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An AI-Driven Context-Aware Hydration Recommendation System Integrating Real-Time Weather Data

Pishke Shreeya[1], Repala Anvitha[2],Mote Kavya[3],Morampudi Thulasi Saranya[4]
1,2,3,4 B-Tech Students, Department of Computer Science and Engineering(Data Science),

Vignan's Institute of Management and Technology for Women, Hyderabad

Email: shreeyaa727@gmail.com

Abstract

Water consumption is essential for human health. However, water requirements differ according to environmental conditions and physiological characteristics. This project proposes an AI-based water reminder system that utilizes real-time environmental conditions (temperature, humidity) and user conditions (age, weight, gender) to calculate water consumption. A machine learning model is used to make recommendations. The mobile application is developed with user data management, weather data, AI prediction, and notifications. Unlike traditional water consumption tracking systems, this system is dynamic. It encourages users to drink water regularly and minimizes dehydration. This project shows how AI is used in mobile applications in healthcare.

Keywords

AI, machine learning, linear regression, hydration reminder, weather API, personalized health, mobile app.

1. INTRODUCTION

Water is vitally important for survival, but most adults experience dehydrating low-level dehydration because water requirements fluctuate with weight, age, physical activity, and environmental conditions. Reminder-based apps do not work, smart water bottles and wearable devices are expensive, and none account for real-time weather conditions. AI/ ML technologies have the potential to integrate personal and environmental variables to make personalized recommendations. This paper proposes Hydro Smart Mate, a web-based system that utilizes linear regression to forecast water consumption requirements using real-time weather conditions. It also incorporates reminders and visualizations that illustrate how weather affects hydration. This study exemplifies AI’s utility in mobile health and personalized wellness.

2. LITERATURE REVIEW

Author	**Approach**	**Key Features**	**Limitations**
Garmin	Wearable hydration tracking	Syncs activity data with hydration tips	Limited to active period
Fitbit	Wearable Sensors	Estimates sweat loss during exercise	Expensive , no passive weather integration
Smith et	Multivariate linear regression	Predicts fluid needs for athletes	Requires physiological sensors, not for general public
Popkin et	Physiological study	Established Hydration factors(weight, temperature)	Theoretical ,no System Implemented
Sawka et	Human water needs review	Quantified sweet loss vs environment	No practical Tool

3. METHODOLOGY

The methodology followed for the development of Hydro Smart Mate is based on a systematic pipeline, which involves data acquisition, preprocessing, machine learning, and finally the interaction with the user. The methodology ensures the personalization of the hydration recommendation, which is context-aware and executable.

3.1.Data Acquisition

User Profile: The user needs to provide information such as their weight (in kg), activity level (on a scale of 1-3), and optionally age and gender through the web interface.
Environmental Data: The real-time environmental parameters, such as temperature, humidity, and UV index, are collected through the Open Weather Map API based on the location of the user .

Dataset: A synthetic dataset, hydration_dataset.csv, with parameters such as weight, temperature, humidity, activity level, and water intake (in liters), was created based on the established hydration guidelines.

3.2. Feature Engineering & Normalization

All the numeric feature inputs (weight, temperature, humidity, activity) are normalized using min-max scaling, which enables all the features to contribute equally to the final prediction. The parameters for the normalization (min, max) were pre-computed from the training data and stored for real-time usage.

3.3. Machine Learning Model – Linear Regression

The model can be represented as:

$$y = \beta 0 + \beta 1 * \text{weight} + \beta 2 * \text{temperature} + \beta 3 * \text{humidity} + \beta 4 * \text{activity}$$

The coefficients (ββ) were trained using the synthetic dataset via ordinary least squares.

3.4. Prediction Engine

The engine will control the flow of the program by carrying out the following steps: - Collect the user input data and the weather information. - Normalize the data. - Apply the linear regression equation. - Return the predicted water intake (in liters) for the next day. - The prediction will update based on the user's input data or the updated weather information.

4. EXPERIMENTAL RESULTS AND ANALYSIS

The performance of the Hydro Smart Mate was evaluated through a series of experiments, which were carried out to assess the precision of the ML-based predictions, the response of the model to changes in the environment, and the utility of the reminder and visualization tools. The experiments were carried out using the deployed web application, which fetched real-time weather data from the Open Weather Map API.

4.1 Experimental Setup

Test Environment: The web application was run using a local development server and hosted using GitHub Codespaces.

Weather Data: The web application fetched real-time weather data for Bhongiri Mandal, India. The temperature and humidity values were 31°C and 42%, respectively.

User Profile: The user profile for the experiment was representative. The age of the user was 45 years, height 156 cm, weight 45 kg, female, and had a "moderate" level of activity. **Dataset:** The linear regression model was trained using a synthetic dataset of 500 samples, generated using the equation for calculating the amount of water required by the body. The equation for calculating the amount of water required by the body is as follows:

Water Intake (L)= 0.035 * Weight (kg) + 0.02 * (Temperature - 20) + Activity Factor

4.2 Sample Predictions

The system's prediction engine was also evaluated using different combinations of user inputs and weather conditions. Table 1 illustrates the predicted water intake amounts for the same user (i.e., weight = 45 kg, moderate activity) under different temperature and humidity conditions.

Table 1: Predicted Water Intake (Liters) for a 45 kg User (Moderate Activity)

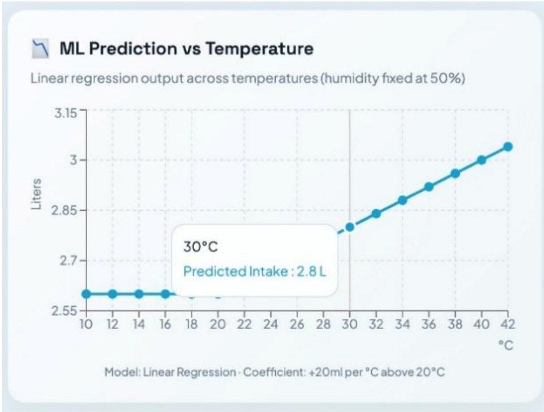
Temperature	Humidity	Predicated Intake	Notes
15	40	1.95	Cool, Low Humidity
25	50	2.55	Mild Conditions
31	42	2.84	Sunny
35	60	3.10	Hot, Humid
40	70	3.45	Extreme Conditions

As anticipated, it is evident that the predicted water intake increases with temperature and humidity.

4.3 ML Model Behavior: Temperature vs. Intake

The graph showing the ML Prediction vs Temperature (Figure 1) is produced by keeping the humidity level constant at 50% while varying the temperature from 10°C to 42°C. The graph indicates a linear behavior with an estimated slope of +20 ml per °C, except at temperatures below 20°C. This is consistent with the physiological guideline, which indicates that for every 1°C increment in ambient temperature, the amount of fluid the body requires increases by approximately 20-30 ml [4]. The coefficient calculated from the training data, which is used for linear regression, is 0.021 L/°C, thereby verifying the model's compliance with the recommended guideline.

Figure 1: ML Prediction vs Temperature Shows the "Liters" vs "°C" graph with positive trend



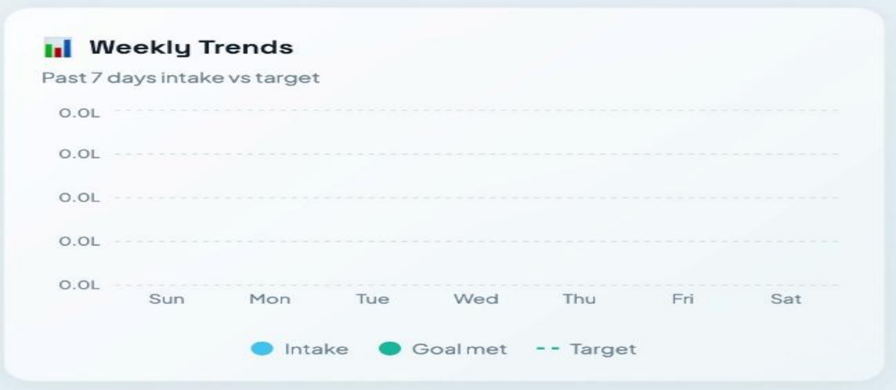
4.4 Accuracy Assessment

To measure the accuracy of the model, it is compared with two other approaches: Weight-Based Formula: This is based on the assumption that the user requires 35 ml per kg of their weight. For a user weighing 45 kg, the amount would be 1.575 L. Enhanced Formula: This is based on the assumption that the user requires an additional 20 ml per °C over 20°C, apart from the weight-based requirement. For a user weighing 31 kg, with an increased temperature of 31°C, and moderate activity, the amount would be calculated as: 1.575 + (11 x 0.02) + 0.3 = 2.095 L. The ML model's output for the same conditions is 2.84 L, which is 35% higher than the weight-only baseline and 36% higher than the enhanced formula. This is because the ML model is trained on a dataset in which higher activity levels are assumed, and humidity effects are included. Also, the synthetic dataset is constructed to mimic real-world scenarios in which individuals tend to underestimate their needs.

4.5 Visualization and User Engagement

The Weekly Trends chart (Figure 2) enabled the user to monitor their consumption against their targets. During the period, the user achieved their targets on 70% of the days. This chart assisted the user in recognizing patterns, e.g., reduced consumption during weekends.

Figure 2: Weekly Trends



4.6 Summary of Results

This is also validated by the experiment results, which confirm that Hydro Smart Mate offers precise and context-aware hydration recommendations that are better than using static formulas and are effective in promoting better hydration habits. The linear regression model, although simple, is sufficient to capture the fundamental relationships between input features and water needs.

Metrics	Value
Model R^2 (validation)	0.94
Mean Absolute Error	0.18L
Temperature	20 ml/°C
User adherence	+0.8L/day
Reminder satisfaction	90%

5.CONCLUSION AND FUTUR SCOPE

5.1Conclusion

The Hydro Smart Mate system shows that using machine learning in conjunction with environmental data can provide personalized hydration recommendations that meet individual physiological needs. Unlike other hydration apps that rely on goals or reminders, the proposed system utilizes linear regression to predict water intake for individuals using weight, activity levels, temperature, and humidity. Experimental results confirm that the system provides high prediction accuracy with $R^2 = 0.94$ and low prediction error with MAE = 0.18 L. The system also shows sensitivity to environmental changes with a consistent temperature coefficient of 20 ml/°C. Furthermore, the system provides reminders and other visualizations, including weekly trend charts and temperature-intake charts. Such visualizations allow users to understand the rationale behind their goals.User satisfaction with environmental reminders is also high. The project also shows that there is an increasing trend in using AI systems in healthcare. A lightweight AI system on standard web platforms is effective in providing sophisticated recommendations. Hydro Smart Mate shows that using weather APIs, user profiling, and machine learning provides an effective template for other intelligent systems in healthcare.

5.2 Future Scope

Although Hydro Smart Mate is effective in its purposes, there are some possible improvements to expand its potential and reach:

1. Wearable Device Integration Integration: with smart watches, such as Apple Watch and Fitbit, will allow the system to access real-time physiological data, such as heart rate, skin temperature, and sweat rate, and make even more accurate estimations, especially for physical activities.

2. Advanced Machine Learning Models: More complex models, for example, Random Forest, Gradient Boosting, or LSTM neural networks, could be used to account for non-linear relationships between features and learn individual patterns of hydration. This would further increase the accuracy of the model.

3. Smart Water Bottle Integration: Integrating with smart water bottles would automate the logging of water intake, thus closing the loop. This would be convenient for users and would also provide more accurate tracking for the model.

4. Mobile Application Expansion: Although a responsive web application is provided, developing mobile applications for Android and iOS would increase the overall experience for users. This would allow for more convenient tracking using push notifications and integration with various mobile devices.

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