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Telemedicine and AI in Remote Prediabetes Monitoring Among Adolescents

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Abstract

The escalating prevalence of prediabetes in Indonesia, particularly among children and adolescents, necessitates the development of lightweight, adaptable, and cost-effective telemedicine solutions for the noninvasive monitoring of blood glucose levels. Existing systems predominantly employ machine learning and deep learning approaches that require substantial computational resources and stable internet connectivity, limiting their applicability in regions with constrained digital infrastructure. The objective of this study is to develop an artificial intelligence (AI)–driven telemedicine system that employs an expert system to determine prediabetes status by utilizing commercially available smartwatches as noninvasive optical sensors. The methodological approach includes an examination of smartwatch capabilities to identify Bluetooth Low Energy (BLE) sensors, service architectures, and the Generic Attribute Profile (GATT); the development of a Rule-Based Reasoning (RBR) expert system to determine prediabetes status using Fasting Plasma Glucose (FPG) and Postprandial Plasma Glucose (PP2) measurements; and the application of Rapid Application Development (RAD) methods in the development of Flutter-based mobile applications and Laravel Inertia Vue–based web applications. The results of this study demonstrate that the telemedicine system operates in both offline and online modes and incorporates AI functionality on mobile devices and servers without requiring extensive computational resources. All system functionalities successfully passed testing, and the expert system achieved 100% accuracy in determining prediabetes status. In conclusion, the integration of telemedicine and AI-based expert systems provides an effective, economical, and flexible solution that can be widely implemented in Indonesia to reduce the increasing incidence of prediabetes through continuous digital health monitoring.

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I. Introduction

At present, Indonesia ranks third globally in the prevalence of prediabetes, following China and the United States. According to a study conducted by the Indonesian Health Research and Development Agency (Balitbang Kemenkes RI) in 2018, the prevalence of prediabetes among individuals aged 15 years and older was 8.5%. A study conducted in the United States reported that during the period from 2005 to 2016, one in five adolescents and one in four young adults were identified as having prediabetes [1]. More recent epidemiological data indicate that the prevalence of diabetes in Indonesia increased from 10.7% in 2013 to 11.8% in 2018, before slightly declining to 11.3% in 2023, while the prevalence of prediabetes decreased from 44.5% in 2013 to 39.2% in 2023. Long-term projections indicate an even more concerning trend, with the number of Indonesians living with diabetes expected to increase sharply from 18.69 million cases (9.19%) in 2020 to 40.7 million cases (16.09%) by 2045, positioning diabetes as a major public health challenge in the coming decades [2], [3]. Globally, diabetes prevalence has also increased substantially, rising from 2,968 per 100,000 population in 1990 to 5,943 per 100,000 in 2019, with the global number of individuals with diabetes projected to grow from 171 million in 2000 to 366 million by 2030. The Southeast Asia region, including Indonesia, currently ranks third in regional prevalence at approximately 10%, following the Middle East and North Africa (18.1%) and North America and the Caribbean (11.9%). Supporting this trend, a study in the United States reported that between 2005 and 2016, one in five adolescents and one in four young adults were

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already living with prediabetes, highlighting the increasing vulnerability of younger populations worldwide [2], [3].

Prediabetes represents the initial stage preceding the onset of diabetes. It is characterized by blood glucose levels that exceed normal thresholds but remain below the diagnostic criteria for diabetes. Individuals diagnosed with prediabetes may return to normoglycemic levels through the adoption of a healthy lifestyle, including dietary regulation and regular physical activity [4]. In contrast, once an individual progresses to diabetes, the condition is irreversible and requires lifelong management through lifestyle modification and pharmacological therapy, including insulin administration [5]. This progression renders diabetes a degenerative condition that affects not only older adults but also children and adolescents. The increasing prevalence of prediabetes and diabetes among children and adolescents is primarily associated with unhealthy lifestyle patterns, particularly the consumption of sugar-rich foods and beverages that are readily accessible in various environments. Consequently, blood glucose levels may increase further when physical activity is limited among these populations.

Blood glucose assessment can be performed using invasive or noninvasive methods. The invasive method, which remains the clinical standard, involves blood sample collection followed by laboratory analysis [6]. However, this approach may cause discomfort, particularly among children and adolescents, due to the associated pain. In contrast, noninvasive blood glucose measurement methods—most commonly utilizing near-infrared optical sensors—offer greater comfort and practicality [7]. Notably, contemporary devices used for noninvasive monitoring are commonly integrated into smartwatches, enabling routine daily use among children and adolescents. As a result, noninvasive blood glucose monitoring using wearable devices presents a feasible approach for supporting early detection and prevention of prediabetes among adolescents in Indonesia.

Currently, extensive studies are underway to enhance noninvasive blood glucose measurement devices that utilize optical sensor technology. One such study [8] developed an Internet of Things (IoT)–based device employing the MAX30105 optical sensor to simultaneously measure blood glucose, cholesterol, and uric acid levels. The resulting device is configured as a box measuring 15 × 15 cm, in which measurements are obtained by placing a finger on the sensor, with the results displayed on an LCD screen. In addition, measurement data can be accessed through web applications using the Adafruit IO platform as well as through Android mobile applications. Comparable studies on the development of IoT-enabled devices integrated with web and mobile applications have been conducted by other researchers [9], [10]. However, the device has not been optimized for prediabetes detection, and its physical dimensions are considered impractical for routine daily use.

Additional studies have focused on the development of smartwatch-based systems that incorporate sensors for real-time blood glucose measurement, thereby improving user convenience at any time [11]. These smartwatches are designed to integrate with mobile applications that record measurement results and subsequently use the data to predict future blood glucose levels based on user activities. The system employs deep learning–based artificial intelligence to support these predictions. Similar systems that use smartwatches as wearable sensors in combination with mobile applications as user interfaces have also been examined by other researchers [12], [13], [14]. Although these systems are effective for individuals with type 1 diabetes, they currently lack features that allow monitoring by healthcare professionals or family members.

In another study, wearable sensors were attached to three different locations on a patient's body to measure temperature, pressure, and glucose levels. The system was also integrated with the insulin delivery device used by the patient. In addition, the system included data transmission capabilities to cloud-based platforms, enabling access through medical tablet devices monitored by healthcare professionals. The system further incorporated artificial intelligence algorithms to manage cloud-stored data, enabling predictive analysis and supporting healthcare professionals in providing targeted therapeutic interventions [15]. However, such integrated systems are largely limited to hospital-based patient care, and the implementation of smartwatches as sensing devices has not yet been realized. Moreover, the system is restricted to monitoring patients diagnosed exclusively with diabetes.

This study is motivated by several gaps that remain unaddressed in previous studies. Most existing systems focus exclusively on individuals who have already been diagnosed with diabetes, despite the fact that early identification at the prediabetes stage is more impactful because individuals at this stage retain the potential to return to normal glycemic conditions. Prior systems also rely heavily on machine learning or deep learning models that require substantial computational resources and cloud-based processing, limiting their suitability for cost-effective mobile telemedicine applications. In contrast, this study employs a lightweight rule-based expert system that operates efficiently on smartphones. In addition, although commercially available smartwatches equipped with noninvasive glucose sensors are increasingly accessible, their affordability and suitability for adolescent users have not been systematically assessed. Finally, earlier telemedicine systems generally offer limited monitoring capabilities, whereas this study introduces a multi-role system that allows adolescents, parents, and healthcare professionals to collaboratively monitor glucose data through an integrated mobile and web platform. Building upon the identified gaps, this study aims to develop an integrated telemedicine system that utilizes commercially available smartwatches as noninvasive glucose sensors, combined with mobile and web applications, for prediabetes monitoring in children and adolescents. To achieve this objective, the study is guided by three key questions: (1) How can glucose measurement data be programmatically accessed and

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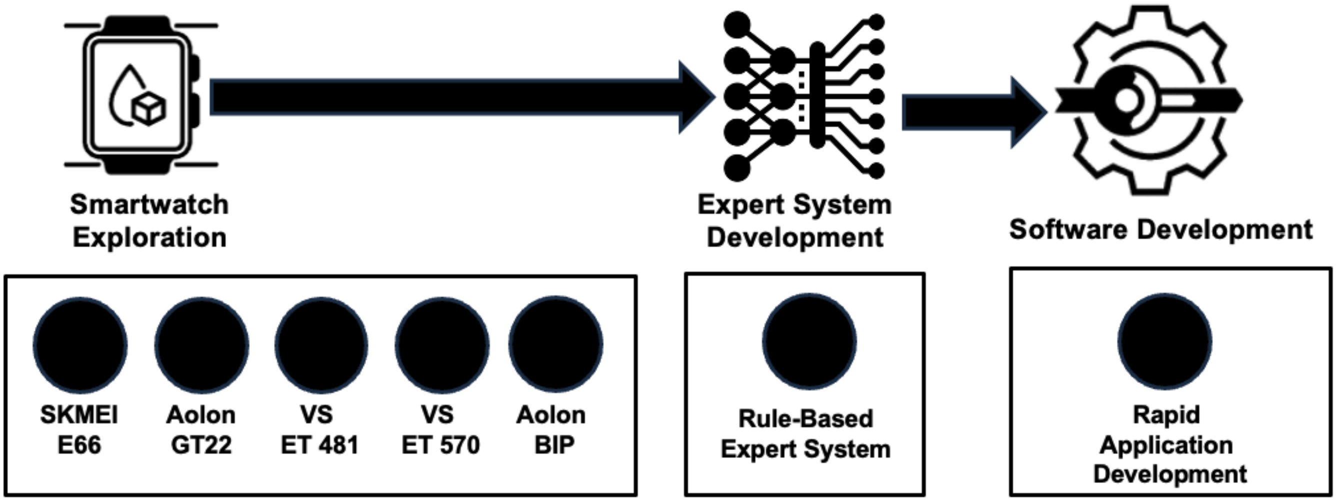

Fig. 1. **Research stages.**

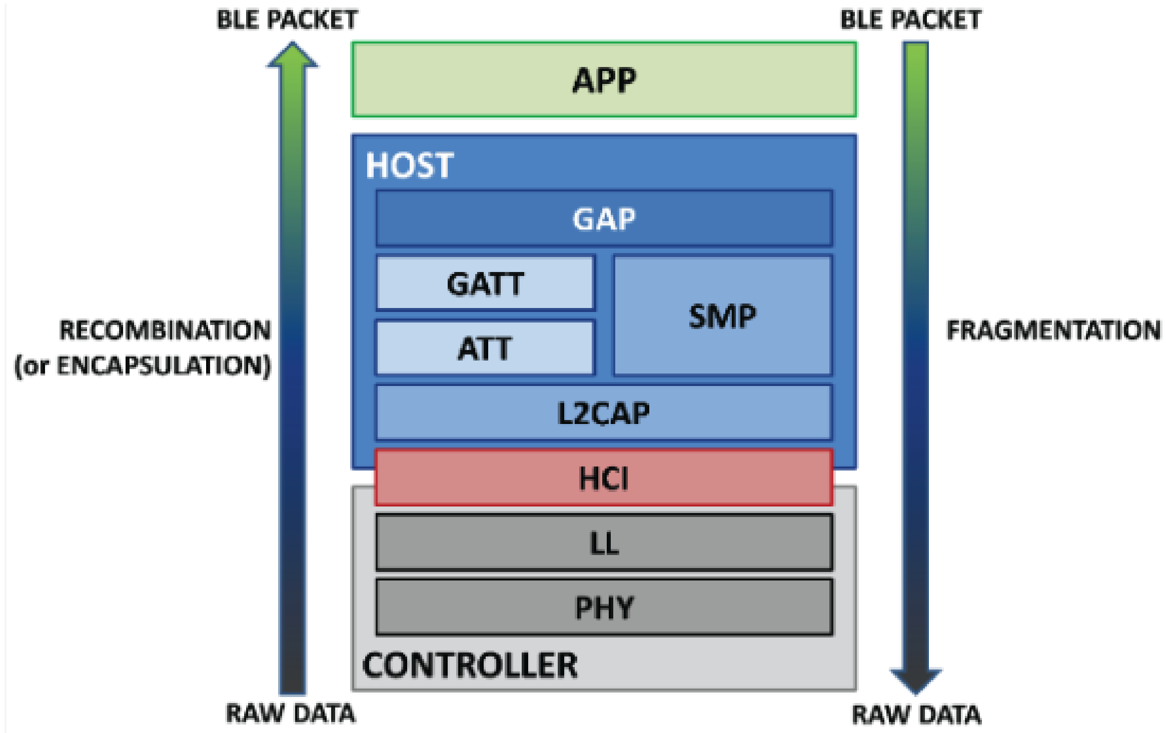

Fig. 2. **BLE Protocol Stack** [21].

retrieved from commercial smartwatches for integration into mobile applications? (2) What rule-based expert system can accurately determine prediabetes status using Fasting Plasma Glucose (FPG) and Postprandial Plasma Glucose (PP2) values? (3) What functional features are required for mobile and web platforms to support multi-role telemedicine involving adolescents, parents, and healthcare professionals? Addressing these questions enables the development of a real-time, noninvasive, and cost-efficient monitoring system. The resulting platform supports collaborative monitoring among users and healthcare providers, offering a practical early-intervention tool to help prevent progression from prediabetes to diabetes.

This study is organized as follows: Section II describes the methodologies employed in this study and outlines the study trajectory. Section III presents the study findings. Section IV discusses the study outcomes and associated limitations. Section V presents the conclusions, summarizing the objectives, main findings, and future work.

II. Methods

The study methodology comprises three principal stages, as illustrated in Fig. 1. The initial stage includes (A) Smartwatch Exploration, (B) Expert System Development, and (C) Software Engineering.

A. Smartwatch Exploration

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This stage aims to identify a smartwatch suitable for use as a wearable device equipped with blood glucose measurement sensors. The selection criteria are based on the following attributes:

- Infrared noninvasive blood glucose sensor
- Bluetooth Low Energy (BLE) connectivity
- Generic Attribute Profile (GATT)
- Data security
- Price

The infrared-based noninvasive blood glucose sensor enables blood glucose assessment without blood sampling, thereby improving convenience for pediatric and adolescent users. This technology uses infrared radiation directed at the skin surface, where the absorption and reflection of light by body tissues are analyzed to detect changes in optical characteristics associated with glucose concentration. This approach applies principles of optical spectroscopy, including the Beer–Lambert Law and artificial intelligence algorithms, to convert optical signals into estimated glucose concentrations. By applying machine learning techniques capable of identifying complex patterns in light signal variations, blood glucose levels can be estimated [16], [17], [18].

Bluetooth Low Energy (BLE) connectivity is a critical component, as it enables efficient transmission of measurement data from smartwatches with minimal energy consumption. BLE supports continuous communication with low latency and adequate throughput for sensor data, allowing health metrics to be transmitted to smartphones in real time without excessive battery drain in wearable or mobile devices [19], [20]. Fig. 2 illustrates the Bluetooth Low Energy (BLE) protocol stack, which is organized into three main blocks: the Controller (gray), the Host (blue), and the Application (App) (green). The Application layer, located at the top of the stack, serves as the direct interface with the user and defines application profiles that ensure interoperability across devices by standardizing common functionalities, as specified by the Bluetooth Special Interest Group (SIG), while still allowing vendor-specific profiles for specialized use cases. The Host layer comprises the Generic Access Profile (GAP), Generic Attribute Profile (GATT), Logical Link Control and Adaptation Protocol (L2CAP), Attribute Protocol (ATT), Security Manager Protocol (SMP), and the host-side Host Controller Interface (HCI), which collectively manage device discovery, attribute handling, logical connections, and security processes. Meanwhile, the Controller integrates the controller-side HCI, the Link Layer (LL), and the Physical Layer (PHY), which together handle low-level radio operations and data transmission [21], [22]. Within this architecture, GATT plays a critical role in ensuring that sensor data from the smartwatch can be accessed and managed in a standardized format. GATT defines the service structure and characteristics used to store and transmit measurement values, enabling the application to read glucose data, receive update notifications, and send commands to the device [23], [24]. This structured communication framework ensures reliable and secure integration of smartwatch sensor data with the mobile application developed in this study.

To ensure compatibility and determine the BLE service structure of smartwatches, GATT was examined using BLE diagnostic applications such as nRF Connect [25], Wireshark [26], and Bluetooth LE Explorer. Through these software tools, researchers can observe service UUIDs, characteristic UUIDs, access modes (read, write, notify), and descriptors such as the Client Characteristic Configuration Descriptor (CCCD), thereby facilitating the integration of sensor data with mobile applications under development [23], [27].

B. Expert System Development

An expert system is an artificial intelligence framework designed to replicate the decision-making processes of a specialist within a specific domain. The development of such a system requires several core components, including a knowledge base that encapsulates expertise and rules provided by specialists, an inference engine that executes reasoning mechanisms to correlate user inputs with predefined rules, and a user interface that facilitates interaction between users and the system. Through the integration of these components, expert systems are capable of autonomously generating decisions [28], [29].

In this study, the methodological approach employed is Rule-Based Reasoning (RBR). Rule-Based Reasoning represents an inferential technique used in expert systems that applies rules structured in an IF–THEN format to support decision-making and problem-solving processes [30], [31]. RBR includes the following essential components [32], [33]:

I. Knowledge Base: The knowledge base is developed through consultations with domain experts, particularly health professionals specializing in prediabetes and diabetes, as well as through the synthesis of conclusions derived from published studies. The resulting set of rules is subsequently formalized in IF–THEN statements [34].
II. Fact Base: The Fact Base consists of data and events obtained from user inputs [32], [33].
III. Inference Engine: The Inference Engine matches facts with rules to generate conclusions [32], [33].

RBR is characterized by straightforward implementation, minimal computational requirements during execution, and transparency in decision-making processes. These characteristics make RBR more suitable for deployment on resource-constrained devices such as smartphones, compared with machine learning or deep learning approaches that require greater processing power and memory resources [30], [31]. After the rules governing the expert system are established, the next stage involves translating these rules into algorithms or program code. The IF–THEN rules are implemented using conditional control structures, enabling applications to process inputs and automatically generate decisions. This approach allows direct integration of expert system logic into mobile application frameworks.

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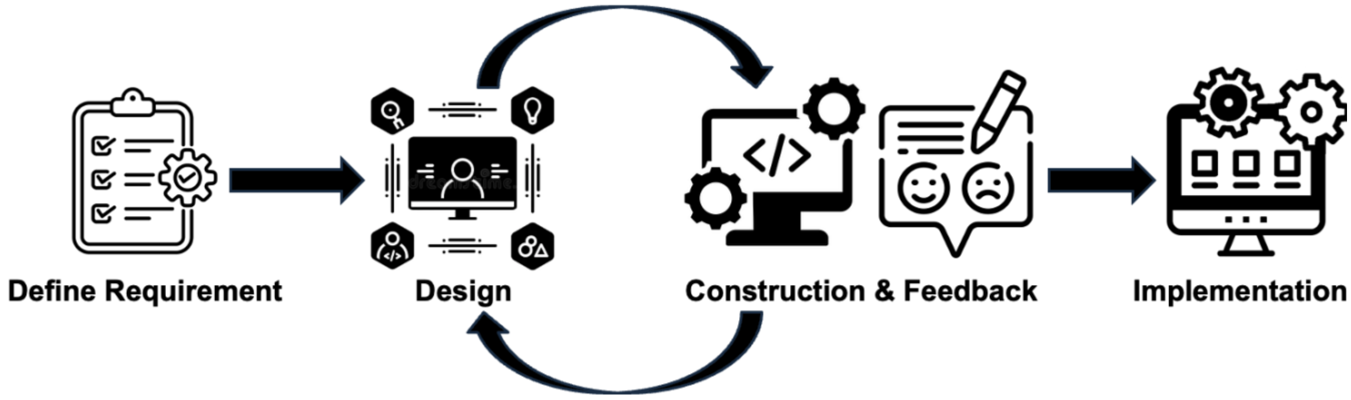

Fig. 3. Rapid Application Development (RAD)

A. Software Development

The software development methodology applied in this study is Rapid Application Development (RAD), selected for its emphasis on rapid prototyping, iterative development, and continuous user involvement throughout each stage [35], [36]. Each iteration follows the procedure illustrated in Fig. 3. The initial stage is Requirement Definition, which aims to identify the system requirements. The methodology employed involves requirements engineering using Unified Modeling Language (UML) modeling. This process is carried out through the identification of system actors, the specification of functional features, and the analysis of system workflows. Supporting this stage are a use case diagram, which represents functional features and their associated user actors, and an activity diagram, which illustrates the application workflow [37], [38]. These two external elements serve as the foundational basis for the subsequent design stage. The subsequent stage is Design, which aims to formulate technical solutions based on the requirements established in the preceding stage. The methodology applied includes software modeling using UML diagrams in conjunction with UI/UX prototyping. Outputs of this stage include the system architecture, database design, interface design, and prototypes [35], [36].

The third stage is Construction and Feedback, which aims to incrementally develop the system while obtaining validation of system functionalities from users and health professionals. During this stage, mobile applications are developed using the Flutter programming language, while web applications are implemented using a frontend–backend architecture that integrates PHP and JavaScript. System usability testing is conducted using a five-point Likert scale to assess user perceptions of functionality, clarity, and ease of use across both mobile and web applications. This method follows black-box testing principles, whereby users evaluate system features based on observable behavior without reference to the internal code structure. Feedback derived from Likert-scale responses provides a quantitative measure of system usability and identifies areas for improvement, supporting the assessment of system readiness for wider implementation [39]. The range of Likert scale scores is presented in TABLE 1 [40].

Table 1. Likert Scale Interpretation for Software Usability

Likert Score	Category	Interpretation
1	Strongly Disagree	The feature does not function properly or is unacceptable
2	Disagree	The feature performs poorly and requires major improvement
3	Neutral	The feature is adequate but may require further evaluation
4	Agree	The feature works well and is considered acceptable
5	Strongly Agree	The feature performs very well and is highly suitable for use

The final stage is Implementation, which aims to ensure that the system operates fully and is applicable in real-world scenarios. During this stage, comprehensive integration is conducted among smartwatches, mobile applications, and web applications, followed by rigorous testing performed by relevant stakeholders, namely the child as the primary user, the parent as the health overseer, and health personnel as the medical validators. Testing is conducted through field trials to ensure that system workflows function as intended and that performance testing yields satisfactory results. Anticipated externalities include user feedback for further refinement, as well as development strategies based on the outcomes of the implementation evaluation [35], [36].

III. Results

B. Smartwatch

The study conducted a comprehensive investigation of various commercially available smartwatches that are

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readily accessible. A compilation of these commercially available smartwatches is presented in TABLE 2.

Table 2. List of Smartwatches

	SKMEI E66	Aolon GT22	Aolon BIP	**VS ET 482**	**VS ET 570**
Glucose Sensor	×	√	√	√	√
Blood Sensor	×	×	×	√	√
Body Sensor	×	×	×	√	√
BLE	√	√	√	√	√
GATT	√	√	√	√	√
Security	×	×	×	√	√
Price (K IDR)	380	390	249	419	439

The smartwatches selected for this study are the VS ET 482 and VS ET 570 due to their comprehensive range of sensors, which include not only blood glucose measurement sensors but also sensors designed to assess blood components and body composition. These additional sensors facilitate the acquisition of auxiliary data relevant to the monitoring of prediabetic and diabetic conditions. The blood sensors integrated into the smartwatches generate values corresponding to uric acid levels and lipid profiles, including triglycerides (TG), high-density lipoprotein (HDL), and low-density lipoprotein (LDL). Empirical studies have demonstrated that elevated uric acid levels are associated with an increased risk of prediabetes [41], [42]. Furthermore, additional studies have indicated that dysregulation of lipid profiles, including TG, HDL, and LDL, contributes to impaired glucose metabolism.

Table 3. Smartwatch codes

Code	Description
`f0080001-0451-4000-b000-000000000000`	UUID utilized as an identification mechanism to facillitate access to smartwatch devices
`0x89`	Header code corresponding to real-time glucose data
`0xDF`	Header code associated with historical glucose level data.
`[0x89, 0x01, 0x01, 0x00]`	Byte payload constituting a command code intended to initiate blood glucose monitoring

This study evaluated the Bluetooth Low Energy (BLE) and Generic Attribute Profile (GATT) functionalities of each smartwatch using nRF Connect and Wireshark to identify services, characteristics, UUIDs, properties (read, write, notify), and descriptors, such as the Client Characteristic Configuration Descriptor (CCCD), relevant to the smartwatches under analysis. This procedure is essential to ensure that access to the selected smartwatches enables command execution and retrieval of data from the blood glucose sensor. Table 3 presents the findings of this examination regarding the codes required to access and control the VS ET 482 and VS ET 570 smartwatches utilized in this study.

Subsequently, the UUID code is used to establish a connection with the smartwatch via the notify() and write() functions. To initiate blood glucose level calculation, the write() function is used to transmit a payload byte to the smartwatch. Following this step, data transmitted by the smartwatch are monitored using the notify() function. The received data are then filtered based on the header codes `0x89` or `0xDF`. The dataset, consisting of 8 bytes, follows the format outlined in Table 4.

Table 4. Format of data

# Byte	Description
0	Header (`0x89` atau `0xDF`)
1	Unknown flag
2	Unknown flag
3	Status indicator, where a value of 0 or 1 signifies a successful outcome. A status value of 2 denotes a low-power condition, a value of 3 indicates that the system is in a busy state, and a value of 4 reflects the presence of a wear-related error.
4	Progress
5-6	Raw data
7	Optional bytes

The concluding stage involves extracting raw blood glucose measurement data from byte 5 or 6 and converting these values into standard units of mmol/L and mg/dL, which are commonly used for blood glucose reporting. Furthermore, the code and procedural workflow governing smartwatch connection and blood glucose measurement are transcribed into algorithms and implemented using the Dart/Flutter programming language to support the development of Android-based mobile applications.

C. Knowledge Base

The most significant outcome of the Expert System Development stage is the Knowledge Base. The Knowledge Base is compiled through discussions with experts, specifically healthcare professionals with extensive expertise in prediabetes and diabetes, as well as expert conclusions derived from studies published in scholarly journals. The established rules are based on fasting blood glucose measurements (Fasting Plasma Glucose, FPG) and glucose measurements obtained two hours after meals (2-Hour Postprandial Glucose, PP2). The knowledge base used to determine prediabetes status based on blood glucose values consists of two

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decision-making stages. In the first stage, the system receives fasting blood glucose (FPG) input values. If the value falls within the range of 100–125 mg/dL, it is classified as prediabetes. If the value is less than 100 mg/dL, the evaluation proceeds to the two-hour postprandial glucose (PP2) value. If the value exceeds 125 mg/dL, the result is considered inconclusive, as it indicates a potential for diabetes and requires further examination. In the second stage, which evaluates the PP2 value, a range of 140–199 mg/dL is classified as prediabetes. Values below 140 mg/dL are classified as normal, whereas values equal to or exceeding 200 mg/dL are considered inconclusive and suggest the possibility of diabetes, thereby requiring additional examination.

Subsequently, these rules are translated using the Rule-Based Reasoning (RBR) method, as described in Algorithm 1.

Algorithm 1: Prediabetes Status Determination

Input : FPG (Fasting Plasma Glucose), PP2 (2-Hour Postprandial Glucose)
Output: status ∈ {Normal, Prediabetes, Diabetes}

```
Read FPG and PP2
// Check Prediabetes based on FPG
if (FPG ≥ 100) and (FPG ≤ 125) then
    status ← Prediabetes
    return status
end if

// Check Prediabetes based on PP2
if (PP2 ≥ 140) and (PP2 ≤ 199) then
    status ← Prediabetes
    return status
end if

// Check Normal: all results below prediabetes thresholds
if (FPG < 100) and (PP2 < 140) then
    status ← Normal
    return status
end if

// Check Diabetes: all results above prediabetes thresholds
if (FPG > 125) and (PP2 > 199) then
    status ← Diabetes
    return status
end if

// Default case (e.g., inconsistent or missing data)
status ← Undefined
return status
```

This algorithm is subsequently implemented in mobile and web applications to process data derived from the Fact Base and Inference Engine components.

D. Requirement

The definition of requirements constitutes a critical stage in the software development lifecycle, particularly when employing the Rapid Application Development (RAD) methodology. The outcome of this stage is a use case diagram that delineates an overview of interactions between actors and the functional capabilities available to each actor. Within this system, four distinct actors are identified: the administrator, the adolescent user, the parent, and the doctor. The analysis of the requirements yields two distinct categories of applications, each encapsulating the primary functional features. These categories are represented by the mobile application group as illustrated in Fig. 4 and the web application group as illustrated in Fig. 5.

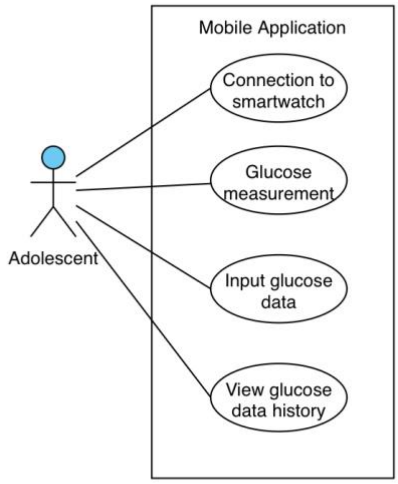

Fig. 4. Use case diagram for mobile application.

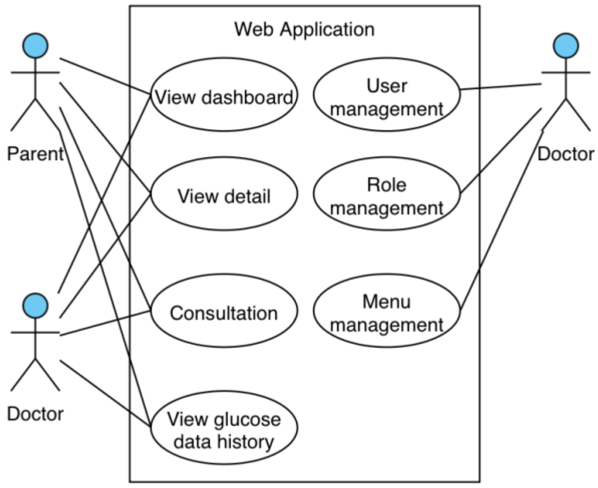

Fig. 5. Use case diagram for web application.

A selection of significant use cases is presented in Table 5. Furthermore, detailed examination of the web application use cases reveals that they share identical feature descriptions with the glucose data history use cases presented in the mobile application.

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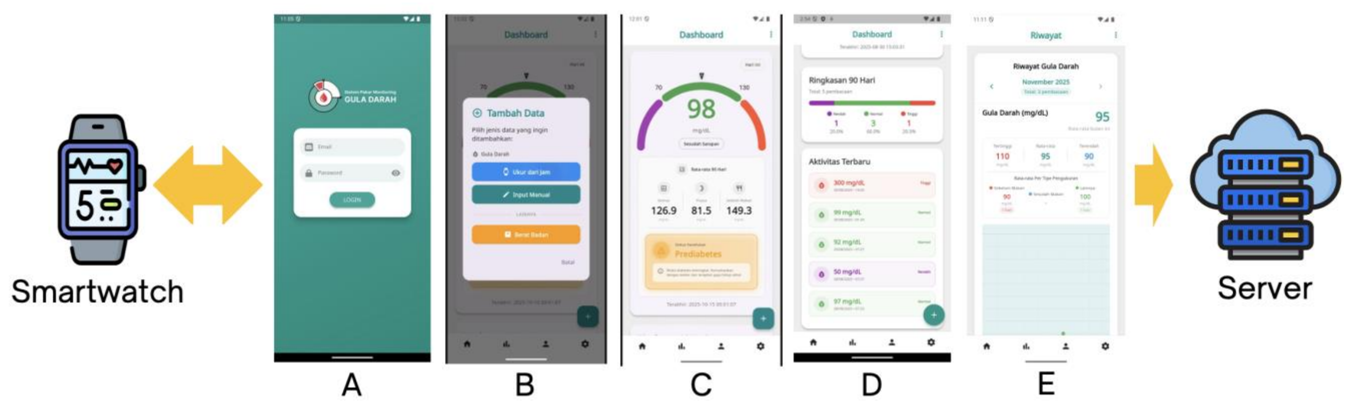

Fig. 7. **Mobile application (A) user login, (B) manual and automatic input data, (C) predicted glucose status, (D) tabular blood glucose data history, (E) chart of blood glucose data history.**

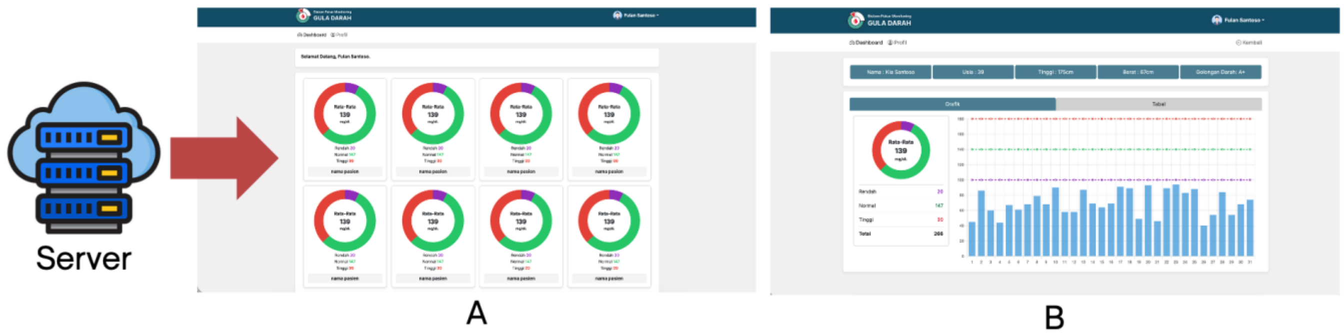

Fig. 8. **Web application (A) dashboard of patients' blood glucose status, (B) a patient's blood glucose history**

Table 5. **Use case description**

Actor	Adolescent
Use Case	Glucose measurement
Description	This functionality allows the initiation of blood glucose measurements through the smartwatch during fasting period and following breakfast consumption. After the blood glucose value is acquired by the smartphone, the resulting data are stored in the local storage system.
Actor	Adolescent
Use Case	Input glucose data
Description	This functionality enables users to manually input blood glucose measurement data. These measurement results may originate from devices other than smartwatches or from laboratory examinations. Users are able to enter blood glucose data during fasting periods or after breakfast consumption.
Actor	Adolescent
Use Case	View glucose data history
Description	This functionality facilitates the review of historical blood glucose measurement data and provides corresponding health status information categorized as normal, prediabetes, or diabetes.
Actor	Parent, Doctor
Use Case	View dashboard
Description	This functionality presents a consolidated overview of the blood glucose history and health status of adolescents under observation. When the observer is a parent, access is limited to a summary of their child's data. Healthcare professionals are able to review summaries for multiple patients.

The consultation use case within the web application serves as a communication conduit between parent and doctor actors. Use cases executed by the administrator actor are characterized by the capability to perform Create, Retrieve, Update, and Delete (CRUD) operations on user data, role assignments, and menu configurations.

E. Design

The outcome at this stage pertains to the architectural framework of the database employed in both mobile and

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web applicationsFor mobile application data storage, a local NoSQL database specifically designed for Flutter and Dart, namely Hive, is utilized. The data architecture within Hive is characterized by a structure consisting of keys and corresponding values. The key attribute functions as the identifier of the attribute, while the value represents the associated data. Table 6 delineates the data architectures employed within the mobile applications.

Table 6. Data structure in the mobile application

Key	Description
date	Date corresponding to blood glucose measurement
blood_glucose	Quantitative results of blood glucose levels
context	Includes a classification of blood glucose measurements that includes one of the following descriptors: before_breakfast, after_breakfast, or random.

Conversely, the database architecture in the mobile application is designed for implementation using MariaDB database. The outcomes of this design yielded the creation of 13 tables. This structure comprises three transaction tables dedicated to storing blood glucose measurement results obtained from patients. The remaining tables function as application support tables, including those related to menus, roles, users, and security. The design of the three transaction tables intended for archiving blood glucose measurement results is illustrated in Fig. 6.

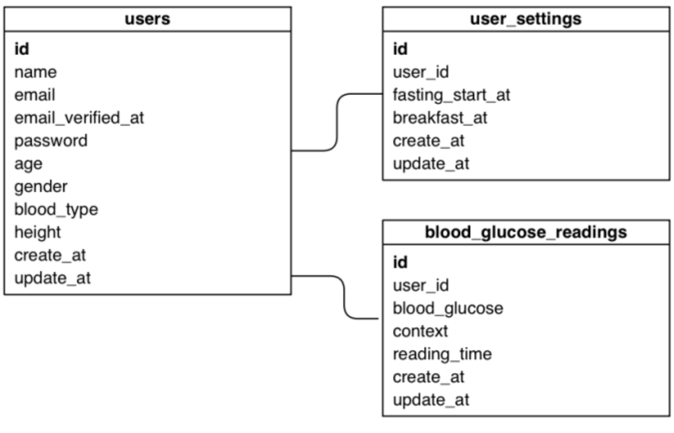

Fig. 6. Data structure in the web application.

The users table is used to store user information relevant to blood glucose monitoring. The user_settings table is designated for storing data related to the initiation of fasting and the timing of breakfast. The blood_glucose_reading table is utilized to archive blood glucose data derived from measurement results. At this stage, the design of interfaces for both mobile and web applications is also conducted. The resulting designs are subsequently implemented, as described in the following section, Development.

F. Development

At this stage, the development of mobile and web applications is carried out in accordance with the predetermined features and design elements established during the preceding stage. Mobile applications are developed using the Dart programming language in conjunction with the Flutter framework. The resulting interface is shown in Fig. 7. Fig. 7 illustrates the graphical user interface of the mobile application. The application login is shown in Fig. 7 part A. The execution of the Glucose measurement and Input glucose data functionalities is depicted in Fig. 7 part B. Fig. 7 part C displays the predicted blood glucose status generated by the expert system, indicating whether the user is categorized as normal, prediabetes, or diabetes; this functionality serves as a practical implementation of the Knowledge Base, Fact Base, and Inference Engine components inherent to the expert system–based artificial intelligence. Historical blood glucose data are presented in tabular format in Fig. 7 part D, while Fig. 7 part E presents a visualization of historical glucose data, which illustrates trends over time and supports users in comprehensively interpreting blood glucose status.

Fig. 8 presents the outcomes of the web application development process. In Fig. 8, Part A illustrates the implementation of the View dashboard feature, while Fig. 8 part B illustrates the Detail View feature. The detail view feature similarly incorporates the Knowledge Base, Fact Base, and Inference Engine components associated with the expert system. In addition, this section includes a consultation feature that facilitates communication between parents and healthcare professionals for child health consultations. The interconnectivity among smartwatches, mobile applications, and web applications is further elucidated in Fig. 7 and Fig. 8. Fig. 7 delineates the integration flow from left to right, beginning with communication between the mobile application and the smartwatch, employing the code information from Table 3 and the flutter_blue_plus package to streamline the communication process. Following the successful storage of blood glucose measurement data from the smartwatch within the mobile application, subsequent communication between the mobile application and the server is established to enable data storage in the server database. This communication is enabled by a backend web application implemented as an Application Programming Interface (API). Meanwhile, Fig. 8 demonstrates that the frontend web applications shown in Parts A and B can retrieve data from the server database through the use of a RESTful API.

The developed RESTful APIs consist of several groups, including (1) Auth for authentication purposes, (2) BloodGlucose for the retrieval and storage of blood glucose data by mobile and web applications, (3) Dashboard for extracting data to be displayed on dashboard pages, (4) Profile for presenting and updating user profile information, and (5) Settings for modifying and updating blood glucose measurement time parameters. Table 7 lists the key RESTful API functions

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that have been implemented to support communication between mobile and web applications.

Table 7. Function list of RESTful API

Name	Method	Path
Auth	POST	api /login
BloodGlucose	GET	api/blood-glucose
	POST	api/blood-glucose
	GET	api/blood-glucose/list
	GET	api/blood-glucose/history
Dashboard	GET	api/dashboard
Profile	GET	api/me
	PATCH	api/me
Setting	GET	api/me/settings
	PATCH	api/me/settings

G. Testing

The examinations conducted in this study were carried out on a limited scale and have not yet involved large or heterogeneous user groups. Functional testing of the mobile and web applications was conducted using a black-box testing methodology to assess each feature and interaction flow. A total of eight individuals participated in this stage, consisting of two members of the software development team and six members of the study team, who assumed the roles of adolescents, parents, and physicians. In addition to functional verification, these participants also evaluated system usability using a five-point Likert scale. Table 8 presents the usability evaluation of the system using a five-point Likert scale, measuring user perceptions of functionality, clarity, and operational reliability across both the mobile and web applications. All functional features received high mean scores ranging from 4.4 to 4.8, indicating that users “Agree” or “Strongly Agree” that the system operates effectively and is suitable for use. The overall mean score of 4.6 indicates that the system is highly acceptable and suitable for user adoption. These results suggest that the system is considered highly acceptable and user-ready within the scope of this limited internal assessment. However, although the consistently high Likert scores demonstrate encouraging initial usability and system stability, broader testing involving actual end users and more diverse demographic groups is required to validate generalizability and ensure robust performance in real-world conditions.

Table 8. User Acceptance Testing (UAT) result using usability

No	Functional Feature	Mean Likert Score
Mobile Application		
1	Connect to smartwatch	4.7
2	Disconnect from smartwatch	4.6
3	Glucose measurement	4.5
4	Input glucose data	4.8
5	View glucose status	4.7
6	View glucose data history – table	4.6
7	View glucose data history – chart	4.7
Web Application		
1	Login	4.8
2	Logout	4.8
3	View profile	4.6
4	Update profile	4.5
5	View dashboard	4.7
6	View detail – glucose status	4.6
7	View detail – data history	4.6
8	Consultation	4.4
9	User management – CRUD	4.5
10	Role management – CRUD	4.5
11	Menu management – CRUD	4.6
Overall mean score		4.6

A separate evaluation of the rule-based expert system was conducted to assess its classification performance. This testing was performed by two members of the development team using 150 manually prepared test records containing variations of FPG and PP2 values. The test results are presented in Table 9.

Table 9. Test result of rule-based expert system

Class	# record	Correctly Classified	Misclassified
Normal	50	50	0
Prediabetes	50	50	0
Diabetes	50	50	0
Total	150	150	0

Under these controlled conditions, the expert system achieved a 100% accuracy rate. However, this result reflects performance within a constrained testing environment, and further validation using real clinical data and larger sample sizes is required to ensure generalizability and reduce potential bias.

IV. Discussion

A. Smartwatch Exploration

Based on the findings of this study, the sensors embedded in each smartwatch can be identified through official product documentation, enabling the compilation

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of a catalog of devices and their respective features, as shown in Table 2. A comprehensive analysis using nRF Connect and Wireshark software demonstrated effectiveness in identifying service UUIDs, characteristic UUIDs, and command codes required to establish connections and retrieve data via BLE and GATT protocols. However, these applications do not provide direct information regarding sensor nomenclature or the specific functionality associated with each service. Consequently, manual inspection of each service was required to determine which service transmitted glucose measurement data. In addition, the retrieved codes are applicable only to specific smartwatch models, namely the VS ET 482 and VS ET 570, and are not compatible with other smartwatches such as the Aolon GT22, Aolon BIP, or other devices currently available on the market.

The evaluation results indicate that commercially available smartwatches are equipped with multiple health sensors integrated into a single compact device. This development enables the use of smartwatches as a core component of telemedicine systems in a more efficient and rapid manner compared with earlier study approaches, such as those described in studies [13], [14], and [12], which required the design and assembly of custom wearable devices. However, this study did not validate smartwatch-derived glucose measurements against clinical gold-standard instruments, such as laboratory-based glucose analyzers or certified glucometers. As a result, although the smartwatch data were sufficient for testing the expert system workflow, the accuracy and clinical reliability of the glucose measurements could not be confirmed. Future work should include formal validation studies comparing smartwatch-derived glucose values with medically validated devices to ensure reliable data inputs for decision-making in real-world healthcare settings.

B. Expert System Development

The empirical findings indicate that the rule-based expert system performs efficiently under the controlled conditions of this study. The system achieved a 100% accuracy rate when tested using 150 manually prepared records consisting of balanced variations of FPG and PP2 values (50 normal, 50 prediabetes, and 50 diabetes). This high accuracy is attributable to the limited test set, the deterministic nature of the IF–THEN rules, and the constrained variability of the input data. With a small number of rule conditions and clearly defined glucose thresholds, the expert system can accurately classify test cases with minimal ambiguity. One notable advantage of the expert system approach, compared with machine learning and deep learning models, lies in its low computational requirements. Because inference is based on direct rule evaluation rather than iterative model training or large-scale matrix operations, the system operates with minimal processing power, memory usage, and energy consumption. This efficiency enables deployment on both mobile devices and web platforms without reliance on high-performance servers, making the approach particularly suitable for low-resource settings.

However, several limitations must be acknowledged. First, the evaluation was conducted by only two members of the development team and used a relatively small dataset of 150 records, all generated in a controlled environment. This limited diversity reduces the likelihood of encountering ambiguous or borderline cases that commonly occur in real-world medical data. As a result, the reported accuracy does not yet reflect system performance under broader clinical or population-level variability. Second, unlike machine learning and deep learning models, which can learn complex patterns, adapt to new data distributions, and handle high-dimensional signals, rule-based systems lack flexibility and do not generalize beyond the predefined rule structure. Such systems may fail to accommodate atypical glucose patterns or mixed clinical conditions unless additional rules are manually incorporated by domain experts, thereby limiting scalability and adaptability.

Despite these limitations, the expert system developed in this study offers a practical and economical solution for early prediabetes monitoring, particularly in settings with limited computational resources and unstable network infrastructure. The telemedicine system can operate autonomously on smartwatches and mobile applications without requiring an internet connection, as glucose classification is performed locally through rule-based analysis. This offline capability enhances versatility compared with machine learning and deep learning approaches, which generally require substantial computational resources and server-based processing, making them less feasible for low-resource environments [15]. To strengthen clinical applicability and generalizability, future work should incorporate broader testing using real clinical datasets, larger and more diverse participant groups, and evaluations across varying demographic and environmental conditions.

C. Software Development

The Rapid Application Development (RAD) methodology enables the generation of continuous outputs at every stage of development, culminating in the establishment of a comprehensive and fully operational telemedicine system. This methodology prioritizes rapid iterations and direct collaboration between developers and users, thereby minimizing the time allocated to documentation. Feature enumeration is concisely represented in the form of a use case diagram, accompanied by corresponding use case descriptions. A detailed examination of the functional flow is conducted through interactive dialogue between the developer and the user. This approach accelerates the development process without compromising design integrity, as feedback can be promptly incorporated into subsequent iterations, thereby eliminating the need for an extended documentation cycle [35].

During the development stage, this study implements advanced technology to enhance the functionality of artificial intelligence–driven telemedicine systems. Mobile

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applications are developed using the Dart programming language in conjunction with the Flutter framework. In contrast, web applications are developed using the Laravel Inertia Vue framework, which integrates frontend and backend components in a modern and efficient manner. The application of these technologies results in a system that is robust, responsive, and suitable for cross-platform deployment. The system architecture illustrated in Fig. 7 and Fig. 8 demonstrates the system's capability to operate in both offline and online environments. In offline mode, users can measure blood glucose levels using smartwatches and mobile applications without requiring an internet connection. This capability is particularly important for areas with limited network access. Parents can continue to monitor their child's health status directly through the application, and data can be collected for subsequent consultation with local healthcare professionals. In online mode, the system automatically transmits data to the server, enabling physicians and parents to monitor patient health status remotely.

With this adaptable architectural framework, the deployment of expert system–oriented artificial intelligence using the Rule-Based Reasoning (RBR) methodology can be implemented on both mobile devices and server platforms, as this approach is resource-efficient and does not require substantial computational power. This contrasts with the study cited in [13], which employs machine learning–based artificial intelligence and deep learning techniques, where inference operations must be performed exclusively on server infrastructure due to high computational demands. The empirical findings indicate that all components of the pass test system, together with the integrated expert system, achieved a 100% accuracy rate in identifying prediabetes status. The integration of telemedicine and artificial intelligence through this methodology results in a system not only functional but also cost-effective and readily scalable. Given its ability to operate independently of internet connectivity and its high resource efficiency, this system demonstrates strong potential as an effective intervention to adress the increasing prevalence of prediabetes and diabetes in Indonesia, particularly in regions with limited healthcare resources and inadequate digital infrastructure.

Based on the findings derived from this study, several constraints must be acknowledged for future development. The Bluetooth Low Energy–Generic Attribute Profile (BLE–GATT) connection and the associated communication protocols identified during the smartwatch exploration stage are applicable only to specific categories of devices and therefore cannot be directly implemented on other commercial smartwatches. This limitation restricts system interoperability and necessitates application reconfiguration when deployed with different smartwatch models. From a testing perspective, the current study remains limited to internal evaluation involving a small number of participants and controlled scenarios. It does not include extensive field testing across diverse device configurations and varying network conditions. In addition, the evaluation does not encompass white-box testing, which is intended to assess the internal logic of the system, nor does it include stress testing designed to evaluate system robustness under conditions of high utilization. Furthermore, the knowledge base of the expert system developed in this study is based exclusively on two primary parameters, namely Fasting Plasma Glucose (FPG) and Postprandial Glucose (PP2). This limitation indicates that the inferential rule model remains relatively simple and does not incorporate additional health variables that may significantly influence blood glucose levels, such as lipid profiles, uric acid levels, body mass index, or physical activity factors. Consequently, the diagnostic scope is confined to basic blood glucose indicators.

V. Conclusion

This study aimed to develop an AI-driven telemedicine system for determining prediabetes status using a rule-based expert system integrated with commercially available smartwatches as non-invasive glucose sensors. The study successfully achieved this objective through three major technical contributions. First, smartwatch data acquisition was implemented via Bluetooth Low Energy (BLE) communication using the GATT architecture, enabling real-time retrieval of glucose measurements. Second, a Rule-Based Reasoning (RBR) expert system was constructed using IF–THEN rules derived from Fasting Plasma Glucose (FPG) and Postprandial Glucose (PP2) thresholds, achieving 100% accuracy when tested on 150 test records (50 normal, 50 prediabetes, and 50 diabetes). Third, a comprehensive telemedicine framework utilizing mobile and web applications was implemented with essential functional features, including automatic and manual glucose input, visualization of historical data, and multi-role monitoring. Usability testing using a five-point Likert scale yielded high mean scores ranging from 4.4 to 4.8, with an overall mean of 4.6, indicating that users "Agree" or "Strongly Agree" that the system is highly acceptable and suitable for adoption. While these findings demonstrate the feasibility and practicality of an expert system–based telemedicine solution for early prediabetes detection, several limitations must be acknowledged. The BLE–GATT implementation is currently compatible only with specific smartwatch models, and the expert system relies exclusively on two clinical parameters (FPG and PP2), which limits its diagnostic depth. Moreover, system testing was conducted using a small internal group and simulated data, without validation against clinical-grade reference standards.

Future work will focus on developing a more universal BLE–GATT communication module to support a broader range of wearable devices, expanding the expert system knowledge base to include additional physiological parameters, and conducting large-scale usability and clinical validation studies involving adolescents, parents, and healthcare professionals. These enhancements are expected to improve accuracy, interoperability, and real-

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world adaptability, thereby supporting wider adoption of the system as an accessible and cost-effective digital healthcare solution for prediabetes prevention.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Author Contribution

All authors contributed equally to the conception of the study problem and the design of the study. All authors wrote and revised previous versions of the manuscript. All authors read and approved the final manuscript.

Declarations

Ethical Approval

This study did not involve human participants, patient data, or any procedures requiring medical or ethical clearance. All testing and evaluation activities were conducted exclusively by members of the system development team using simulated and manually generated data. No adolescents, children, or external users were included in the testing process.

Consent for Publication Participants.

Consent for publication was provided by all participants.

Competing Interests

The authors declare that they have no competing interests.

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