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Development of a Document-Based Gait System With Interactive Visualisation for Clinical Analysis

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Abstract

Gait analysis is a crucial aspect of biomechanics and medical rehabilitation, used to detect movement disorders, assess therapy effectiveness, and understand human walking patterns. In Indonesia, gait research remains limited, with most data sourced from abroad, which may not reflect the characteristics of the local population. This study uses data from Vicon camera recordings that track marker movements on the subject's body and convert them into kinematic data in spatial coordinates, stored in Excel files. To support clinical applications, an efficient system is needed to manage gait data and present analysis results interactively. Therefore, a MongoDB-based gait data management system was developed due to its flexibility in handling unstructured data and scalability. The system was designed to preprocess gait data and display the results through an interactive Streamlit dashboard. The analysis involved calculating gait angle parameters, visualized in a gait cycle angle graph and analyzed statistically using mean and standard error to improve interpretation accuracy. Testing shows that the system can store data in an average of 1.52 seconds, retrieve it in 3.598 seconds, and render visualizations in 0.192 seconds, with high accuracy and only a 0.1-degree error between the input and output. This system effectively addresses the challenge of managing local gait data and supports comprehensive biomechanical analysis, enabling clinicians to make informed decisions regarding rehabilitation needs based on deviations from normal gait angle ranges.

Keywords: biomechanics; dashboard; database; gait analysis; mongoDB

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1. Introduction

Gait, or a person's walking pattern, is a fundamental aspect of the medical field and body biomechanics. Gait analysis is used to detect movement disorders, monitor rehabilitation effectiveness, and understand biomechanical changes due to age or certain medical conditions such as stroke and cerebral palsy [1], [2]. Along with the development of sensor technology and increasingly sophisticated data processing systems, the study of gait is also growing rapidly [3]. However, in Indonesia, gait-related research is still relatively limited. The data used in various studies generally come from overseas populations, so they do not fully represent local characteristics and clinical needs in the country.

In Indonesia, there are still few who have a gait database, even though gait data is very important, especially to help physiotherapists in determining the treatment given to patients. The study by Mahyuddin et al. showed that local gait data collection is needed as a basis for diagnosis and rehabilitation planning, due to differences in gait parameters between populations [4].

The lack of a local Gait database is a major obstacle in biomechanics research in Indonesia. Data from overseas is often less relevant due to differences in physical and environmental characteristics [5]. Factors such as height, weight, and environmental conditions can affect a person's walking pattern, so a system that can efficiently collect and manage Gait data from the Indonesian population is needed [6].

Most of the previous studies only focused on data collection without providing solutions for effective presentation and analysis. In fact, interactive visualization is essential to help medical practitioners and researchers understand walking patterns more intuitively, thus accelerating the analysis and decision-making process [7]. Previous studies have shown that visualization-based approaches, such as deep learning methods and interactive dashboards, can improve the accuracy of walking pattern analysis in a medical context [8]. However, while [7] highlights the lack of effective data presentation, it does not explore how such limitations impact real-world medical outcomes. In contrast, [8] not only presents visualization techniques but also demonstrates their potential to produce actionable insights. This contrast reveals a shift in research focus from passive data collection to active data interpretation through technological tools.

In [7], the authors observed that most previous studies only focused on data collection without offering robust solutions for effective data presentation and analysis. The result is a gap in understanding that hinders the ability of medical practitioners and researchers to intuitively interpret walking patterns. In other hand, the authors in [8] said that visualization-based approaches, such as interactive dashboards and deep learning methods, enhance the accuracy of gait analysis in medical contexts and get more actionable insights that support decision-making. Although both studies agree on the importance of improving analysis techniques, [8] provides concrete evidence and tools, while [7] mainly identifies the problem space. This difference suggests that future research should not only acknowledge visualization as a need but also actively design and evaluate interactive systems tailored for clinical use.

Database of gait specific to the Indonesian population have already been developed by authors in [4], where a 2D optical motion analyzer was used to build a foundational gait dataset for clinical and rehabilitative use. However, the study in [4] primarily focused on collecting normal gait parameters from a limited sample size without integrating advanced data visualization or analysis tools. Compared to [8], which implements interactive methods, [4] lacks the technological layer that transforms raw data into clinically relevant insights. This creates a research gap in terms of utilizing modern database systems and interactive interfaces such as MongoDB and web-based dashboards to manage, explore, and analyze gait data more efficiently and intuitively, especially in clinical settings. Furthermore, unlike studies [7] and [8] which highlight global trends, [4] offers localized data that, if integrated with interactive systems, could support context-specific medical decisions in Indonesia.

Many Gait data management systems still use relational databases that lack flexibility in handling unstructured data such as body movement recordings. Therefore, this research utilizes MongoDB for its flexibility in storing data in JSON format, which is more dynamic and adaptive. The system is also equipped with a Streamlit-based interactive dashboard to visually display analysis results, allowing users to filter and analyze data based on variables such as age, gender, and body mass index (BMI). This method has been tested in various studies and demonstrated effectiveness in optimizing the storage and analysis of biomechanical data [9][10].

The use of MongoDB in healthcare has also been explored in previous research by Oyinloye and Ogunniyi [10], who proposed a NoSQL-based framework for managing diverse and large-scale healthcare data. They highlighted the limitations of traditional relational databases in handling unstructured medical records and demonstrated how MongoDB's schema-less structure enables more efficient storage and retrieval of varied health-related information, such as patient records, sensor outputs, and medical images. This further supports the suitability of MongoDB in managing complex datasets like Gait data.

With this approach, this research not only improves the efficiency of data management but also provides a solution in presenting Gait patterns that are easier to understand. Along with the increasing use of NoSQL databases such as MongoDB, these systems can store and process Gait data from various sensors more optimally than relational databases [11].

In addition to data management, visualization of Gait analysis results is also a challenge. Most studies still focus on data collection without providing an effective visualization system. Web-based dashboards can help researchers and medical practitioners understand Gait patterns more intuitively. Previous studies have shown that real-time data visualization systems can improve the effectiveness of analysis and decision-making in the medical field [12].

This research aims to develop a MongoDB-based Gait data collection and management system and integrate it with an interactive visualization dashboard using Streamlit. The system is designed to collect real-time Gait data from various sensors, store it in a flexible non-relational database, and present it in the form of interactive graphics that support body biomechanics analysis. System evaluation was conducted to measure storage speed, data retrieval time, and visualization effectiveness in assisting Gait analysis.

The urgency of this research lies in the need for a localized, efficient, and clinically useful gait analysis platform tailored to the Indonesian context. Its novelty stems from the integration of a document-based data structure, interactive visual analytics, and local data representation—an approach rarely seen in existing gait systems. By enabling clinicians to interactively explore gait data filtered by variables such as age, gender, and BMI, the system allows for more personalized and context-sensitive assessments. This supports early identification of gait abnormalities, improved treatment planning, and more accurate monitoring of rehabilitation progress. The intuitive dashboard design also facilitates communication between clinicians and patients, making biomechanical data more accessible and actionable. Ultimately, the system contributes not only to better clinical outcomes but also to the advancement of medical practice through data-informed decision-making. In the long term, this research is expected to provide a representative local gait database and foster the development of real-time visualization technologies for broader clinical and biomechanical applications [13].

2. Research Methods

This research develops a gait data management and visualization system based on MongoDB NoSQL database integrated with an interactive dashboard using Streamlit. This approach was chosen because MongoDB has high flexibility in storing unstructured data in a dynamic JSON format, and supports large-scale storage with a structure that is adaptive to data changes. This method has proven effective in previous studies in managing complex and diverse biomechanical data[11], [14], [15].

The research was conducted in Surabaya, Indonesia, as a representation of the local context in gait data collection. This research is an experiment-based system development that integrates data acquisition, storage, and presentation in a single digital system. The experimental process in this research is designed in a structured manner through several main stages, namely: data collection, data processing, database development, visualization implementation, and overall system evaluation. Each stage is designed to ensure a strong connection between the gait data obtained and the visualization results that can be interpreted clinically and scientifically.

The data used in this study are secondary data from 120 subjects aged between 26 and 60 years old, obtained through a Vicon camera-based motion tracking system. The Vicon camera is an optical tracking system that is widely used in biomechanical analysis, as it is capable of recording the movement of markers mounted on the subject's body and converting them into kinematic spatial coordinate data [16]. After the recording was performed, the data was processed using Nexus software, and then exported into Excel format (.xlsx). The data obtained included anthropometric information such as age, gender, height, weight, and body mass index (BMI), as well as gait kinematics parameters consisting of pelvis, hip, knee, and ankle angles in various phases of the walking cycle.

The BMI categories used in this system refer to the standards applicable in Indonesia, namely based on the Regulation of the Minister of Health of the Republic of Indonesia Number 41 of 2014 concerning Balanced Nutrition Guidelines [17], which is divided into five categories: severe underweight (<17.0), mild underweight (17.0-18.4), normal (18.5-24.9), mild obese (25.0-27.0), and severe obese (≥27.0). These categories allow the system to perform a more in-depth analysis of the relationship between nutritional status and a person's walking pattern [18].

To effectively manage Gait data, the system involves several key actors with specific roles in the workflow. First, the researcher as the main user is in charge of uploading Gait data from various sensors and analyzing it through an interactive visualization dashboard to identify walking patterns, evaluate biomechanical disorders, and support clinical decision-making. Second, the administrator acts as an access and security manager, ensuring access rights according to roles and maintaining data integrity and security. Third, the system uses MongoDB as the data storage and processing medium due to its ability to handle semi-structured data and store complex Gait data documents, such as joint angles and other biomechanical parameters in a single walking cycle. The interaction between the actors and the overall system components is visualized in Figure 1, which shows how the data flow and the roles of each party support each other in the process of collecting, storing, analyzing, and visualizing Gait data in an integrated and efficient manner.

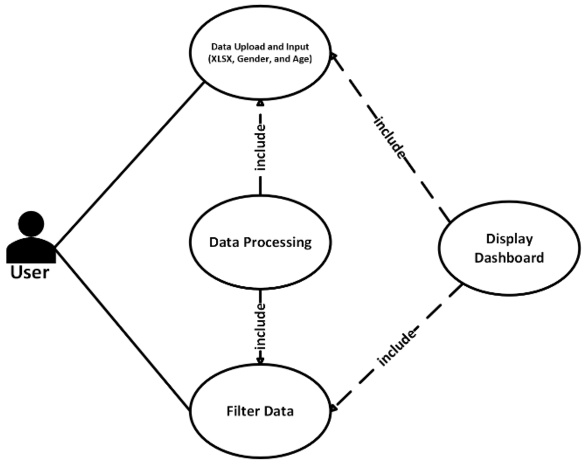


Figure 1. Use case diagram that shows the relationship between the user and the system in the process of managing Gait data.

After the user enters the data into the system, it is stored into the MongoDB database in JSON format. This format was chosen because it is flexible and able to represent complex gait data structures concisely and easily. Data such as joint angles during a gait cycle are verified and adjusted before being stored in the database collection. This process allows the system to quickly access and process data according to analysis needs. The sequence of communication between the user and the system in this storage process is shown in Figure 2, which illustrates the steps from data input to confirmation of successful storage.

In general, the system consists of several main interconnected components: data collection, database storage, data processing, and data visualization. The data collection process is done through sensors that record real-time gait parameters, such as joint angle and step duration. The collected data is then stored in a

MongoDB database, which allows storage in a flexible document format suitable for handling complex biomechanical data. Next, the stored data is processed to generate information that can be analyzed, such as statistical calculations, normalization, and clustering based on certain variables such as age, gender, and BMI. The results of this processing are then visualized through a Streamlit-based interactive dashboard, which is designed to make it easier for users to explore and understand gait data. These four processes run in an integrated manner to ensure that gait data can be managed, analyzed, and displayed efficiently and informatively. The activity flow of each process is further explained in the activity diagram shown in Figure 3.

The data imputation process is carried out gradually and systematically, starting with the upload of an Excel file that must follow a certain structure. The file must have two main sheets, namely subject_info and norm_kinematic. The subject_info sheet contains important information about the subject, such as ID, gender, age, and other relevant demographic data. Meanwhile, the norm_kinematic sheet contains normalized kinematic data pertaining to the subject's body movements during one gait cycle. This file structure is designed to ensure consistency and ease of subsequent data processing. Examples of the format of these two sheets can be seen in Figure 4 and Figure 5, which give a clear idea of how the data should be organized before being input into the system. This approach helps minimize input errors and speeds up data integration into the MongoDB database for further analysis.

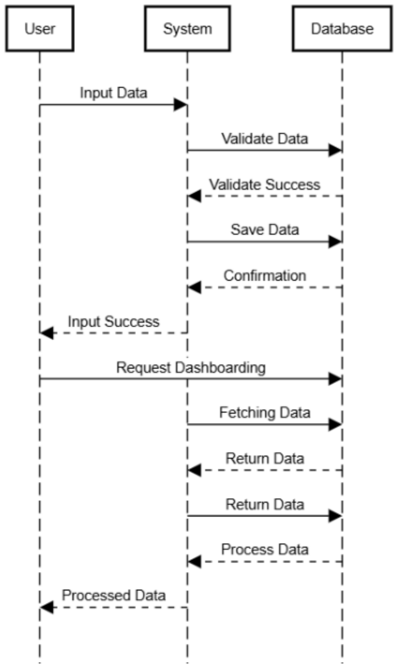
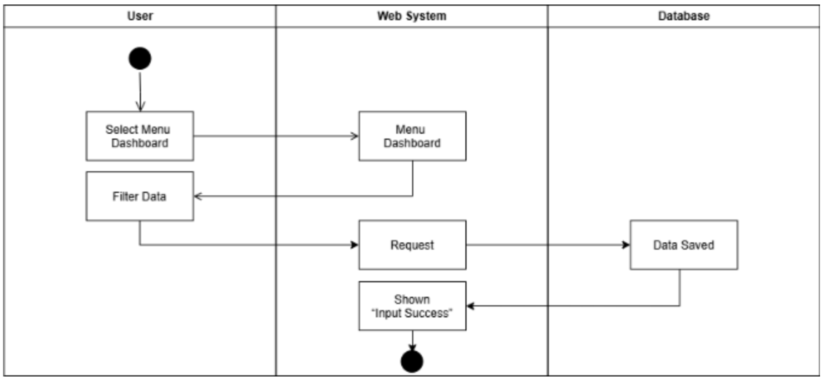
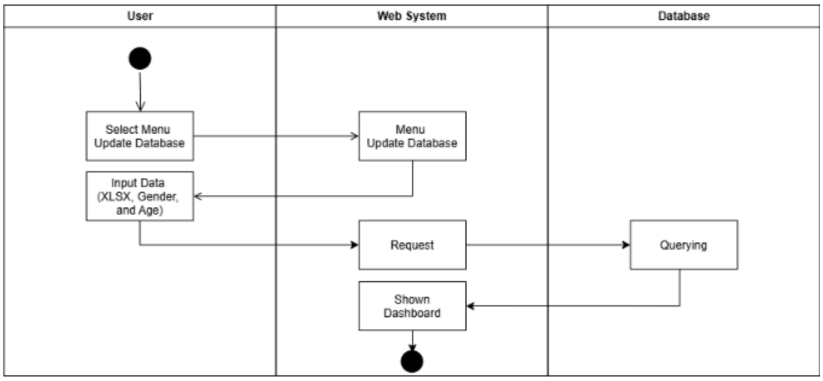


Figure 2. Sequence diagram that illustrates the sequence of communication between the user and the system in storing Gait data.



(a)



(b)

Figure 3. Activity diagrams showing the activity flow in Gait data processing to visualization, (a) activity flow of data imputation processing, (b) activity flow of dashboard visualization

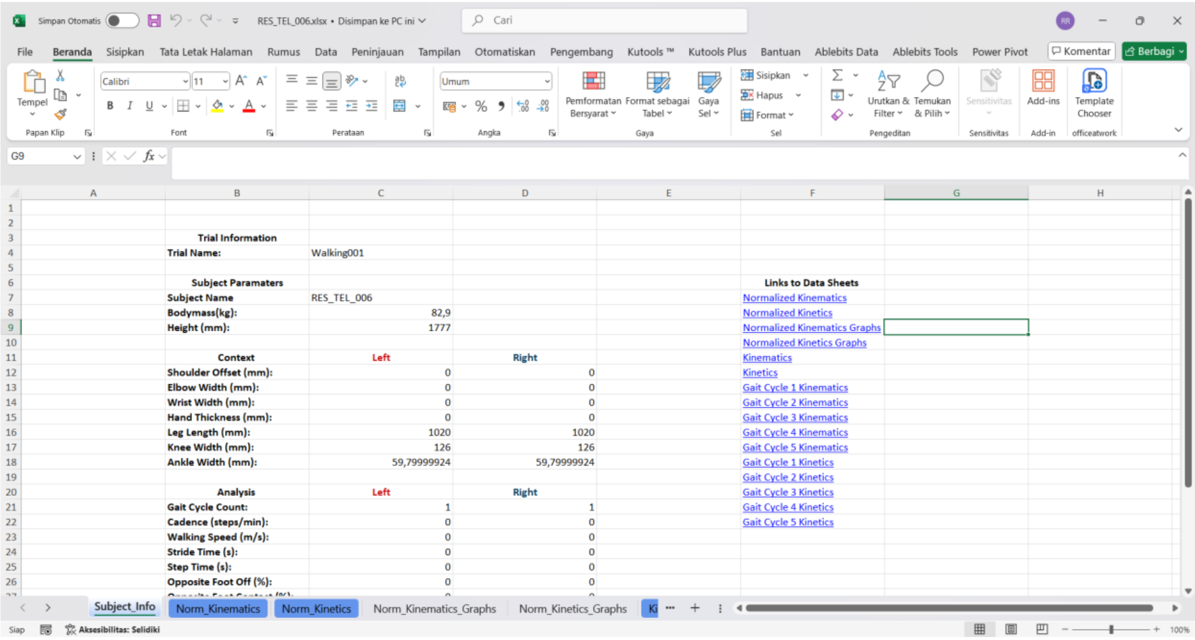


Figure 4. Display of the subject_info sheet in the excel file that will be inputted to the database

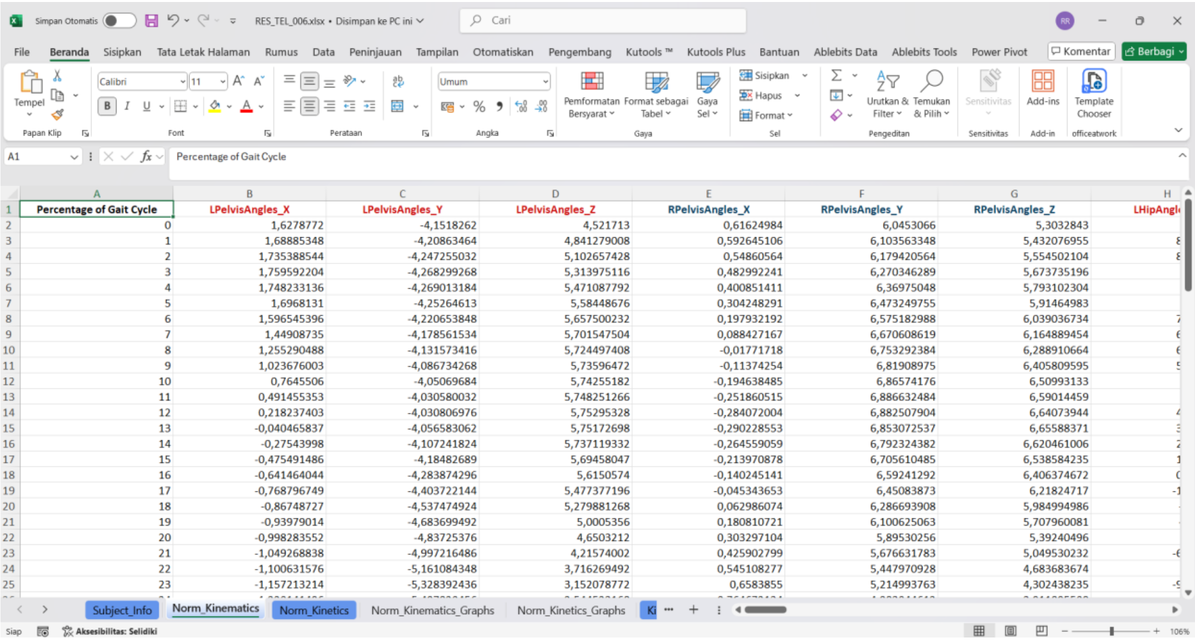


Figure 5. Display of the norm_kinematic sheet in the Excel file that will be inputted to the database

After the file is prepared according to the required format, the next step is to store it in MongoDB. Each gait data entry is saved as a JSON document that includes subject information, body parameters, and kinematic values for a single gait cycle. This storage structure allows for variations between subjects without disrupting the consistency of the database. The relationships between the stored data elements are illustrated in Figure 6.

The file is uploaded through a dedicated page designed for the data imputation process, as shown in Figure 7. On the backend, the system automatically extracts the contents of each sheet and its respective entries using specific functions. For the norm_kinematic sheet in particular, only the percentage of the gait cycle and the Angles x values for each measured body part are extracted. The extracted data is then converted into JSON format and stored in a MongoDB database. The use of MongoDB enables flexible and dynamic schema storage, making it highly suitable for handling complex biomechanical data that often lacks a consistent structure. This flexibility stands in contrast to relational database systems, which require rigid and predefined schemas, making them less effective for managing diverse and evolving datasets such as those commonly found in the field of biomechanics.

The angle data (such as pelvis, hip, knee, and ankle) that has been stored in MongoDB is extracted and processed using Python libraries such as pandas andnumpy. The backend calculates the mean, standard deviation, and standard error at each point in the gait cycle (e.g. from 0% to 100%). These statistical results are visualized using line graphs with Plotly, where the main line shows the mean and the shaded area represents the range of variation of the data (upper and lower bound) based on the standard error. This dashboard enables clinicians and researchers to interactively visualize changes in joint angles throughout the gait cycle, with filters for age, gender, and BMI. These filters allow personalized insights, which are essential for clinical interpretation and decision-making, such as identifying deviations from normal gait in specific patient groups. [6], [18].

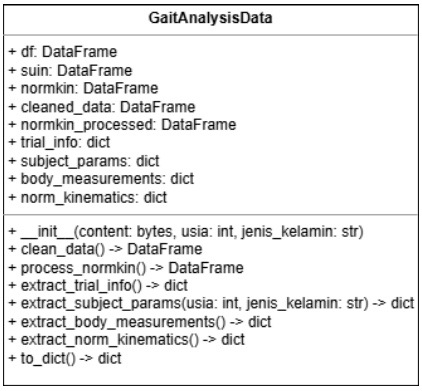


Figure 6. A class diagram showing the classes in the system that manage Gait data.

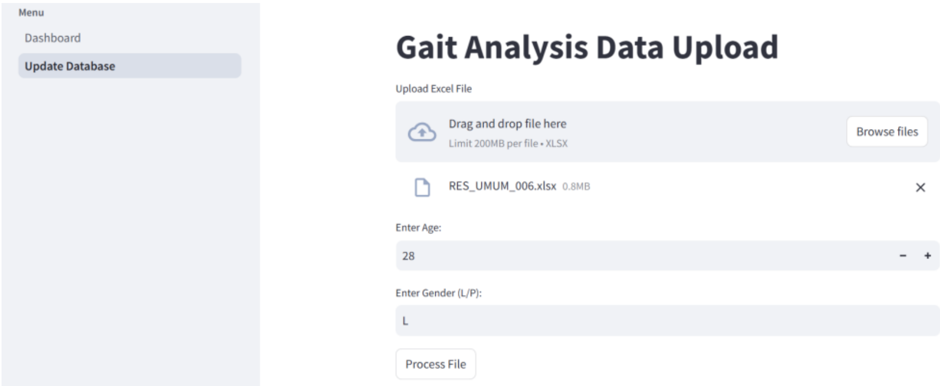


Figure 7. Example of data imputation to the database in the system.

To ensure that the system runs according to specifications, black-box testing is conducted, which focuses on the validity of feature functionality without examining the internal structure of the program code [19]. Tests were conducted on the data storage process, data retrieval from MongoDB, and visualization rendering on the dashboard. In addition, the execution time of each process was also tested iteratively five times to ensure the consistency of system performance [20]. The test results show the average time of data storage is 1.52 seconds, the average time of data retrieval is 3.598 seconds, and the average time of visualization rendering is 0.192 seconds. Data accuracy was also tested by comparing the input and output values of the visualization for five subjects, and the results showed a 100% match, proving the system did not experience data distortion during processing [21].

With this approach, the developed system not only manages gait data efficiently, but also translates it into clinically relevant visualizations that can support real-time analysis and enhance the clinical decision-making process. By providing an accessible and localized gait database for Indonesian populations, the system contributes to more context-sensitive medical care and research in body biomechanics.

3. Results and Discussions

After the gait data management and visualization system was successfully developed, the next step was to implement and test it to assess its performance and reliability. The system was designed to receive secondary data recorded using a Vicon camera, which had previously been processed using Nexus software and converted into Excel (.xlsx) format. The data included two main types of parameters: anthropometric parameters-such as age, gender, height, weight, and body mass index (BMI)-and kinematic parameters, which consisted of the angles of movement at the pelvis, hip, knee, and ankle during one gait cycle (0-100%). This process aims to ensure that the system is capable of handling data from commonly used tools and workflows in biomechanical analysis, as well as testing the effectiveness of the system in storing, processing, and displaying the data through an interactive dashboard.

The data imputation was done gradually and systematically, the page for data imputation can be seen in Figure 5. Each entry was stored in JSON format in MongoDB, allowing flexibility in handling unstructured data. This process reflects the strength of MongoDB as a NoSQL database that supports dynamic schemas, in contrast to relational databases which are rigid and more difficult to extend to complex biomechanical data [11], [15].

The developed visualization system utilizes Streamlit to present a web-based interface. Users can view interactive graphs depicting the pattern of joint angle changes throughout the gait cycle. Each graph displays a mean curve and upper-lower limits based on the standard error, with shaded areas showing the distribution of data between subjects. This visualization refers to the principle of statistical representation in the form of error bars and interval ranges that provide an indication of data variability, as described by Altman and Krzywinski that the presentation of uncertainty in the form of error bars is essential for accurate statistical interpretation in biomedical science [22].

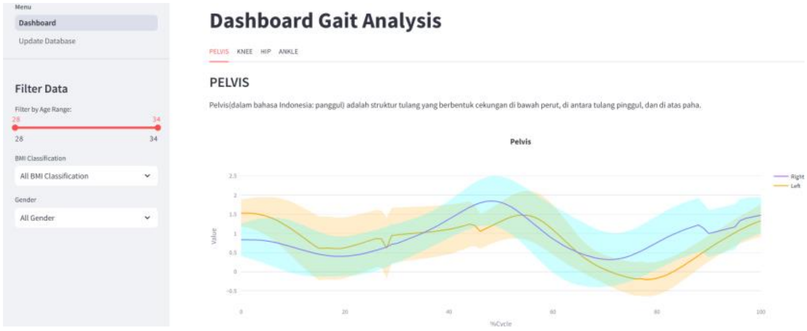


Figure 8. Visualization result of pelvis angle in the system.

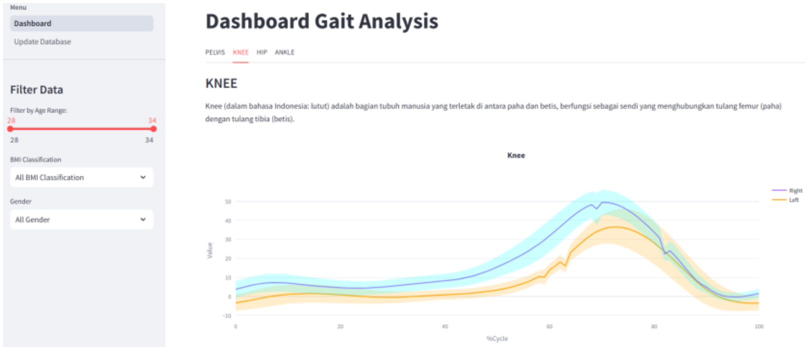


Figure 9. Visualization result of knee angle in the system.

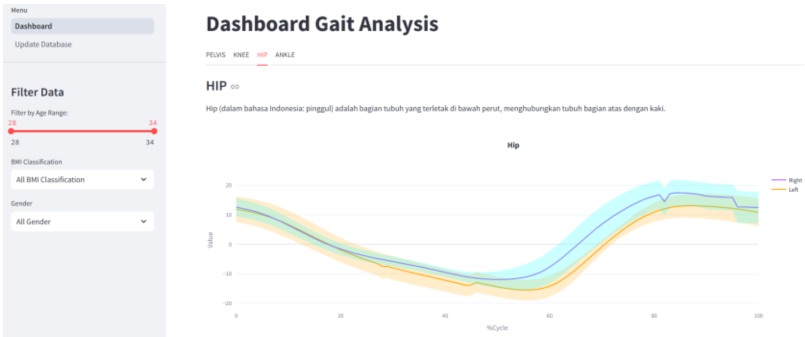


Figure 10. The result of visualizing the hip angle in the system.

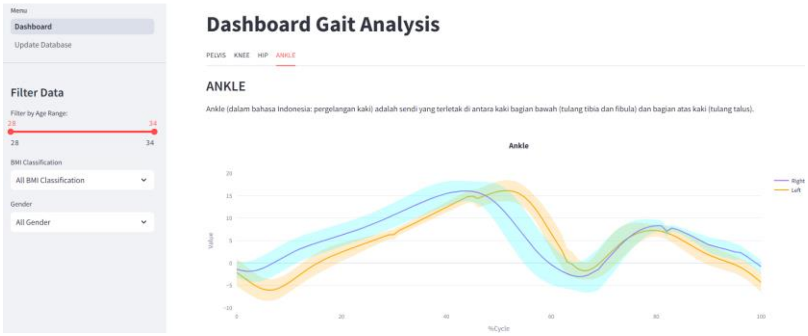


Figure 11. Visualization result of ankle angle in the system.

The visualization results of the system's gait parameters are shown in Figure 8 to Figure 11. The graphs depict the angular changes at the pelvis, hip, knee, and ankle throughout one walking cycle (0-100%). Each graph shows dynamic joint movement patterns from the start to the end phase of the stride, providing a more detailed picture of the body's biomechanics during walking. The interactive dashboard feature allows users to filter and customize data based on age, gender and body mass index (BMI) category variables. Thus, the resulting visualizations are not only informative, but also responsive to more personalized and contextual analysis needs. This is particularly helpful in understanding movement variations between individuals and supports more accurate assessments in clinical contexts and biomechanical research.

To test the reliability of the system, black-box testing was conducted to evaluate the main functions of the system without examining the internal code [19]. This test includes dashboard navigation features, imputation process, data storage to MongoDB, and visualization rendering process based on certain filters. All tests produced outputs that were in line with expectations. A summary of the test results is shown in Table 1.

Table 1. The results of black-box testing

Feature Tested	Input	Expected Output	Status
Navigation Button to Imputation Data	Click the "Upload Data" button.	The system opens the imputation data page.	Success
Gait Data Imputation	Gait Data.	Data is saved in MongoDB.	Success
Save data to MongoDB	Gait Data.	Data is correctly saved.	Success
Navigation Button to Dashboard	Click the "Dashboard" button.	The system correctly opens the dashboard page.	Success
Data Visualization	Imputed data.	Visualization matches the data.	Success
Data Filtering	Filter criteria (age, gender, and BMI) applied to the data.	Filter successfully applied to the data displayed on the dashboard according to the specified criteria.	Success

Performance testing was conducted by measuring the average execution time of three main process stages: data storage to MongoDB, data retrieval from the database, and visualization rendering. Each process was repeated five times to obtain an average value. The test results show that the system is able to store data with an average time of 1.52 seconds, retrieve data in 3.598 seconds, and display visualizations in 0.192 seconds. These results show high efficiency in data processing, making the system suitable for rapid analysis needs in medical and research environments. A summary of the execution time comparison is shown in Table 2.

In addition to speed, the system was also tested in terms of accuracy. Five subjects were selected to test the agreement of the mean and upperbound values between the input data and the visualization output shown in Table 3. No difference was found between the input and output values, meaning that the system successfully maintained the integrity of the data throughout the processing and presentation process. The accuracy test results are shown in Table 4.

Table 2. Results of Execution Time: Data Storage, Retrieval, and Visualization

Trial No.	Data Storage	Data Retrieval	Visualization Rendereing
1	1.4	3.56	0.2
2	2.16	4.26	0.2
3	1.62	3.62	0.19
4	1.28	3.47	0.18
5	1.14	3.08	0.19
Average	1.52	3.598	0.192

Table 3. Subjects used for data accuracy testing

Subject Name	Angle Value
RES_TEL_002	-0.142418
RES_TEL_003	-9.862038
RES_TEL_004	-8.180197
RES_TEL_005	1.256239
RES_TEL_006	1.256239

The application of gait cycle graphs in a standardized and visual form is essential for clinicians to recognize walking pattern abnormalities. This is in line with the study by [23] who emphasized that a visual approach to gait data allows for more intuitive and efficient observation-based diagnosis, particularly for clinical and rehabilitative applications.

Table 4. Results of Comparison of Mean and Upperbound Input-Output Values for Accuracy Validation

Number of Input Data	Mean Input	Upper bound Input	Mean Output	Upper bound Output	Result
1	-	-	-	-	-
2	-5.00	-0.14	-5.00	-0.14	Accurate
3	-6.06	-3.06	-6.06	-3.06	Accurate
4	-4.23	-1.43	-4.23	-1.43	Accurate
5	-2.12	0.89	-2.12	0.89	Accurate

To see where this study stands in the landscape of previous studies, a comparison was made with the study by [4] which was one of the early initiatives to develop a gait database for the Indonesian population. The study used a high-speed 2D video camera and LED markers to record marker movements on the subject's body. The data generated included stride length, cycle time, and joint angles that were manually calculated from the video recordings. The sample size in the study reached 212 people, making it an important contribution in providing a local gait reference in Indonesia.

However, [4] approach has limitations in terms of data storage flexibility and system accessibility. Their system is not equipped with interactive visualization features nor modern database-based storage. In contrast, the system developed in this study integrates an extensible NoSQL database, real-time web-based visualization, and an in-depth demographic data filter system. A comparison of the two systems is summarized in Table 5.

Although different in approach, the contribution of Mahyuddin et al. remains significant as a foundation for further system development. This research not only continues that spirit but also adds value by applying the latest technology, as well as opening up opportunities for integration with AI and machine learning systems in the future.

Thus, the developed system proves to be able to meet the challenge of managing local gait data efficiently and adaptively. It supports comprehensive biomechanical analysis, including the comparison of a patient's gait joint angle patterns with normative average values. This comparison is visualized through an interactive dashboard, enabling clinicians to make informed decisions on whether a patient requires rehabilitation or not, based on significant deviations from the normal gait angle ranges. The system can therefore be effectively utilized by clinicians, researchers, and developers of data-driven rehabilitation systems.

Table 5. Comparison of research results with previous research

Aspects	This Study	Mahyuddin et al. (2012)
Key Technologies	MongoDB (NoSQL), Streamlit, Plotly, Vicon 3D secondary data	High-speed 2D video camera, LED marker, manual video processing
Data Type	3D kinematic data (pelvis, hip, knee, ankle angles).	Spatial-temporal 2D data (stride length, joint angle, cycle time, velocity)
Data Source	120 Indonesian subjects, secondary data of Vicon capture results	212 Indonesian subjects, primary data from direct laboratory recordings
Storage Method	Non-relational, flexible JSON structure, scalable	Manual/file storage, no flexible database structure
Visualization	Real-time, interactive, web-based, filterable (age, gender, BMI)	Static, conventional tables and graphs without user interaction
Excellence	Interactive, flexible, web-based, easily extensible and integrative, establishes a digital-based local gait baseline	Provide a local gait baseline from primary data with direct measurement.
Limitations	Relies on secondary data, no direct acquisition in the field yet	Inflexible, manual processing does not support the integration of modern technologies

4. Conclusions

This study demonstrates that a MongoDB-based gait data management and visualization system can effectively support clinical and research efforts, especially within the Indonesian context. Beyond achieving technical goals—such as high-speed data handling, flexible JSON formatting, and accurate visualization—the system addresses a crucial gap in accessible biomechanical data infrastructure in Indonesia.

The system offers an intuitive, interactive dashboard that presents gait cycle data in a clear and actionable form. This facilitates clinicians' ability to compare patient gait patterns against normative data filtered by age, gender, and BMI, enhancing the precision of diagnosis and rehabilitation planning. The real-time visualization and filtering capabilities promote rapid interpretation, which is crucial in clinical environments where timely decisions impact patient outcomes.

These findings suggest that localized, scalable systems like this can empower researchers, clinicians, and institutions to better understand gait patterns across different populations and demographics. More importantly, this approach can be a stepping stone toward future integration with advanced tools such as AI-based diagnostics or real-time monitoring systems, although such models were not implemented in this study.

Future work could explore the application of machine learning models on the collected data to detect abnormalities automatically, assist in rehabilitation planning, or even develop mobile-based real-time gait tracking for remote areas. This research contributes not only to the digital health ecosystem but also offers a model that can be adapted to other low-resource contexts globally. This study also bridges a significant gap in Indonesia's biomechanical data infrastructure by delivering a scalable, clinically relevant system underpinned by advanced NoSQL database technology. It lays a strong foundation for future innovations in data-driven gait analysis and personalized rehabilitation strategies.

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