International Journal of Life Sciences and Biotechnology
Caf, et al., Smartphone-Based Point-of-Care Urinalysis Vivoo App: A Validation Study. International Journal of Life Sciences and Biotechnology, 2024 7(1): p. 60-73.
https://doi.org/10.38001/ijlsb.1371191
Araştırma Makale/ Research article

Smartphone-Based Point-of-Care Urinalysis Vivoo App: A Validation Study

Balım Bengisu Caf[1,2*], Gizem Cebi[1,3], Haluk Çelik[1,4], Aliasghar Noroozi[1], Ali Atasever [1], Miray Tayfun[1]

ABSTRACT
Point-of-care (POC) analysis has emerged as a pivotal approach in providing rapid and convenient medical diagnostics. Smartphone-based solutions further augment the accessibility and ease of POC, enabling efficient on-the-go analysis. The integration of smartphone technology with POC has paved the way for innovative applications such as the Vivoo App, which empowers users to monitor various health parameters conveniently. Our study validated the accuracy and reliability of the smartphone-based POC urinalysis Vivoo mobile application. A comparative approach was followed wherein artificial urine samples were analyzed using both the Vivoo and traditional laboratory methods. A diverse range of health parameters were assessed. A total of 2618 strips were used over the course of this study to evalate the accuracy of Vivoo. The test strips results appeared to match exactly the expected measurement results. In addition, when the ±1 color block acceptance criterion was applied, 2608 of 2618 measurements of the tested strips were found to have met the expected measurement results completely. Based on the results, the 95% confidence interval for the exact match agreement proportion of Vivoo is 87.55% ± 1.27% and 99.62% ± 0.24%. As a wellness product, this study thus concludes that the Vivoo is appropriate in terms of both device reliability and performance. The app's ability to provide accurate and timely health results offers promising opportunities to improve individual health management.

ARTICLE HISTORY
Received
05 October 2023
Accepted
20 December 2023

KEYWORDS
Point of care,
urinalysis,
artificial intelligence,
wellness,
healthcare

Introduction

Point-of-care (POC) analysis is a form of testing that allows for the immediate testing of medical samples at the point of care without the need for conventional laboratory analysis [1]. Point-of-care testing is described as conducting tests at the patient care site or in its nearby vicinity [2]. This method offers several benefits, such as rapid results, reduced costs, and improved patient outcomes [3]. In recent years, one emerging trend in POC analysis has been the use of smartphone-based technology for diagnostics, including through urine analysis [4]. Point-of-care technology delivers relevant data directly at the location of treatment, facilitating quick clinical judgments. As the healthcare focus moves towards precision medicine, overall population well-being, and the effective handling of chronic conditions, the significance of its potential is on the rise. Over the past ten years, various notable trends in POC have surfaced or gained more prominence.
Urine analysis is one of the most common diagnostic tests in clinical practice, providing valuable information about kidney function, urinary tract infections, and other medical conditions [5, 6, 7, 8]. Urine analysis, a fundamental diagnostic tool in medical practice, plays a pivotal role in assessing and monitoring various health conditions [9]. Urine analysis provides crucial insights into an individual's health, revealing information about kidney function, hydration levels, and potential underlying medical conditions [2, 10]. This non-invasive method provides critical insights into an individual's metabolic, renal, and systemic health. Analyzing components such as pH, specific gravity, and the presence of proteins, glucose, ketones, and blood cells can help in the early detection and management of conditions like diabetes, kidney disease, urinary tract infections,

[1] Vivosens Inc., 44 Tehama Street, Suite 409, San Francisco, CA, US 94105
[2] Program of Bioengineering, Faculty of Chemical and Metallurgical Engineering, Yildiz Technical University, 34210, Istanbul, Türkiye
[3] Program of Chemical Engineering, Faculty of Chemical and Metallurgical Engineering, Istanbul Technical University, 34469, Istanbul, Türkiye
[4] Program of Stem Cell and Tissue Engineering, Institute of Health Sciences, Istinye University, 34010, Istanbul, Türkiye
*Corresponding Author: Balım Bengisu Caf, e-mail: bengisu.caf@std.yildiz.edu.tr

and liver problems. The advent of home urine test kits has further revolutionized this field, enabling patients to conduct preliminary assessments in the comfort of their homes. These test, which often use dipsticks with color-changing pads, offer a convenient and rapid means to track health indicators. By allowing for frequent monitoring, home urine analysis can facilitate early intervention and timely consultation with healthcare professionals [4]. This not only empowers individuals in their health management but also aids in reducing the burden on healthcare systems by preventing the escalation of untreated conditions. Thus, urine analysis, especially when accessible at home, stands as a cornerstone in preventive healthcare and patient empowerment. Traditional urine analysis involves laboratory-based testing, which can be both time-consuming and expensive. However, smartphone-based urine analysis offers a rapid and cost-effective alternative that typically utilizes a disposable test strip that is dipped into a urine sample [11, 12, 13]. The smartphone app provides a visual readout of the test results, which can be used by healthcare professionals for diagnosis and treatment of different diseases, medical conditions, and overall health and wellness [14, 15, 16, 17].

Smartphone-based POC urinalysis is a rapidly growing field that has the potential to revolutionize the ways in which patients are diagnosed and treated for various conditions. It is a promising technology due to its rapid and low-cost diagnosis of urine biomarkers [18, 19]. Smartphone-based urine analysis typically involves the use of mobile devices equipped with high-resolution cameras and specialized software applications. The purpose of these applications is to evaluate images of urine test strips and calculate the concentration of different analytes in the urine. This process is done by comparing color changes to a pre-calibrated colorimetric scale. This process becomes more complex when AI algorithms are used. AI significantly improves accuracy and makes it possible to identify small variations that might be overlooked by the human eye. The idea assumes that smartphones which are widely available and equipped with advanced imaging software, can be used for rapid and cost-effective urine analysis. This approach has significant implications for healthcare, especially in the diagnosis and management of medical conditions [20, 21]. The process typically involves dipstick preparation, image capture, image analysis, and results. This system has several advantages, such as rapid results, cost-effectiveness, remote monitoring, and accessibility. Smart-phone based POC systems can be applied to chronic disease management, infection detection, pregnancy testing, and wellness-associated parameter testing. Advancements in artificial intelligence and machine learning could further enhance the accuracy and capabilities of smartphone-based urine analysis. Integration with electronic health records and telehealth platforms could also broaden its impact [22, 23]. Traditionally, urinalysis has been performed in laboratory settings using specialized equipment, which can be time-consuming and require patients to travel to a healthcare facility [24, 25]. With the increasing ubiquity of smartphones and the development of innovative POC diagnostic technologies, it is now possible for patients to perform their own urinalysis at home or in a healthcare facility by using their smartphone as a diagnostic platform [25].

The widespread accessibility of smartphones and tablets offers several significant prospects for the integration of point-of-care testing (POCT) [26]. Incorporating POCT with these platforms also facilitates the storage of data on a cloud-based server for telemedicine purposes. While a standardized approach for seamlessly integrating this data into regular medical records is yet to be established, enabling the sharing of this information beyond the limitations of a specific hospital or device will set the stage for future advancements. Numerous POCTs under development have capitalized on the optical sensing functionalities of the integrated complementary metal oxide semiconductor cameras found in smartphones and tablets [28, 29]. These cameras can be employed for tasks such as capturing images or spectra and subsequently analyzing them.

The accuracy and reliability of smartphone-based POC analysis rely heavily on artificial intelligence (AI) and image processing algorithms [30, 31]. AI algorithms can detect subtle changes in color or intensity that may be difficult for the human eye to discern. Image processing algorithms can help reduce noise and improve the signal-to-noise ratio, leading to more accurate and reliable results [32, 33]. AI and image processing can also be used to develop predictive models for diagnosing and treating diseases based on large datasets of POC analysis results [34, 35].

In recent years, machine learning (ML) techniques have been increasingly used for the analysis of POC urinalysis test results [36, 37]. ML algorithms can be trained to analyze images of urine test strips captured by smartphone cameras and provide diagnostic information based on test results [38, 39, 40]. This approach has the potential to significantly improve the accuracy and speed of POC urinalysis, as well as increase its accessibility and affordability [41, 42]. However, the development of ML algorithms for POC urinalysis requires extensive validation studies to ensure their accuracy and reliability [43].

Due to advancements in POC, urinalysis has evolved into a trustworthy and efficient diagnostic method. Recent progress in AI technology has enhanced the precision, reliability, and efficiency of urine analysis diagnostics. These tools now have the capacity to recognize various medical issues and deliver precise insights into an individual's health by examining the physical and chemical attributes of urine. Urine test strips provide a rapid

and convenient means of initial urinalysis, swiftly detecting substances such as glucose, nitrite, urobilinogen, bilirubin, protein, ketone, albumin, creatinine, pH, and leukocyte esterase. The development of multi-component test strips enables the simultaneous identification of these substances using just one urine sample. The focus of this study is on the accuracy and reliability of smartphone-based POC urinalysis, particularly the use of AI and ML algorithms for analyzing test results. The aim of the study is to validate the accuracy of the Vivoo urine analysis platform for measuring different chemical components found on the Vivoo test strip. In this study, artificial urine solutions were used to test the accuracy of the Vivoo results. The results of our study suggest that the Vivoo urine analysis is a reliable method for measuring various chemical components in urine. The use of AI and image processing algorithms in POC urinalysis has the potential to significantly improve the accuracy and speed of diagnosis and increase its accessibility and affordability to consumers.

Material and Methods

The Vivoo App processes each strip image in three steps: 1) sensor and reference detection, 2) color correction, and 3) sensor value prediction.

Detecting the strip through sensors and references

In our patented process, named "Analysis of urine test strips with mobile camera analysis and providing recommendation by customizing data" (patent number: US20220405973A1) [44], we first began by employing an object detection model to localize the Vivoo test strip and its sensors and reference boxes. Next, we used segmentation to extract the sensors and references. With the extracted references and object detection results, we conducted a series of checks, including on strip position, distance, movement, perspective, and lighting conditions.

We then positioned the strip carefully to achieve optimal test results. To do this, we used the strip's bounding box as a reference for its position, defined edge margins to the screen, and hit the test bounding box. Although it was not necessary for the strip to be positioned exactly, we were conscious of the possibility of the strip failing the check if positioned at an angle or too close, even if it is centered correctly. We also took into account the appropriate strip distance, as this was crucial for improved test outcomes. We ensured that the strip was not too far away, which would present challenges in extracting sensor colors accurately, or too close, which can cause blurriness or shadow interference. The width and height of the strip bounding box helped determine the distance, and we ensured they were within a predefined range. During testing, we also maintained the strip's movement and stability, recognizing that if the strip moved, the resulting image could become blurry, leading to incorrect test results. To maintain stability during the image-capturing process, we used the strip's bounding box as a reference for its position and ensured that its movement speed was slower than its predefined value. Overall, these steps were critical for ensuring the secure positioning of the strip and producing accurate results during testing.

We recognized the importance of having the strip's face parallel to the camera to obtain accurate test results and proper strip perspective. To achieve this, we calculated the distance between all corner boxes, compared these distances to calculate differences, and used them to determine the strip's vertical and horizontal perspectives. Accurately determining the strip's perspective was a crucial step in achieving reliable test results, as it ensured that the strip was viewed correctly by the camera, allowing for accurate readings during testing. Additionally, consistent lighting conditions were essential to achieving accurate test results, as inconsistent lighting could cause partial dark regions over sensors, and shadows could also cause color changes on some regions of the strip surface. To maintain consistent lighting, we calculated the overall brightness and checked for deviations, as well as calculated the overall color changes and analyzed deviations. These steps helped identify any discrepancies in the lighting conditions and allowed for corrections to be made to achieve consistent lighting. Throughout testing, we monitored and adjusted the lighting to maintain consistency, recognizing its importance for achieving accurate and reliable test results.

Color correction

In this step, a dominant color is calculated for each extracted reference box. These reference colors are used to perform color correction on extracted sensors. Color correction normalizes the environment light by comparing extracted reference colors with the original printed reference colors.

Fig 1 depicts a flowchart of how color correction functions in the Vivoo App. 8-bit RGB refers to integer values of color channels R, G, and B, which are between the range of 0 to 255. Float linear RGB refers to float values in range [0, 1]. Precision of float linear values are higher than integer 8-bit values. The inherent component in Fig 1 is Root Polynomial Regression [45], in which a correction matrix is computed from the original reference colors and the observed (extracted) reference colors using least-squares regression. Fig 2 presents the result of applying the color correction to the entire image.

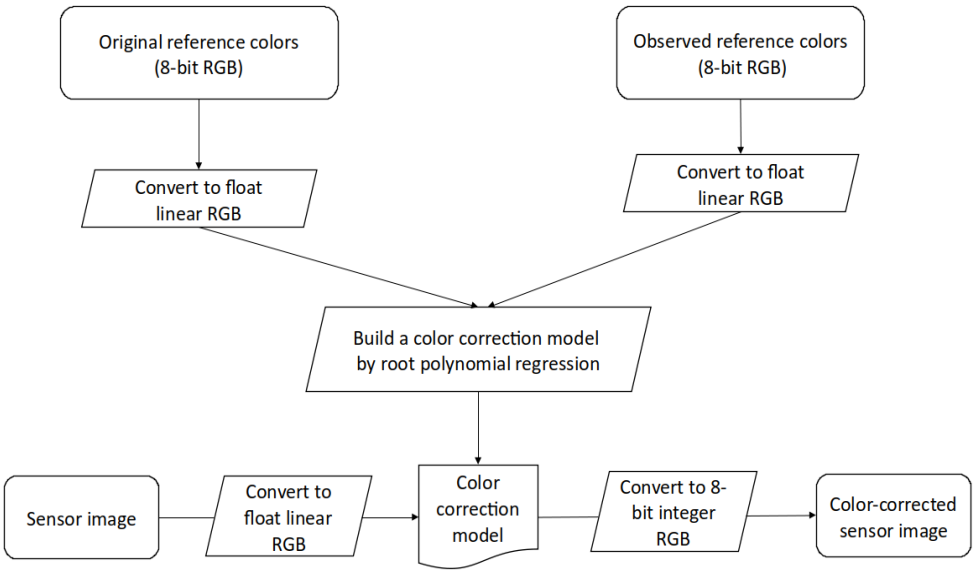

Fig 1 Color correction functioning in the Vivoo App [44]

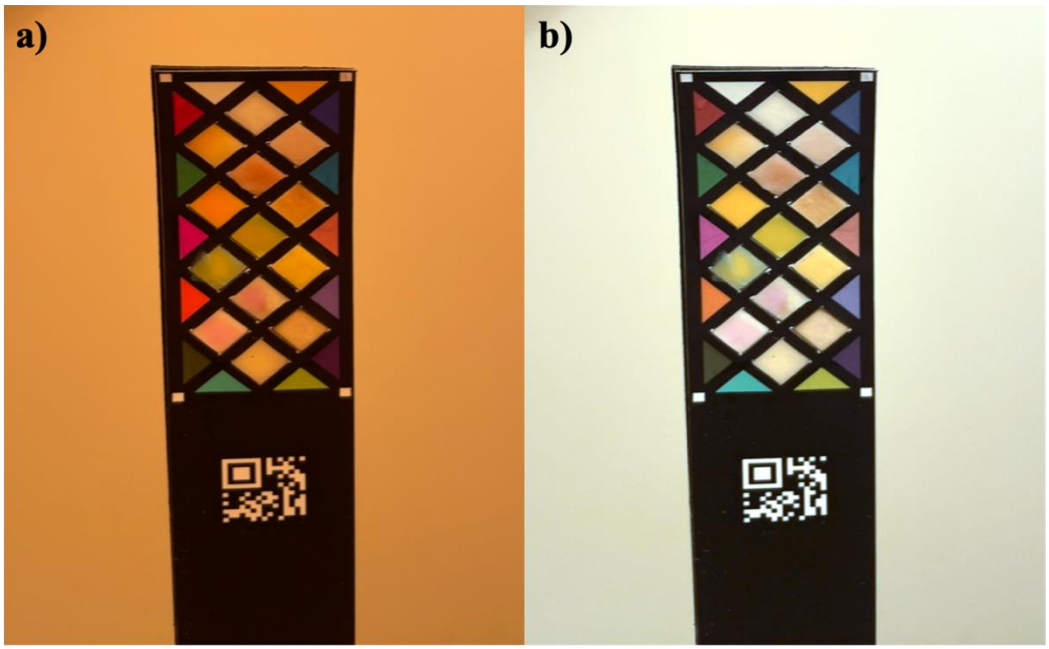

Fig 2 Color correction: (a) the detected Vivoo urine test strip, (b) the Vivoo urine test strip after color correction

Sensor value prediction

The Vivoo App contains an ML model for each sensor called sensor models. They predict the value of each sensor. We used Convolutional Neural Networks (CNNs) [46] as the architectural basis for these models. The models are trained with thousands of lab images, and these lab images are created using urine samples with values that are already established.

While training a sensor model, the CNN automatically learns the features that are crucial for differentiating images of each sensor value. The most important features are the color ranges, the extent of color change in the sensor image, the possible shapes created by sensor reaction to the urine sample, etc. These features are different for each sensor value.

Vivoo app validation

The experimental design covers the validation studies of Vivoo App produced by Vivosens Biotechnology R&D, Ind. And Trade Co. Ltd. This analytical validation study was conducted in the True Testing Services

between October and December 2022. To evaluate the accuracy of the Vivoo, this study employed the use of artificial urine samples. Potential factors that may affect the product's performance include ambient light during scanning, image resolution of the phone camera, and partial shading. To eliminate the effects of these factors, all tests were conducted using the same phone in the same environment, and under the same lighting conditions.

Preparation of urine solutions

This study used the following materials to prepare artificial urine solutions for testing: BIORAD Urinalysis Control 1 and 2, distilled water, Gündüz Kimya Buffer Solutions (pH: 10/pH: 7/pH: 4), sodium chloride salt, Sunlife Vitamin C Tablet, Aromel Kimya Calcium Chloride, MAGNORM tablet, Cayman Chemical Creatinine, and Supelco Malondialdehyde tetrabutylammonium (MDA) salt. We conducted chemical analyses of the BIORAD Urinalysis Control 1 and 2 obtained by the Roche Cobas U-411 Analyzer.

Vivoo was designed to with the purpose of examining the existence and/or quantification of the subsequent chemical constituents in urine: bilirubin, ketones, leukocytes, nitrites, protein, specific gravity, pH, creatinine, calcium, vitamin C, magnesium, sodium, and MDA. As such, we did not consider blood, glucose, and urobilinogen specified in the BIORAD Urinalysis Control solutions when preparing the artificial urine solutions. Additionally, since the BIORAD Urinalysis Control solutions did not account for creatinine, calcium, vitamin C, magnesium, sodium, and MDA, we prepared additional stock solutions using sodium chloride salt, Sunlife Vitamin C Tablet, Aromel Kimya Calcium Chloride, MAGNORM tablet, Supelco MDA, and Cayman Chemical Creatinine (Supplementary file 1).

Verification of urine solutions

We prepared 41 artificial urine solutions for this study, which were verified as follows: the Roche Cobas U-411 Urine Analyzer was used to verify the solutions for testing bilirubin, ketone, leukocyte, nitrite, protein, and specific gravity; the Ohaus ST 2100 F Benchtop pH Meter was used to verify the solutions for testing pH; the enzymatic photometric methodology with the Abbott/Architect C8000 was used to verify the solutions for testing creatinine, calcium, magnesium, and sodium; the Urine Analyzer BC401 (Contec Medical Systems Co., Ltd.) was used to verify the solutions for testing vitamin C; and the solutions for testing MDA were verified visually at the Vivosens Biotechnology laboratory. All solutions used for conducting tests were stored at 4°C.

Experimental procedure and statistical analysis

We performed the following procedure to test the Vivoo test strips. First, we downloaded the Vivoo App from the Apple Store and created a user account. We then applied artificial urine solutions onto the Vivoo test strips and waited for 90 seconds before scanning the test strip onto the Vivoo App via a smartphone (iPhone 13 IOS 15.6.1) (Fig 3). After scanning, we discarded the test strip. We repeated these steps to obtain experimental replicates. We then saved the results that we obtained in a datasheet (Ref. Attachment 11.14 Vivoo). Finally, we conducted a statistical analysis of the results of the Vivoo test strips by using IBM SPSS Statistics Version 26. We performed a two-sided confidence intervals analysis. The sample size for bilirubin, ketones, leukocytes, nitrites, proteins, calcium, creatinine, vitamin C, and MDA solutions was 200. The sample size for pH, specific gravity, magnesium, and sodium solutions were 207, 203, 204, and 204 respectively.

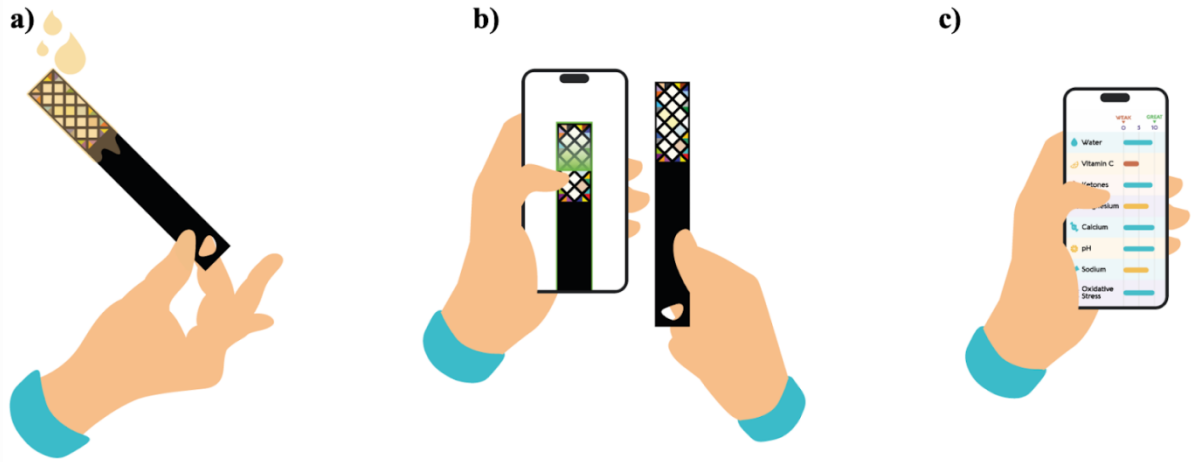

Fig 3 Illustration of the urine test strip analysis process using the smartphone-based reader Vivoo App. a) apply urine to the Vivoo test strip, b) capture the image of the test strip using the Vivoo, c) obtain the results for each artificial urine solution used for this study

Results

Chemical analysis of urinalysis solutions

The results from the chemical analysis conducted on BIORAD Urinalysis Control 1 show that the sample tested negative for bilirubin, blood, ketones, leukocytes, nitrite, and protein (total). The glucose level was within the normal range, and the pH was slightly acidic between 5 - 6.5. The specific gravity was also within the normal range of 1.005 - 1.020, and the urobilinogen level was normal.

In contrast, the BIORAD Urinalysis Control 2 created significantly different results. Bilirubin was present in the sample at a concentration of 3 - 6 mg/dL (50 -100 umol/L) (2+ - 3+), and blood was present at a concentration of 150 - 250 Ery/uL (4+ - 5+). The glucose level was high, ranging from 250 -1000 mg/dL (14 - 56 mmol/L) (3+-4+), and ketones were also present in the sample at a concentration of 50 - 150 mg/dL (5 - 15 mmoI/L) (3+ - 4+). The leukocyte concentration was elevated, ranging between 100 - 500 Leu/uL (2+ - 3+), and nitrite was present in the sample. The pH was alkaline within a range of 7 - 8, and protein (total) concentration was high, ranging between 100 - 500 mg/dL (1.0 - 5.0 g/L) (3+ - 4+). The specific gravity was within the normal range of 1.000 - 1.020, and urobilinogen was present at a concentration of 8 - 12 mg/dL (135 - 203 umol/L) (3+ - 4+) (Table 1).

Table 1 Chemical analysis of the BIORAD Urinalysis Control 1 and 2 measured by the Roche Coban U 411 Analyzer

Parameter	BIORAD Urinalysis Control 1	BIORAD Urinalysis Control 2
Bilirubin	Negative	3 - 6 mg/dL (50 -100 umol/L) (2+ - 3+)
Blood	Negative	150 - 250 Ery/uL (4+ - 5+)
Glucose	Normal	250 -1000 mg/dL (14 - 56 mmol/L) (3+-4+)
Ketones	Negative	50 - 150 mg/dL (5 - 15 mmoI/L) (3+ - 4+)
Leukocytes	Negative - 25	100 - 500 Leu/uL (2+ - 3+)
Nitrite	Negative	Positive
pH	5 - 6.5	7 - 8
Protein (total)	Negative	100 - 500 mg/dL (1.0 - 5.0 g/L) (3+ - 4+)
Specific gravity	1.005 - 1.020	1.000 - 1.020
Urobilinogen	Normal	8 - 12 mg/dL (135 - 203 umol/L) (3+ - 4+)

It is important to note that BIORAD Urinalysis Control 1 and 2 are quality control solutions used for monitoring the performance of urinalysis tests in medical laboratories. These solutions contain various substances that simulate the properties of human urine and can be used to assess the accuracy and precision of urinalysis tests. The results from our analysis indicate that BIORAD Urinalysis Control 1 and 2 had significantly different properties in its chemical composition. We have thus demonstrated that the artificial urine solutions used in this experiment are suitable for use in validating the accuracy of the Vivoo App.

Verification of artificial urine solutions

The results obtained from various verification methods for the artificial urine solutions prepared for testing different parameters were determined to be within the desired value ranges. The verification results of the artificial urine solutions prepared for testing provided in Supplementary file 2.

Descriptive statistics

Descriptive statistics on the test results into the accuracy of Vivoo for measuring each of the 13 chemical components found on the Vivoo test strip are provided as a tables in Supplementary file 3. The Vivoo App was used to analyze various components in artificial urine samples. The app analyzed the levels of bilirubin, ketones, leukocytes, nitrites, pH, specific gravity, protein, magnesium, sodium, calcium, creatinine, vitamin C, and MDA. The analysis was conducted using a total of 200 strips each for bilirubin, ketones, leukocytes, nitrites, protein, calcium, creatinine, vitamin C, and MDA. Additionally, pH, specific gravity, protein, magnesium, and sodium were analyzed using 207, 203, 204, 204, and 204 strips, respectively.

Vivoo categorized bilirubin measurements into four potential outcomes: 0 mg/dL, 1 mg/dL, 3 mg/dL, and 5 mg/dL. To assess Vivoo's bilirubin readings, we employed artificial urine solutions (specifically, solutions 1, 7, 2, and 5) corresponding to these measurements. Our findings revealed that when using solution 1, all tested strips achieved the anticipated bilirubin measurement, with a 100% accuracy rate. For Solution 2, accuracy stood at 98%, while solution 5 demonstrated 92% accuracy, and solution 7 yielded an 86% accuracy rate.

When applying the ±1 color block acceptance criterion, all bilirubin solutions displayed 100% agreement with the expected bilirubin measurement.

Vivoo categorized ketone measurements into five potential outcomes: 0 mg/dL, 5 mg/dL, 15 mg/dL, 50 mg/dL, and 150 mg/dL. To assess the accuracy of Vivoo's ketone readings, we utilized artificial urine solutions (specifically, solutions 1, 7, 3, 2, and 5) corresponding to these measurements. Our findings indicated that solution 1 yielded the expected ketone measurement in 100% of the tested strips, while solution 2 achieved a 97.5% accuracy rate. Solution 5 demonstrated an 80% accuracy rate, solution 3 showed 75% accuracy, and solution 7 resulted in a 70% accuracy rate. When applying the ±1 color block acceptance criterion, all ketone solutions exhibited 100% agreement with the expected ketone measurement.

Vivoo categorized leukocyte measurements into four potential outcomes: 0 Leu/uL, 25 Leu/uL, 100 Leu/uL, and 500 Leu/uL. To assess the accuracy of Vivoo's leukocyte readings, we employed artificial urine solutions (specifically, solutions 1, 2, 4, and 5) corresponding to these measurements. Our findings indicated that when using solution 1 and solution 5, all tested strips achieved the anticipated leukocyte measurement, resulting in a 100% accuracy rate. For solution 4, accuracy stood at 90%, while solution 2 exhibited a 64% accuracy rate. Applying the ±1 color block acceptance criterion, all leukocyte solutions exhibited a 100% agreement with the expected leukocyte measurement.

Vivoo categorized nitrite measurements into two potential outcomes: either positive or negative. To assess the accuracy of Vivoo's nitrite readings, we utilized artificial urine solutions (specifically, solutions 1 and 5) corresponding to these categories. Our findings revealed that all tested strips precisely identified the presence or absence of nitrites in the designated artificial urine solutions for nitrite testing.

Vivoo categorized pH measurements into nine possible outcomes: 5, 5.5, 6, 6.5, 7, 7.5, 8, 8.5, and 9. Artificial urine solutions (solutions 1, 9, 10, 3, 11, 12, 13, 14, and 15, respectively) with these measurements were used to test the accuracy of Vivoo readings of pH. Our results indicated that the Vivoo accurately measured their expected pH values. More specifically, solution 1 was measured accurately by 52.2% of the strips; solution 9 was measured accurately by 69.6% of the strips; solution 10 was measured accurately by 78.3% of the strips; solution 3 was measured accurately by 100% of the strips; solution 11 was measured accurately by 95.7% of the strips; solution 12 was measured accurately by 95.7% of the strips; solution 13 was measured accurately by 82.6% of the strips; solution 14 was measured accurately by 47.8% of the strips; and solution 15 was measured accurately by 95.7% of the strips. Furthermore, when applying the ±1 color block acceptance criterion, it was evident that, except for solutions 1 and 11, all solutions exhibited a complete agreement, reaching 100%, with their anticipated pH values.

Vivoo categorized specific gravity measurements into seven possible outcomes: 1.000, 1.005, 1.010, 1.015, 1.020, 1.025, and 10.30. Artificial urine solutions (solutions 1, 2, 16, 8, 17, 18, and 19, respectively) with these measurements were used to test the accuracy of Vivoo readings of specific gravity. Our results demonstrated that the Vivoo accurately measured their expected specific gravity values. More specifically, solution 1 was measured accurately by 100% of the strips; solution 2 was measured accurately by 75.9% of the strips; solution 16 was measured accurately by 96.6% of the strips; solution 8 was measured accurately by 100% of the strips; solution 17 was measured accurately by 93.1% of the strips; solution 18 was measured accurately by 65.5% of the strips; and solution 19 was measured accurately by 86.2% of the strips. Moreover, when applying the ±1 color block acceptance criterion, it was evident that all solutions exhibited a complete agreement, reaching 100%, with their anticipated specific gravity values.

Vivoo categorized protein measurements into five potential outcomes: 0 mg/dL, 25 mg/dL, 75 mg/dL, 150 mg/dL, and 500 mg/dL. To evaluate the accuracy of Vivoo's protein readings, we employed artificial urine solutions (specifically, solutions 1, 7, 2, 6, and 5) corresponding to these measurements. The strips precisely measured their anticipated protein values, with solution 5 achieving 100% accuracy, and solutions 1, 2, 6, and 7 reaching 97.5%, 77.5%, 95%, and 80% accuracy, respectively. When applying the ±1 color block acceptance criterion, all protein solutions exhibited 100% agreement with their expected protein measurements.

Vivoo categorized magnesium measurements into four potential outcomes: 0.5 mg/dL, 3.6 mg/dL, 6-7.2 mg/dL, and 10.8-14.4 mg/dL. To assess the precision of Vivoo's magnesium readings, we employed artificial urine solutions (specifically, solutions 1, 34, 35, 36, 37, and 38) corresponding to these measurements. The Vivoo accurately measured their expected magnesium measurements, with solution 35 showing 100% accuracy, and solutions 1, 34, 36, 37, and 38 showing 61.8%, 61.8%, 73.5%, 79.4%, and 88.2% accuracy, respectively. When applying ±1 color block acceptance condition, solutions 35, 36, 37, and 38 showed 100% agreement with their expected magnesium measurements, and solutions 1 and 34 showed 97.1% agreement.

Vivoo categorized sodium measurements into four possible results: 0 mg/dL, 100 mg/dL, 200-400 mg/dL, and 500 mg/dL. We employed artificial urine solutions (specifically, solutions 1, 39, 10, 8, 6, and 16) corresponding to these measurements to assess the precision of Vivoo's sodium readings. The results showed

that the strips tested using solution 1 had a 100% accuracy rate. Strips tested using solution 39 had a 91.2% accuracy rate, strips tested using solution 10 had a 64.7% accuracy rate, strips tested using solution 8 had a 97.1% accuracy rate, strips tested using solution 6 had a 94.1% accuracy rate, and strips tested using solution 16 had a 79.4% accuracy rate. When applying the ±1 color block acceptance criterion all strips tested using solutions 1, 39, 10, 8, 6, and 16 exhibited 100% agreement with their expected sodium measurements.

Vivoo categorized calcium measurements into five potential outcomes: 4 mg/dL, 10 mg/dL, 20 mg/dL, 30 mg/dL, and 40 mg/dL. To assess the precision of Vivoo's calcium readings, we utilized artificial urine solutions (specifically, solutions 1, 25, 26, 27, 28, and 29) corresponding to these measurements. The outcomes revealed that strips tested with solutions 1 and 25 achieved a perfect accuracy rate of 100%. Strips tested with solution 26 displayed a 72.5% accuracy rate, while those with solution 27 had a 77.5% accuracy rate. Strips tested using solution 28 showed a 90% accuracy rate, and those tested with solution 29 reached a 67.5% accuracy rate. When applying the ±1 color block acceptance criterion, all calcium solutions exhibited 100% agreement with their anticipated calcium measurements.

Vivoo categorized creatinine measurements into five potential outcomes: 10 mg/dL, 50 mg/dL, 100 mg/dL, 200 mg/dL, and 300 mg/dL. We utilized artificial urine solutions (specifically, solutions 20, 21, 22, 23, and 24) corresponding to these measurements to evaluate the precision of Vivoo's creatinine readings. The outcomes indicated that 60% of strips measuring solution 20, 60% of strips assessing solution 21, 87.5% of strips analyzing solution 22, 85% of strips examining solution 23, and 80% of strips testing solution 24 accurately measured their expected creatinine levels. When applying the ±1 color block acceptance criterion, all creatinine solutions demonstrated 100% agreement with their anticipated creatinine measurements, underscoring the accuracy of Vivoo's creatinine readings, particularly when employing the ±1 color block acceptance criterion.

Vivoo categorized vitamin C measurements into five potential outcomes: 0 mmol/L, 0.6 mmol/L, 1.4 mmol/L, 2.8 mmol/L, and 5 mmol/L. We utilized artificial urine solutions (specifically, solutions 1, 30, 31, 32, and 33) corresponding to these measurements to assess the precision of Vivoo's vitamin C readings. The outcomes indicated that the Vivoo accurately measured their expected vitamin C levels for 97.5% of strips tested with solution 1, 87.5% of strips tested with solution 30, 82.5% of strips tested with solution 31, 97.5% of strips tested with solution 32, and 100% of strips tested with solution 33. Moreover, when applying the ±1 color block acceptance criterion, all vitamin C solutions exhibited a 100% agreement with their anticipated vitamin C measurements, highlighting the high accuracy of Vivoo's vitamin C readings, particularly when employing the ±1 color block acceptance criterion.

Vivoo categorized MDA measurements into two potential outcomes: either positive or negative. We utilized artificial urine solutions (specifically, solutions 1 and 40 without MDA, and 41 with MDA) corresponding to these categories to assess the precision of Vivoo's MDA readings. The outcomes revealed that all strips precisely detected the absence of MDA for solutions 1 and 40, while 99.5% of Vivoo accurately identified the presence of MDA for solution 41. Moreover, when applying the +1 color block acceptance criterion, all MDA solutions demonstrated 100% agreement with their expected results, emphasizing the high accuracy of Vivoo's MDA readings, especially when employing the +1 color block acceptance criterion.

Confidence intervals

The analysis evaluated 2618 strip measurements, of which 2292 measurements were consistent with their expected values. With the ±1 color block acceptance criterion, 2608 strip measurements met their expected values.

When applying the ±1 color block acceptance criterion, all values aligned with their anticipated measurement outcomes, with a 95% confidence interval for the exact match agreement proportion of Vivoo at 94% ± 3.29% for bilirubin, 81.5% ± 5.38% for calcium, 84.5% ± 5.02% for ketones, 74.5% ± 6.04% for creatinine, 88.5% ± 4.42% for leukocytes, 99.5% ± 0.98% for MDA, 90% ± 4.16% for protein, 87.75% ±4.51% for sodium, and 88.18% ± 4.44% for specific gravity. In the case of magnesium, when we employed the ±1 color block acceptance criterion, the 95% confidence interval for Vivoo's exact match agreement proportion is 77.45% ± 5.74%, and the agreement proportion falls within a 95% confidence interval of 97.06% ± 2.31%. As for pH, with the same ±1 color block acceptance criterion, Vivoo's exact match agreement proportion has a 95% confidence interval of 79.71% ± 5.48%, while the agreement proportion is within a 95% confidence interval of 98.07% ± 1.88%.

Out of the total number of tested strips (2618), 2292 exhibited an exact match with their expected measurement results. Furthermore, when we applied the ±1 color block acceptance criterion, 2608 out of 2618 measurements conformed entirely to the expected results. We conducted a 95% confidence interval calculation for Vivoo's exact match agreement proportion, resulting in 87.55% ± 1.27%. Upon the application of the ±1 color block acceptance criterion, Vivoo's exact match agreement proportion's 95% confidence interval was 99.62% ±

0.24%. When we individually assessed each of Vivoo's 13 components, the 95% confidence interval for the exact match agreement proportion varied between 74.50% and 99.50%, depending on the specific component. Following the application of the ±1 color block acceptance criterion, 11 out of 13 components on Vivoo displayed results that perfectly aligned with the expected measurement values.

We observed a lack of exact match percentages for 2 out of the 13 components on Vivoo, namely magnesium and pH. However, in terms of Vivoo's presentation of its results to users, magnesium exhibited an exact match percentage of 77.45%. While this component didn't achieve a 100% match, the exact match percentage remains relatively high. When considering the confidence intervals for these components under the ±1 color block acceptance criterion, magnesium, and pH yielded values of 97.06% and 98.07%, respectively (Table 2).

Table 2 Confidence intervals results of Vivoo

Chemical Component	frequency	n	proportion	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Standard Error of the Estimate	±
Total	2292[a]	2618	87.55 %	86.28 %	88.81 %	0.65 %	1.27 %
	2608[b]	2618	99.62 %	99.38 %	99.85 %	0.12 %	0.24 %
Bilirubin	188[a]	200	94.00 %	90.71 %	97.29 %	1.68 %	3.29 %
Ketone	169[a]	200	84.50 %	79.48 %	89.52 %	2.56 %	5.02 %
Leukocyte	177[a]	200	88.50 %	84.08 %	92.92 %	2.26 %	4.42 %
pH	165[a]	207	79.71 %	74.23 %	85.19 %	2.80 %	5.48 %
	203[b]	207	98.07 %	96.19 %	99.94 %	0.96 %	1.88 %
Specific gravity	179[a]	203	88.18 %	83.74 %	92.62 %	2.27 %	4.44 %
Protein	180[a]	200	90.00 %	85.84 %	94.16 %	2.12 %	4.16 %
Magnesium	158[a]	204	77.45 %	71.72 %	83.19 %	2.03 %	5.74 %
	198[b]	204	97.06 %	94.74 %	99.38 %	1.18 %	2.31 %
Sodium	179[a]	204	87.75 %	83.25 %	92.24 %	2.30v	4.51 %
Calcium	163[a]	200	81.50 %	76.12 %	86.88 %	2.75 %	5.38 %
Creatinine	149[a]	200	74.50 %	68.46 %	80.54 %	3.08 %	6.04 %
Vitamin C	186[a]	200	93.00 %	89.46 %	96.54 %	1.80 %	3.54 %
MDA	199[a]	200	99.50 %	98.52 %	100.00 %	0.50 %	0.98 %

a: True/False (Exact Match), **b:** True/False (± 1 Color Block)

The experiment conducted aimed to validate the accuracy of Vivoo urine analysis for measuring 13 different chemical components found on the Vivoo test strip. The study used artificial urine solutions to test the accuracy of the Vivoo readings for bilirubin, ketones, leukocytes, nitrites, pH, specific gravity, protein, magnesium, sodium, calcium, creatinine, vitamin C, and MDA. Overall, the results show that the Vivoo provided accurate measurements for all chemical components tested.

The results of this study suggest that the Vivoo urine analysis is an accurate method for measuring various chemical components in urine. These findings are in line with previous studies that have demonstrated the reliability of urine analysis as a diagnostic tool [32]. In addition, the use of artificial urine solutions allowed

for controlled testing conditions, ensuring that the results were not influenced by other factors. Ho wever, it should be highlighted that this study successfully demonstrated the accuracy of the Vivoo in measuring chemical components in artificial urine solutions, indicating its potential effectiveness for testing real human urine samples.

Discussion

In the realm of medical diagnostics, the integration of smartphone technology with urinalysis presents a transformative approach, revolutionizing how urine analysis is conducted and interpreted. This integration leverages the ubiquity and advanced capabilities of smartphones to offer a convenient, rapid, and user-friendly means of conducting urine tests. By utilizing smartphone cameras and specialized apps, individuals can perform self-testing, where the smartphone interprets the results from urine test strips [47]. Furthermore, the advent of smartphone and AI-based technologies has revolutionized the landscape POC diagnostics of urine analysis. This innovative approach combines the accessibility of smartphones with the advanced analytical capabilities of AI, paving the way for rapid, accurate, and user-friendly urine testing methods [17]. Our study presents a comprehensive analysis of the accuracy of Vivoo App which is a AI integrated urine analysis app, which are designed to measure various chemical components in urine. The methodology involved using 2618 strips with artificial urine solutions to measure 13 different chemical components by Vivoo App, including bilirubin, ketones, leukocytes, nitrites, pH, specific gravity, protein, magnesium, sodium, calcium, creatinine, vitamin C, and MDA.

The chemical analysis of BIORAD Urinalysis Control 1 and 2 provides insightful data for understanding the efficacy and reliability of urinalysis testing, particularly in relation to the Vivoo App, a health monitoring tool. Control 1's results are indicative of a normal urinary profile.

In contrast, Control 2's results simulate a pathological urinary state. The presence of bilirubin and blood at significant levels suggests hepatic pathology or hematuria, potentially indicative of liver dysfunction or urinary tract damage [48]. Elevated glucose and ketones are hallmarks of uncontrolled diabetes mellitus [49]. The elevated leukocyte count and the presence of nitrite are suggestive of a urinary tract infection. The alkaline pH (7 - 8) can be associated with certain renal tubular acidosis or urinary tract infections [50]. High protein concentration points towards possible kidney damage or disease [51]. The presence of urobilinogen at elevated levels could indicate liver disease or hemolytic conditions [52].

The contrast between Control 1 and Control 2 is crucial for validating the Vivoo App. It demonstrates the app's ability to differentiate between normal and pathological conditions, a key feature for a reliable urinalysis tool. This differentiation is essential for users relying on the app for health monitoring, as it can guide them in seeking professional medical advice when abnormal results are detected. Tchemical analysis of BIORAD Urinalysis Control 1 and 2 highlights their suitability as quality control solutions for urinalysis tests. Their distinct chemical compositions, simulating both normal and pathological conditions, provide a robust platform for validating the accuracy and precision of the Vivoo App. This analysis underscores the importance of comprehensive quality control in the development and maintenance of digital health monitoring tools.

The comprehensive analysis of the Vivoo App's performance in measuring various chemical components in artificial urine solutions presents a robust picture of its accuracy and reliability. The study meticulously evaluated the App's ability to quantify 13 distinct chemicals, including bilirubin, ketones, leukocytes, nitrites, pH, specific gravity, protein, magnesium, sodium, calcium, creatinine, vitamin C, and MDA. The initial verification of the artificial urine solutions, as outlined in Supplementary file 2, confirmed that the preparations were within the desired value ranges. This step was critical to ensuring the validity of subsequent tests and analyses.

The accuracy assessment of bilirubin, ketones, leukocytes, nitrites, pH, specific gravity, protein, magnesium, sodium, calcium, creatinine, vitamin C and MDA are demonstrated high accuracy, The findings from this study underscore the reliability and accuracy of the Vivoo App in measuring a range of chemical components in artificial urine. The use of the ±1 color block acceptance criterion significantly enhanced the agreement rates, highlighting the importance of considering minor variations in color readings. The study's methodology, involving a large number of strips for each test, lends credibility to the results.

A significant portion of the analysis focuses on the assessment of exact match agreement proportions, both with and without the ±1 color block acceptance criterion. Our results show that a high percentage of measurements were consistent with their expected values. Notably, with the ±1 color block acceptance criterion, the vast majority of strip measurements aligned with anticipated outcomes, as evidenced by the 95% confidence intervals calculated for each component. These confidence intervals provide a quantitative measure of the accuracy of Vivoo App’s readings, indicating a high level of precision across most of the tested components.

The overall exact match agreement proportion of Vivoo, considering all 13 components, falls within a 95% confidence interval of 87.55% ± 1.27%. However, this proportion dramatically increases to 99.62% ± 0.24% when the ±1 color block

acceptance criterion is applied. This criterion's application seems to significantly enhance the match agreement, demonstrating the potential flexibility and reliability of Vivoo App in different analytical settings.

In conclusion, our study robustly demonstrates the accuracy of Vivoo App in measuring a range of chemical components. The high exact match percentages and narrow confidence intervals indicate the reliability of Vivoo App. Our study aligns with previous research underscoring the reliability of urine analysis apps as a diagnostic tool, adding to the growing body of evidence supporting the use of such non-invasive testing methods with potential applications in medical diagnostics, research, and personal health monitoring.

Conclusion

Smartphone-based POC urinalysis is a rapidly evolving field that has the potential to revolutionize health monitoring and disease prevention. With the widespread availability of smartphones and their ability to integrate various sensors and devices, it is now possible to perform a range of medical tests using just a smartphone and a urine sample. One of the most promising applications of smartphone-based POC is the detection of various biomarkers in urine, which can provide valuable insight into a person's health status and risk of developing certain diseases.

Despite the promising results of smartphone-based POC urine analysis, there are still some limitations that must be addressed before this technology can be widely adopted. One of the main challenges is the lack of standardization in urine analysis methods and the potential for user error. The accuracy of urine analysis can be affected by factors such as the timing of the sample collection, the sample volume, and the user's technique in using the smartphone app. Therefore, it is essential to develop standardized protocols and guidelines for smartphone-based POC urine analysis to ensure consistency and accuracy across different users and devices.

Another limitation of smartphone-based POC urine analysis is the need for further validation and testing to ensure the accuracy and reliability of the results. While the Vivoo App has shown promising results in smartphone-based POC urinalysis, there is a need to develop more sophisticated urine analysis technology that can measure a wider range of biomarkers with higher accuracy and sensitivity.

Looking to the future, there are many exciting possibilities for the development of smartphone-based POC urine analysis. One such possibility is the integration of AI and machine learning algorithms for improving the accuracy and reliability of urine analysis results. AI can aid in identifying patterns and correlations in urine analysis data that may not be visible to the human eye, which can in turn enable more precise and personalized health recommendations. Another direction for future research is the development of new sensors and devices that can measure a wider range of biomarkers in urine. In conclusion, smartphone-based POC urine analysis has the potential to transform the way we monitor our health and prevent diseases. The validation of the Vivoo Application is thus a significant step forward in this field, but there are still many challenges and opportunities that need to be addressed. By collaborating with healthcare providers, technology companies, and regulatory bodies, we can ensure that smartphone-based POC urine analysis is safe, effective, and accessible to all. With continued research and innovation, we can unlock the full potential of this technology to improve our health and well-being.

Abbreviations

POC: Point-of-care; POCT: Point-of-care testing; AI: Artificial Intelligence; ML: Machine Learning; CNN: Convolutional Neural Networks; MDA: Malondialdehyde tetrabutylammonium.

Acknowledgements

We would like to express our sincere gratitude to C. Balkı Germinter for her invaluable guidance and support throughout the process of preparing this manuscript. Also, we would like to express our sincere gratitude to Senay Tayfun and Ece Unal for their exceptional contributions in designing the figures presented in this manuscript.

Funding

This study received no external funding but the all analysis was carried out by Vivosens Biotechnology.

Data availability statement

Please contact the corresponding author for any data request. The authors declare that the data supporting the findings of this study are available within the paper and its Supplementary files.

Compliance with ethical standards

Conflict of interest

The authors declare no conflicts of interest.

Ethical standards
The study is proper with ethical standards.

Authors' contributions
BBKC and GC designed the experiments. GC performed the experiments. Writing—original draft preparation HÇ, GC, and AN; review and editing by HÇ, AA, MT, and BBKC. All authors contributed to the final version of the manuscript. All authors contributed equally to the study.

References

1. Liu, D., et al., Trends in miniaturized biosensors for point-of-care testing. TrAC Trends in Analytical Chemistry, 2020. 122, 115701. https://doi.org/10.1016/j.trac.2019.115701.
2. Hou, Y., et al., Recent advances and applications in paper-based devices for point-of-care testing. Journal of Analysis and Testing, 2022. 6(3), 247-273. https://doi.org/10.1007/s41664-021-00204-w.
3. Trenti, T., Synergy between point-of-care testing and laboratory consolidations. The electronic Journal of the International Federation of Clinical Chemistry and Laboratory Medicine, 2021. 32(3):328.
4. Lei, R., Huo, R., Mohan, C., Current and emerging trends in point-of-care urinalysis tests. Expert review of molecular diagnostics, 2020. 20(1):69-84. https://doi.org/10.1080/14737159.2020.1699063.
5. Mahoney, E., et al., Point-of-care urinalysis with emerging sensing and imaging technologies. Journal of The Electrochemical Society, 2019. 167(3), 037518. https://doi.org/10.1149/2.0182003JES.
6. Echeverry, G., Hortin, G.L., Rai, A.J., Introduction to urinalysis: historical perspectives and clinical application. Methods Molecular Biology, 2010. 641:1-12. https://doi.org/10.1007/978-1-60761-711-2_1.
7. Boon, H. A., et al., Point-of-care tests for pediatric urinary tract infections in general practice: a diagnostic accuracy study. Family Practice, 2022. 39(4), 616-622. https://doi.org/10.1093/fampra/cmab118.
8. Zhang, Z., et al., Urine analysis has a very broad prospect in the future. Frontiers in Analytical Science, 2022. 1, 812301. https://doi.org/10.3389/frans.2021.812301.
9. Kavuru, V., et al., Dipstick analysis of urine chemistry: benefits and limitations of dry chemistry-based assays. Postgraduate Medicine, 2020. 132(3), 225-233. https://doi.org/10.1080/00325481.2019.1679540.
10. Rysz, J., et al., Novel biomarkers in the diagnosis of chronic kidney disease and the prediction of its outcome. International journal of molecular sciences, 2017. 18(8), 1702. https://doi.org/10.3390/ijms18081702.
11. Kutter, D., The urine test strip of the future. Clinica chimica acta, 2000. 297(1-2):297-304. https://doi.org/10.1016/s0009-8981(00)00255-2.
12. Lepowsky, E., et al., Paper-based assays for urine analysis. Biomicrofluidics, 2017. 11(5):051501. https://doi.org/10.1063%2F1.4996768.
13. Rink, S., & Baeumner, A.J., Progression of paper-based point-of-care testing toward being an indispensable diagnostic tool in future healthcare. Analytical Chemistry, 2023, 95(3), 1785-1793. https://doi.org/10.1021/acs.analchem.2c04442.
14. Ventola, C.L., Mobile devices and apps for health care professionals: uses and benefits. Pharmacy and Therapeutics, 2014. 39(5):356.
15. Baxter, C., et al., Assessment of mobile health apps using built-in smartphone sensors for diagnosis and treatment: systematic survey of apps listed in international curated health app libraries. JMIR mHealth and uHealth. 2020;8(2):e16741. https://doi.org/10.2196/16741.
16. Yeasmin, S., et al., Current trends and challenges in point-of-care urinalysis of biomarkers in trace amounts. TrAC Trends in Analytical Chemistry, 2022. 157, 116786. https://doi.org/10.1016/j.trac.2022.116786.
17. De Bruyne, S., De Kesel, P., & Oyaert, M., Applications of Artificial Intelligence in Urinalysis: Is the Future Already Here?. Clinical Chemistry, 2023. 69(12), 1348-1360. https://doi.org/10.1093/clinchem/hvad136.
18. Karlsen, H., Dong, T., Smartphone-based rapid screening of urinary biomarkers. IEEE transactions on biomedical circuits and systems, 2017. 11(2):455-463. https://doi.org/10.1109/TBCAS.2016.2633508.
19. Ra, M., et al., Smartphone-based point-of-care urinalysis under variable illumination. IEEE journal of translational engineering in health and medicine, 2017. 6:1-11. https://doi.org/10.1109/JTEHM.2017.2765631.
20. Zhang, S., Tis, T.B., & Wei, Q., Smartphone-based clinical diagnostics. In Precision Medicine for Investigators, Practitioners and Providers, 2020. (pp. 493-508). Academic Press. https://doi.org/10.1016/B978-0-12-819178-1.00048-4.
21. Shi, Z., et al., Smartphone-based portable photoelectrochemical biosensing system for point-of-care detection of urine creatinine and Albümin. Lab on a Chip, 2023. 23(15), 3424-3432. https://doi.org/10.1039/D3LC00238A.
22. Shrivastava, S., Trung, T.Q., & Lee, N.E., Recent progress, challenges, and prospects of fully integrated mobile and wearable point-of-care testing systems for self-testing. Chemical Society Reviews, 2020. 49(6), 1812-1866. https://doi.org/10.1039/C9CS00319C.
23. Yang, M., et al., SARS-CoV-2 point-of-care (POC) diagnosis based on commercial pregnancy test strips and a palm-size microfluidic device. Analytical Chemistry, 2021. 93(35), 11956-11964. https://doi.org/10.1021/acs.analchem.1c01829.
24. Kibria, I. E., Ali, H., & Khan, S. A., Smartphone-based point-of-care urinalysis assessment. In 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2022. (pp. 3374-3377). IEEE. https://doi.org/10.1109/embc48229.2022.9870917.
25. Oyaert, M., and Delanghe, J., Progress in automated urinalysis. Annals of laboratory medicine, 2019. 39(1):15-22. https://doi.org/10.3343/alm.2019.39.1.15.

26. Zayed, B. A., Ali, A. N., Elgebaly, A. A., Talaia, N. M., Hamed, M., & Mansour, F. R. (2023). Smartphone-based point-of-care testing of the SARS-CoV-2: A systematic review. Scientific African, e01757. https://doi.org/10.1016/j.sciaf.2023.e01757.
27. Christodouleas, D.C., Kaur, B., and Chorti, P., From point-of-care testing to eHealth diagnostic devices (eDiagnostics). ACS Central Science, 2018. 4(12), 1600-1616. https://doi.org/10.1021/acscentsci.8b00625.
28. Gove, R.J., Complementary metal-oxide-semiconductor (CMOS) image sensors for mobile devices, High performance silicon imaging, Daniel Durini, 2014, Woodhead Publishing. p. 191-234. https://doi.org/10.1533/9780857097521.2.191.
29. Kandasamy, K., et al., Complementary metal-oxide-semiconductor (CMOS) image sensor: an insight as a point-of-care label-free immunosensor. Analytical Sciences, 2010. 26(12):1215-1217. https://doi.org/10.2116/analsci.26.1215.
30. Gani, M.O., et al., A light weight smartphone based human activity recognition system with high accuracy. Journal of Network and Computer Applications, 2019. 141:59-72. https://doi.org/10.1016/j.jnca.2019.05.001.
31. Susanto, A.P., et al., Building an artificial intelligence-powered medical image recognition smartphone application: What medical practitioners need to know. Informatics in Medicine Unlocked, 2022. 101017. https://doi.org/10.1016/j.imu.2022.101017.
32. White, P., Baumann, O., and De Stefano, A., On improving the noise reduction algorithms using image segmentation. In: 2004 12th European Signal Processing Conference. IEEE, 2004. p. 501-504.
33. Shi, W., et al., Change detection based on artificial intelligence: State-of-the-art and challenges. Remote Sensing, 2020. 12(10):1688. http://dx.doi.org/10.3390/rs12101688.
34. Kumar, Y., et al., Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. Journal of Ambient Intelligence and Humanized Computing, 2022. 1-28. https://doi.org/10.1007/s12652-021-03612-z.
35. Undru, T.R., et al., Integrating Artificial Intelligence for Clinical and Laboratory Diagnosis–a Review. Maedica, 2022. 17(2):420. https://doi.org/10.26574/maedica.2022.17.2.420.
36. Wang, H.Y., et al., Increase Trichomonas vaginalis detection based on urine routine analysis through a machine learning approach. Scientific reports, 2019. 9(1):11074. https://doi.org/10.1038/s41598-019-47361-8.
37. Xie, Q., et al., Deep learning for image analysis: Personalizing medicine closer to the point of care. Critical Reviews in Clinical Laboratory Sciences, 2019. 56(1):61-73. https://doi.org/10.1080/10408363.2018.1536111.
38. Downing, H., et al., The diagnosis of urinary tract infections in young children (DUTY): protocol for a diagnostic and prospective observational study to derive and validate a clinical algorithm for the diagnosis of UTI in children presenting to primary care with an acute illness. BMC infectious diseases, 2012. 12(1):1-15. https://doi.org/10.1186/1471-2334-12-158.
39. St-Louis, P., Status of point-of-care testing: promise, realities, and possibilities. Clinical biochemistry, 2000. 33(6):427-440. https://doi.org/10.1016/s0009-9120(00)00138-7.
40. Suarez-Ibarrola, R., et al., Current and future applications of machine and deep learning in urology: a review of the literature on urolithiasis, renal cell carcinoma, and bladder and prostate cancer. World journal of urology, 2020. 38:2329-2347. https://doi.org/10.1007/s00345-019-03000-5.
41. Davenport, M., et al., New and developing diagnostic technologies for urinary tract infections. Nature Reviews Urology, 2017. 14(5):296-310. https://doi.org/10.1038/nrurol.2017.20.
42. Faidah, N., et al., Detection of voluntary dehydration in paediatric populations using non-invasive point-of-care saliva and urine testing. Journal of Paediatrics and Child Health, 2021. 57(6):813-818. https://doi.org/10.1111/jpc.15325.
43. Park, S.M., et al., A mountable toilet system for personalized health monitoring via the analysis of excreta. Nature biomedical engineering, 2020. 4(6):624-635. https://doi.org/10.1038/s41551-020-0534-9.
44. Tayfun, M., Noroozi, A., Atasever, A., Karacaoglu, B.B., Radman, G., Buyukacaroglu, G., U.S. Patent Application No. 17/821,936.
45. Finlayson, G.D., Mackiewicz, M., and Hurlbert, A., Color correction using root-polynomial regression. IEEE Transactions on Image Processing, 2015. 24(5):1460-1470. https://doi.org/10.1109/TIP.2015.2405336.
46. Gu, J., et al., Recent advances in convolutional neural networks. Pattern recognition, 2018. 77:354-377. https://doi.org/10.1016/j.patcog.2017.10.013.
47. Flaucher, M., et al., Smartphone-based colorimetric analysis of urine test strips for at-home prenatal care. IEEE Journal of Translational Engineering in Health and Medicine, 2022. 10, 1-9. https://doi.org/10.1109/JTEHM.2022.3179147.
48. Parker, J. L., et al., Reliability of urinalysis for identification of proteinuria is reduced in the presence of other abnormalities including high specific gravity and hematuria. In Urologic Oncology: Seminars and Original Investigations 2020. (Vol. 38, No. 11, pp. 853-e9). Elsevier. https://doi.org/10.1016/j.urolonc.2020.06.035.
49. Saasa, V., et al., Blood ketone bodies and breath acetone analysis and their correlations in type 2 diabetes mellitus. Diagnostics, 2019. 9(4), 224. https://doi.org/10.3390%2Fdiagnostics9040224
50. Suresh, J., et al., Diagnostic accuracy of point-of-care nitrite and leukocyte esterase dipstick test for the screening of pediatric urinary tract infections. Saudi Journal of Kidney Diseases and Transplantation, 2021. 32(3), 703-710. https://doi.org/10.4103/1319-2442.336765.
51. Kamińska, J., et al., Diagnostic utility of protein to creatinine ratio (P/C ratio) in spot urine sample within routine clinical practice. Critical reviews in clinical laboratory sciences, 2020. 57(5), 345-364. https://doi.org/10.1080/10408363.2020.1723487.
52. Guerra Ruiz, A.R., et al., Measurement and clinical usefulness of bilirubin in liver disease. Advances in Laboratory Medicine/Avances en Medicina de Laboratorio, 2021. 2(3), 352-361. https://doi.org/10.1515/almed-2021-0047.