Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 8, No. 2, July 2025, pp. 397 – 406
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Interactive Real-Time Weight Management Platform Using Machine Learning Methods

[1]Febrina Rosadah Haksa, [2]Jon Endri, [3*]Aryanti
[1,2,3]Telecomunication Engineering, State Polytechnic of Sriwijaya, Indonesia
Email: [1]fbrnahks@gmail.com, [2] jon_endri@polsri.ac.id, [3]aryanti@polsri.ac.id

Article Info
Article history:
Received May 09th, 2025
Revised Jun 16th, 2025
Accepted Jul 23th, 2025

Keyword:
BMI Calculator
Decision Tree
Disease Risk Detection
Interactive Platform
Machine Learning

ABSTRACT
This research develops an interactive and real-time web-based weight management platform that integrates machine learning methods using decision tree algorithms to detect the risk of weight-related diseases. The platform features an automatic Body Mass Index (BMI) calculator as well as a risk prediction system for diseases such as obesity and cardiovascular disorders. The data used includes the user's weight, height, eating habits, and physical activity level parameters collected through a live user interface. Based on the data, a decision tree algorithm is used to classify the health risk level and provide personalized recommendations to the user to help with preventive weight management. Initial testing showed that the decision tree model applied was able to achieve a prediction accuracy rate of 97%, demonstrating reliable performance in identifying health risks based on lifestyle data. This platform is expected to be an accessible technology solution to increase public awareness of the importance of weight management and disease prevention independently.

Corresponding Author:
Aryanti Aryanti
Telecomunication Engineering,
State Polytechnic of Sriwijaya,
Palembang, South Sumatera, Indonesian.
Email: aryanti@polsri.ac.id.

DOI: http://dx.doi.org/10.24014/ijaidm.v8i2.36874

1. INTRODUCTION

The development of Machine Learning (ML)-based interactive platforms is important because traditional approaches such as manual record-keeping, common diets, and periodic consultations are often unresponsive, impersonal, and unable to provide real-time feedback [1]. Meanwhile, obesity is on the rise globally and is closely linked to chronic diseases such as type 2 diabetes and cardiovascular disorders [2]. Strategies such as calorie reduction and physical activity have proven to be effective [3], supported by cognitive behavioral changes to maintain healthy eating habits [4]. In severe obesity, medical interventions such as pharmacotherapy or bariatric surgery can be performed [5], as well as regular social monitoring to maintain program sustainability [6]. ML platforms are able to overcome the limitations of conventional approaches with automated risk detection, personalized recommendations, and continuous monitoring, thus supporting both prevention and individual empowerment in health management [7].

The development of real-time interactive weight management platforms using ML is becoming increasingly evident not only in the realm of research, but also in real-world applications. For example, Samsung has integrated ML features on their wearable devices to monitor sleep quality and provide personalized feedback, where “AI-powered coaching tools are designed to offer users actionable advice based on sleep patterns” [8]. In addition, research based on wearable data showed that “body weight loss of ≥ 2% could be predicted with 84.44% Area Under Curve (AUC) using gradient boosting models trained on 2-week activity, biomarker, and sleep data” [9], Another chatbot-based approach also shows significant potential in digital personalization for weight management. In the SlimMe chatbot trial, users reported that “67% of the chatbot's messages were perceived as relevant, accurate, and motivating” during a seven-day interaction using text, emoticons, and GIFs as forms of emotional support [10]. Meanwhile, the Graph Neural Network-based nudging model used by the Co-Pilot for Health platform successfully increased users' physical activity by “6.17% in daily steps and 7.61% in MVPA weekly” within 12 weeks through adaptive personalized messages [11]. On the commercial side, India's HealthifyMe app has used an AI-nutritionist named Ria to help users set personalized diet and exercise plans, with response performance “able to answer 80% of user queries accurately” according to a Wikipedia report [12]. All these findings reinforce that systems that combine real-time feedback, risk detection, Body Mass Index (BMI) calculation, and ML-based personally adaptive support are indeed not just concepts, but integrated solutions relevant to today's health challenges.

Various previous studies have utilized ML for obesity classification or weight prediction, but most still have limitations in terms of integration and personalization. Many studies only focus on one main function such as classification or prediction without including automatic disease risk detection features or real-time customized BMI calculators based on individual data [13]. Moreover, “existing solutions often lack comprehensive personalization and rely on static recommendation systems”, leading to results that are less responsive to the dynamics of changing user habits [14]. In addition, the approach used in such systems is generally one-way and does not allow for dynamic interaction between the system and the user, thus failing to provide contextually adaptive recommendations [15]. Other limitations include the lack of integration of data from various sources such as wearable devices and daily applications, which can provide important inputs for multimodal data-driven personalization [16]. assert that “multimodal biosensing (e.g., glucose, HRV, motion) is essential to enable robust, real-time personalized nutritional and weight feedback.” Systems that do not support continuous monitoring are also a major obstacle in maintaining consistency in lifestyle changes [17].

Based on a review of previous studies, the author proposes the development of an interactive platform for real-time weight management using ML methods, specifically the decision tree algorithm, to detect disease risks and calculate BMI automatically. This research aims to develop a ML-based interactive platform with disease risk detection and BMI calculator features that can be personalized based on individual data and conditions. This goal is directed at increasing the effectiveness of independent and sustainable health monitoring. The novelty of this research lies in the comprehensive integration of health risk detection, automatic BMI calculation tailored to user characteristics, and real-time interaction that enables adaptive feedback. In contrast to previous research and existing applications that generally only offer weight monitoring or simple classification, this platform emphasizes a personalized, predictive, and responsive approach in supporting weight management and disease risk prevention simultaneously.

2. RESEARCH METHOD

2.1. Research framework

The results of this research are presented in a visual form that is informative, systematic, and easily understood by various parties, both researchers and technical users. One of the main visual elements is the block diagram, which plays an important role in illustrating the system workflow and the stages of tasks executed during the testing and evaluation process. These diagrams not only show the relationships between components, but logically map out the functional steps aimed at creating an optimized system. This kind of visualization is consistent with the approach used in the development of the Decision Tree web-based Body Mass Index (BMI) prediction system, where block diagrams serve as the foundation for visualizing the system architecture and the flow of user interaction with the system and the automatic prediction process [18].

The block diagram used displays the steps starting from input data-such as gender, weight, and height-that are then processed using the Classification and Regression Trees (CART) algorithm to calculate BMI and classify BMI categories. This process is illustrated graphically so that users can clearly see how the data is converted into meaningful outputs [19]. In addition, this diagram also reflects common practices in disease and obesity classification systems using decision trees or C5.0, where the block diagram helps highlight the input variables, classification process, and model interpretation results [20]. In a related study on obesity prediction using a Support Vector Machine, block diagrams were used to visualize the sequence of processes from data collection, feature extraction, model training, to accuracy evaluation, similar to the approach in this platform [21]. The use of block diagrams was also presented in a study on weight fluctuation prediction with XGBoost and deep learning, which emphasized the importance of visual representation of computational and data processing flow for technical stakeholders [22].

Thus, the final representation of the block diagram serves not only as a visual representation, but also as a system validation tool. It helps to identify potential technical constraints as well as highlight the advantages of the system design. Overall, the block diagram reflects the entire analysis process underlying the development of the proposed interactive weight management platform. The structure of the designed research framework provides a clear visual guide to the main objective: building a system that works efficiently, is adaptive, integrated, and user-friendly, as shown in detail in Figure 1.

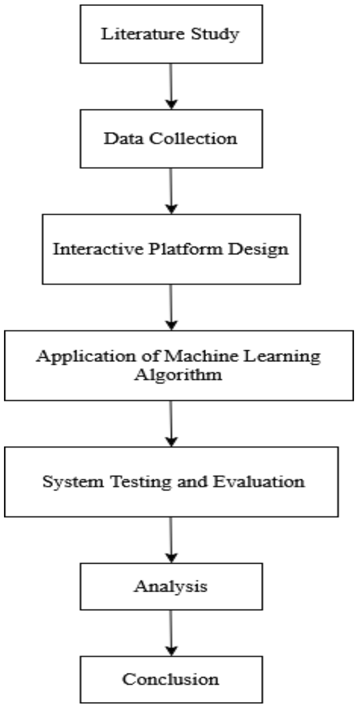

Figure 1. Block Diagram of Research Method

This research begins with a literature study, which aims to understand basic concepts related to weight management, ML, and relevant previous studies. From this study, researchers identified the shortcomings of previous studies and set the direction of the research. Next, data collection is carried out, namely data collection in the form of health parameters such as weight, height, age, as well as data on physical activity and sleep patterns, which can be obtained through surveys or wearable devices. This data becomes the basis for the modeling process and system testing.

The next stage in this research is the design of an interactive platform, which is a digital system designed to allow direct interaction between users and the system in a dynamic and responsive manner. The platform is built with a user-centered approach, where the interface design and workflow are made as intuitive as possible to facilitate users in entering personal data related to their health conditions. Data that can be entered includes basic information such as weight, height, eating habits, physical activity patterns, as well as other factors that may affect overall health status. In addition to receiving input from users, the platform is also designed to provide real-time feedback in the form of health condition analysis results, BMI status, as well as personalized recommendations based on the data entered by users. Once the platform design process is complete, the next step is the implementation of ML algorithms to support the analytical functions of the system. In this case, the Decision Tree algorithm was chosen as the main method as it has advantages in data classification and result interpretation, especially in the context of health. This algorithm is used to classify the user's health risk level and automatically calculate BMI based on the available data. The built model will be trained using relevant datasets and validated to test its accuracy. This training and validation process is important to ensure that the algorithm used is able to produce recommendations that are accurate, adaptive, and in accordance with the characteristics of each individual.

After the system has been fully developed, a testing and evaluation stage is carried out on the performance of the system to ensure that all functions run in accordance with the predetermined objectives. This includes evaluating the accuracy of the ML model in performing classification, the speed and responsiveness of the platform in displaying real-time results, and the quality of the user experience when using the system. All test results were then analyzed to identify the strengths and weaknesses of the system, both in terms of technical and user convenience. This analysis plays an important role in determining the extent to which the developed system is able to meet user needs and the objectives of the research as a whole.

The end of this process is marked by the conclusion stage that summarizes all the findings during the research. These conclusions include the extent to which the system succeeded in achieving its goal of creating a real-time, personalized, and adaptive technology-based weight management platform. In addition, the conclusion also highlights the contribution that this research makes to the development of digital health technologies, particularly in the context of disease prevention and healthy lifestyle management. This research is expected to be a strong first step in bringing technological solutions that are able to effectively and sustainably address the challenges in modern health management.

2.2. Desain System Website

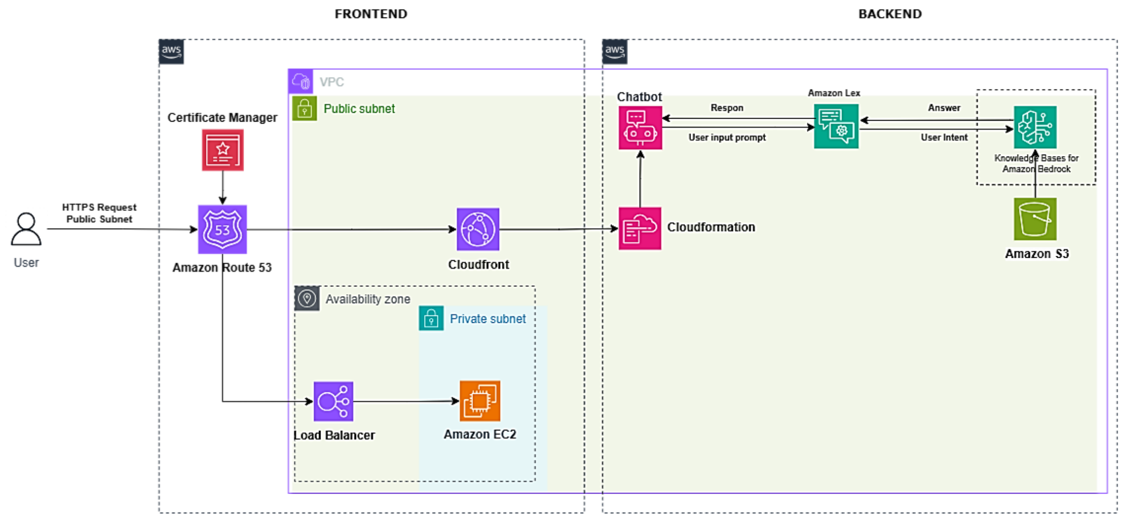

Figure 2. Wellnes Healty Guard Website System Design

Figure 2 is a diagram illustrates the modular and integrated architecture of the system, consisting of two main components: frontend and backend. At the frontend, users interact with the system through Hypertext Transfer Protocol (HTTP) requests that are first routed by Amazon Route 53, a cloud-based Domain Name System (DNS) service responsible for directing user traffic to the appropriate application resources, based on traffic management policies and service availability. The security layer is strengthened by using AWS Certificate Manager, which automatically manages the provisioning, issuance and renewal of SSL/TLS certificates, ensuring data communication between users and servers is encrypted and secure from potential third-party attacks. To avoid bottleneck or system failure due to high data traffic, Elastic Load Balancer (ELB) is used to distribute traffic evenly across multiple Amazon Elastic Compute Cloud (EC2) instances. EC2 serves as a cloud-based flexible computing engine capable of running various applications and services required in the system. This approach not only improves the overall performance efficiency of the system, but also enables vertical as well as horizontal scalability according to user requirements or the volume of data being processed.

On the backend, the system is built on a Virtual Private Cloud (VPC) that provides an isolated and secure virtual network environment, complete with access control configuration, private and public subnets, and security settings through network access control lists (ACLs) and security groups. This backend infrastructure is automatically managed using AWS CloudFormation, which enables the implementation of Infrastructure as Code (IaC) principles, where configuration and management of infrastructure resources is declarative and reproducible, supporting a fast and reliable deployment process. In the context of user interaction, the system also includes a chatbot module tasked with receiving and processing user input in the form of text or voice commands. The chatbot is powered by Amazon Lex, a Natural Language Processing (NLP) service from AWS that enables the development of intelligent conversational interfaces. Amazon Lex provides the ability to recognize user intent, handle dialogue dynamically, and integrate analysis results into the application flow seamlessly. It enhances the user experience by providing more intuitive, natural and contextualized responses to inputs.

As part of the storage needs, the system utilizes Amazon Simple Storage Service (S3), a cloud-based object storage service that can be used to store various types of data such as images, documents, system logs, or other configuration files. Amazon S3 offers very high data durability and availability, and supports policy-based access settings to maintain data confidentiality and integrity.

With this overall architecture, the system is able to accommodate the needs of the process from start to finish, from user interaction on the frontend, processing and decision-making on the backend, to the delivery of information back to users in a fast, secure, and efficient manner. The diagram visually shows the complete workflow underlying the performance of this cloud-based management system, which not only prioritizes technical performance, but also security, scalability, and optimal user experience.

2.3. Website Workflow

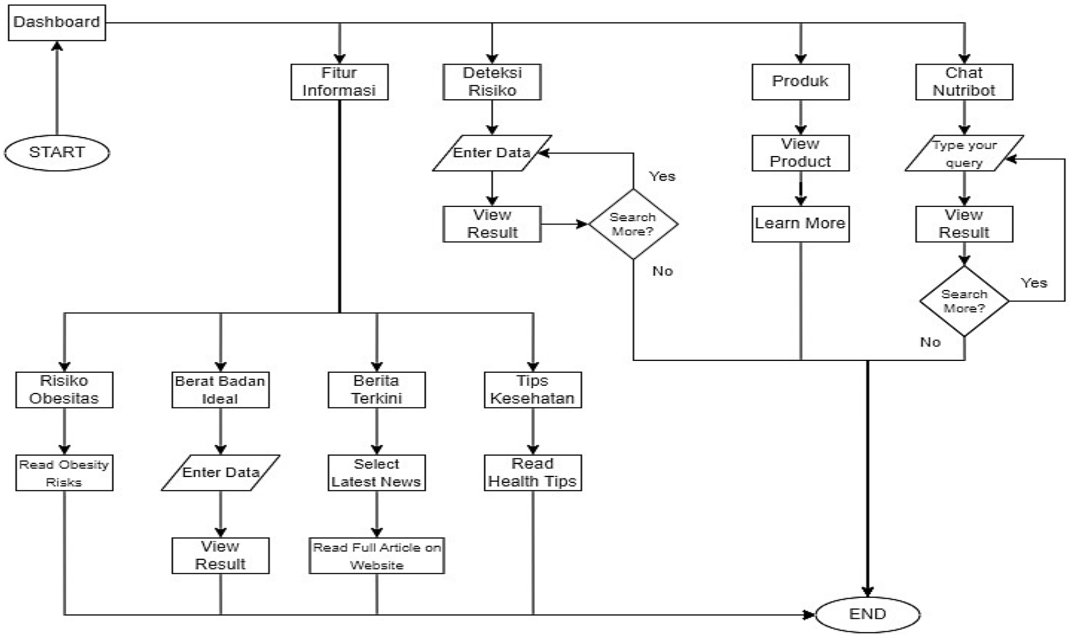

Figure 3. Website Workflow

Figure 3 above illustrates the process flow in the system that includes various features and user interactions. The process starts from the dashboard, where users can select health-related information features. Users can then enter data to detect health risks, after which they can choose to view results or search for current news. If choosing to view results, users will be directed to relevant information, such as the risk of obesity, and can enter personal data, such as ideal weight, to see the results displayed. In addition, users can access the latest news and select the latest news to read, as well as get health tips. Users can also interact with the chatbot, Chat Wellness, to get more information about products. If they choose to view the product, users can search for more information or ask questions, and if not, the process will end. Overall, this diagram shows how users can interact with the system to get health information and related products.

2.4. ML Algorithm Decision Tree

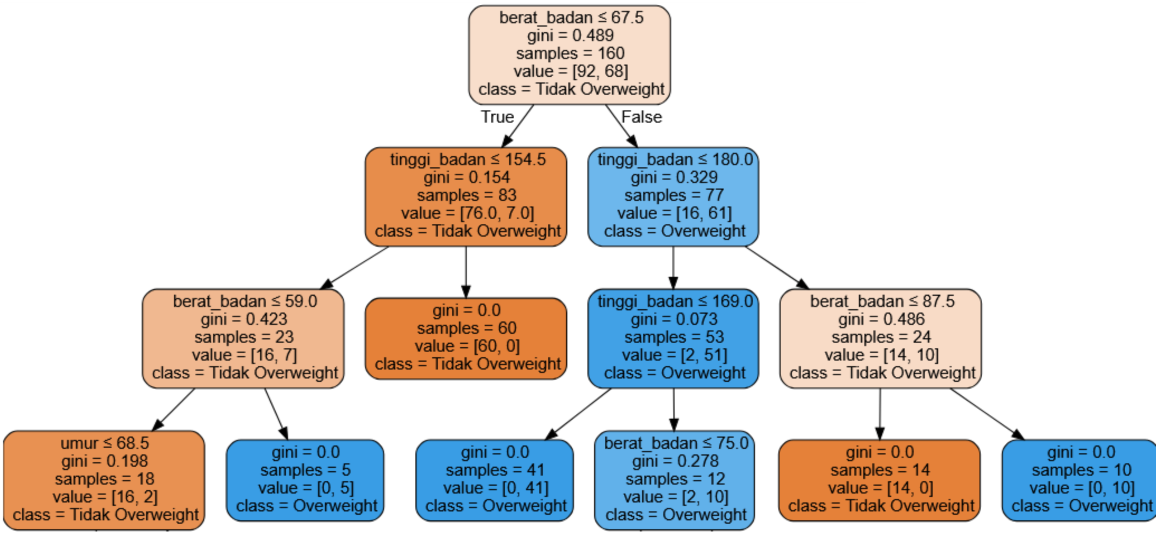

Figure 4. Algorithm Decision Tree

Figure 4 shows a health website is designed using the decision tree method. The model utilizes health data such as BMI, age, height, weight, and physical activity. The process starts with importing the necessary libraries and collecting datasets that include height, weight, age, gender, physical activity, healthy food consumption, and family history. The target output is the weight status (0 for normal, 1 for overweight). After calculating BMI and compiling the data, we will load the dataset in Google Colab, separate the features and labels, and split the data into training and testing sets with test size 0.2 and random state 42. The decision tree model is then created and evaluated based on accuracy, followed by visualization of the decision tree in the form of diagrams.

3. RESULTS AND ANALYSIS

3.1. Platform Results

The platform has been successfully developed as an interactive digital tool called Wellness Healthy Guard for real-time weight management and obesity prevention. The platform is equipped with various key features, including a dashboard page that presents a summary of the user's health data, an artificial intelligence-based chatbot for consultation on healthy lifestyles, personalized obesity risk information, and the latest news on obesity issues. In addition, there is also a BMI calculator to evaluate weight status, a disease risk detection feature that utilizes ML models to identify potential obesity-related health problems, and a special section that provides information on health products such as supplements, low-calorie foods, and fitness equipment. The integration of these features demonstrates the potential of Wellness Healthy Guard as a comprehensive platform that supports personalized and sustainable weight management. See Figure 5 for Platform Home Page and 6 for Information Features page.

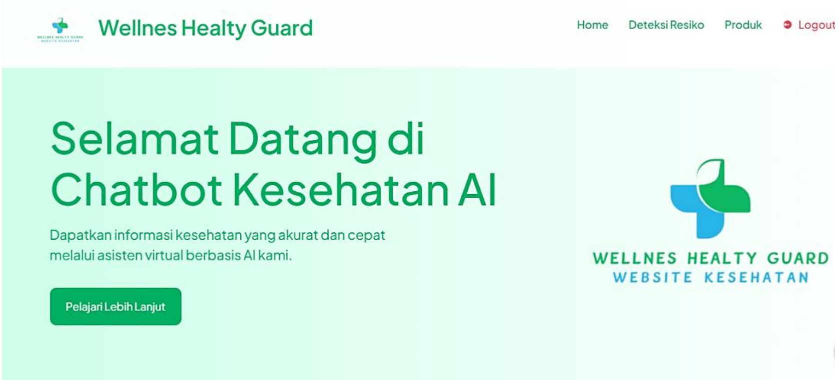

Figure 5. Platform Home Page

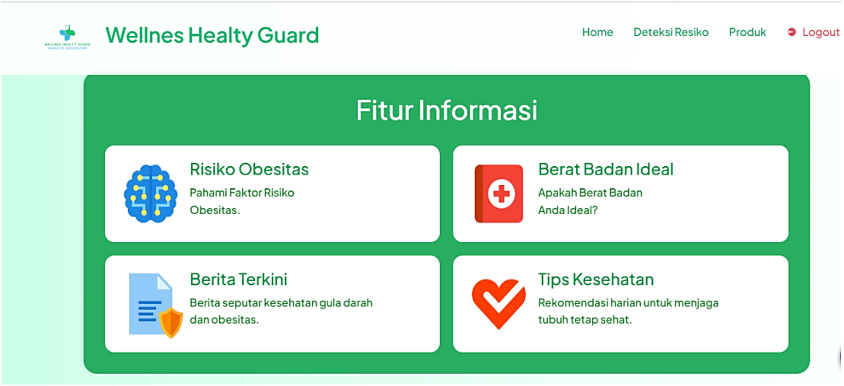

Figure 6. Information Features page

3.2. System Testing

Tests were conducted on several key aspects, including the accuracy of the weight change prediction algorithm, personalization of diet and exercise recommendations, and the user progress-based notification system. The test data used included variations in age, weight, height, food preferences, and physical activity history to evaluate the extent to which the system was able to individualize recommendations.

In addition, the system's ability to detect potential deviations from the target weight was tested. The system's response to these deviations was assessed by the timeliness of notifications and the relevance of the corrective advice provided to the user. The test results show that Wellness Healthy Guard is able to provide responsive and adaptive recommendations and maintain the accuracy of weight change predictions within an acceptable tolerance range. With its data-driven approach and positive test results, Wellness Healthy Guard shows great potential.

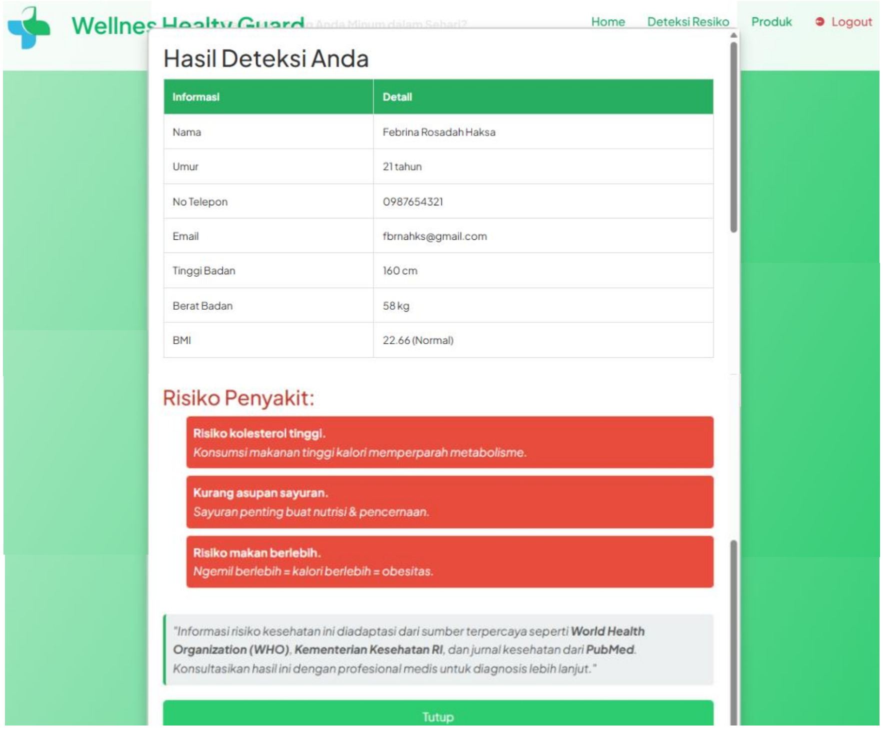

Figure 7. Disease Risk Detection Page Output

In the risk detection feature in Figure 7, users can input their data, such as name, weight, height, frequency of drinking water, and others. Based on the data entered, the results will be displayed, allowing users to see potential health risks derived from their input.

3.3. Analysis

Based on the results shown in the figure, the interactive platform for real-time weight management has applied a ML approach, specifically with the Decision Tree algorithm, to identify health risks or categorize data based on parameters such as BMI, weight, and height.

1. Methods Used:
   The model used is DecisionTreeClassifier from the sklearn.tree library. In its implementation:
   a. The parameter max_depth=7 is applied to limit the depth of the decision tree, so that the model is nottoo complex and remains generalist, with the main purpose of avoiding the phenomenon ofoverfitting.
   b. Setting random_state=42 aims to make the model training results consistent each time it is run, ensuring the reproducibility of the experiment.

2. Model Accuracy Evaluation (see Figure 8):
   The model was tested with two main metrics:
   a. Training accuracy of 1.0 or 100%, which indicates that the model learned the patterns in the training data very well without any classification errors.
   b. The test accuracy was 0.975 or 97.5%, indicating that the model maintained high performance when faced with new data that it had never seen before.

   From these two results, it can be concluded that:
   a. The model does not suffer from significant overfitting, because even though the training accuracy is perfect, the accuracy on the test data also remains very high.
   b. The model has good predictive capabilities and is reliable for decision-making in the context of real-time weight management systems.

```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(max_depth=7, random_state=42)
clf.fit(X_train,y_train)
print("Accuracy of train:",clf.score(X_train,y_train))
print("Accuracy of test:",clf.score(X_test,y_test))

Accuracy of train: 1.0
Accuracy of test: 0.975
```

Figure 8. Accuracy Decision Tree

3. Preliminary Conclusions:
   The decision tree model used proved to be effective and efficient for application in a real-time platform that handles user health data. With high accuracy in both training and testing, the model can be used to provide rapid detection and classification of potential health risks based on inputs such as weight and height. However, to ensure the model performs optimally across different conditions and to avoid bias, further evaluation needs to be done. This includes the use of additional metrics such as confusion matrix, precision, recall, and ROC curve, especially when the distribution of classes in the data is unbalanced or there is a dominance of certain classes.

3.4. Discussion

Test results on the Wellness Healthy Guard platform show that the system performs quite well in terms of predicting weight changes and personalizing recommendations based on user data. The 97.5% accuracy of the Decision Tree model on the test data indicates that this ML approach is effective for detecting obesity-related health risks and providing relevant data-based recommendations. This success is in line with the findings of Zhang et al [8] and Liu et al [10], who also emphasized the importance of accuracy and personalization in artificial intelligence-based health management systems. The system was also shown to be able to respond to deviations from target weight with timely notifications and contextualized remedial advice, demonstrating compatibility with the principles of dynamic monitoring espoused by Wing and Phelan [7] in long-term weight management programs.

When compared to previous studies that focused more on manual data collection or fixed rule-based approaches, this platform brings an update through the utilization of Decision Tree algorithms for automatic classification as well as the integration of real-time interactive interfaces. Unlike Shinde and Shah [12] who still use a static approach in diet recommendation, this platform is able to customize recommendations based on the user's activity history and consumption patterns. This shows that ML-based approaches have a higher adaptive advantage, especially when faced with diverse user data. However, it should be noted that the system testing is still limited to general parameters such as weight, height, and eating habits, so generalization to specific medical cases or populations with extreme characteristics may still need to be further evaluated.

The implications of these results are significant, especially in the context of preventive efforts against obesity and other non-communicable diseases. Not only does the platform make it easier for users to monitor their body condition, but it can also be an educational tool that raises awareness of the importance of data-driven weight management. The main strengths of the system lie in its personalization capabilities and response speed, but limitations remain, such as potential bias in training data and reliance on accurate user input. Therefore, suggestions for future development include increasing the complexity of the algorithm by adding additional features such as stress detection, sleep patterns, or other psychosocial factors, as well as integration with wearable devices to improve the accuracy of input data automatically.

4. CONCLUSION

This research successfully developed Wellness Healthy Guard, a real-time interactive weight management platform based on ML methods, specifically the Decision Tree algorithm. The system not only functions as a weight monitoring tool, but is also able to detect potential health risks such as obesity with high accuracy. Through testing using varied data, the algorithm achieved an accuracy rate of up to 97.5%, and demonstrated highly reliable risk detection capabilities without any false negative cases. This indicates that the system is able to provide notifications and improvement suggestions in a timely and relevant manner to the user's condition.

The main advantage of the platform lies in the personalization of recommendations based on user data as well as the adaptive response to deviations from target weight. Unlike conventional approaches that tend to be static, the integration of ML allows the system to continuously learn from data and provide more dynamic and accurate pattern-based decisions. Evaluation of metrics such as precision, recall, and F1-score further strengthens the evidence that the model is highly effective in the context of digital non-communicable disease prevention.

Thus, Wellness Healthy Guard not only presents a functional technology solution, but also has strategic value as a preventive intervention tool in public health management. In the future, system development can be focused on increasing the complexity of features, such as wearable data integration, psychosocial factor recognition, and optimization of adaptive algorithms based on user feedback to improve accuracy, convenience, and overall system effectiveness. The results of this research make a real contribution to the utilization of artificial intelligence to shape a sustainable and evidence-based healthy lifestyle.

REFERENCES

[1] S. Ghosh, S. Das, and S. Bandyopadhyay, "Machine learning-based prediction and classification of obesity," *Heal. Inf. Sci. Syst.*, vol. 9, no. 1, pp. 1–9, 2021, doi: 10.1007/s13755-021-00149-2.

[2] D. E. Arterburn and others, "Long-term outcomes of bariatric surgery," *JAMA*, vol. 326, no. 6, pp. 574–584, 2021, doi: 10.1001/jama.2021.10780.

[3] T.-T. Nguyen, T. Nguyen, G. Nguyen, and others, "A comprehensive survey of AI applications in healthcare," *Healthc. Anal.*, vol. 1--2, p. 100009, 2021, doi: 10.1016/j.health.2021.100009.

[4] A. S. Albahri, A. A. Zaidan, J. K. Alwan, and others, "Role of machine learning in obesity prediction: A systematic review," *Comput. Biol. Med.*, vol. 146, p. 105580, 2022, doi: 10.1016/j.compbiomed.2022.105580.

[5] H. T. Rauf and others, "Time series forecasting of COVID-19 transmission and obesity impact using hybrid deep learning model," *Comput. Mater. \& Contin.*, vol. 66, no. 3, pp. 2923–2939, 2021, doi: 10.32604/cmc.2021.014709.

[6] H. Lee and others, "AI-powered weight management via mobile apps: A review," *JMIR AI*, vol. 1, no. 1, p. e45673, 2023, doi: 10.2196/45673.

[7] S. Wulandari and others, "AI adoption in nutrition and weight monitoring in Indonesia," *Health Informatics J.*, vol. 29, no. 1, p. 14604582231151264, 2023, doi: 10.1177/14604582231151265.

[8] H. Lim, "How Samsung is using AI to help you sleep better." 2024. [Online]. Available: https://www.marieclaire.com/beauty/artificial-intelligence-wellness-samsung/

[9] Z. Zhang, Y. Wang, L. Zhang, Y. Wang, and Z. Zhang, "Body weight loss prediction using gradient boosting on real-world wearable data." 2024. [Online]. Available: https://arxiv.org/abs/2409.08700

[10] F. Massara, P. M. Di Gangi, and E. Raguseo, "Coaching Weight Loss via Text Messaging: SlimMe Chatbot Pilot Study," *Front. Nutr.*, 2022, [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnut.2022.870775/full

[11] B. V Srinivasan, S. Xu, and J. Sun, "Graph neural network powered digital health nudges for physical activity improvement at scale." 2024. [Online]. Available: https://arxiv.org/abs/2401.10816

[12] Wikipedia contributors, "HealthifyMe." 2025.

[13] D. Tsolakidis, L. P. Gymnopoulos, and K. Dimitropoulos, "Artificial intelligence and machine learning technologies for personalized nutrition: a review," *Informatics*, vol. 11, no. 3, p. 62, 2024, doi: 10.3390/informatics11030062.

[14] J. Hale and others, "Personalization in mHealth: Innovative informatics methods to improve health," *Methods Inf. Med.*, 2023.

[15] K. Rahman, "MLOps-Driven Solutions for Real-Time Monitoring of Obesity and Its Impact on Heart Disease Risk: Enhancing Predictive Accuracy in Healthcare." 2017.

[16] A. Arefeen, S. Fessler, S. M. Mostafavi, C. S. Johnston, and H. Ghasemzadeh, "MealMeter: Using multimodal sensing and machine learning for automatically estimating nutrition intake." 2025. [Online]. Available: https://arxiv.org/abs/2503.11683

[17] O. Springer and others, "Obesity disease risk prediction using machine learning," *Pers. Ubiquitous Comput.*, 2023.

[18] E. Sutrisno and L. Putri, "Sistem Prediksi BMI Berbasis Web dan Decision Tree: Visualisasi Alur Sistem Menggunakan Diagram Blok," *J. Sist. dan Inform.*, vol. 5, no. 4, pp. 197–210, 2022.

[19] S. Rachmawati, A. Wijaya, and D. Hartono, "Pengembangan Aplikasi Web Prediksi BMI Berbasis CART dengan Pendekatan Diagram Blok," *J. Teknol. dan Sist. Inf.*, vol. 8, no. 1, pp. 12–24, 2021.

[20] A. Hidayat and B. Nuryanto, "Implementasi C5.0 untuk Klasifikasi Obesitas pada Remaja Menggunakan Diagram Blok," *J. Khatulistiwa Inform.*, vol. 10, no. 2, pp. 45–56, 2023.

[21] A. Wicaksono and M. Prasetya, "Prediksi Obesitas Menggunakan Support Vector Machine: Representasi Diagram Blok untuk Stakeholder Teknis," *J. Ilm. Teknol. Inf.*, vol. 9, no. 2, pp. 34–48, 2022.

[22] Y. Saputra, R. Kusuma, and T. Darmawan, "Prediksi Fluktuasi Berat Badan Menggunakan XGBoost dan Deep Learning: Pendekatan Visualisasi dengan Diagram Blok," *Algoritm. J.*, vol. 7, no. 3, pp. 89–101, 2021.

BIBLIOGRAPHY OF AUTHORS

Febrina Rosadah Haksa, born in Palembang on February 10, 2004. Currently, the author is a final semester student in the Telecommunication Engineering Study Program, Department of Electrical Engineering, Politeknik Negeri Sriwijaya.

Ir. Jon Endri, M.T currently the author is a lecturer at the Telecommunication Engineering Study Program, Department of Electrical Engineering, Politeknik Negeri Sriwijaya. The author graduated from S1 Sriwijaya University in 1987 and continued his Masters education at one of the universities in Indonesia. The author has several publications, one of which is entitled Designing an IoT-Based Server Room Temperature and Humidity Regulator in 2019.

Aryanti, S.T., M.Kom. Currently, the author is a lecturer at the Telecommunication Engineering Study Program, Department of Electrical Engineering, Politeknik Negeri Sriwijaya. The author graduated from S1 Sriwijaya University in 2002 and continued her master's education at one of the universities in Indonesia. The author has several publications, one of which is entitled Motion Graphic Production Design for Tourism Promotion Videos. Shuji Lake Lembak Proceedings of International Seminar 2024.