile application, achieving a classification accuracy of 0.95. While dataset size and diversity could be increased to further improve performance, the approach demonstrates practical real-time glucose detection and is adaptable for deployment on both Android and iOS platforms.

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