AI-Driven Mobile Application for Water Footprint Calculation: Integrating Image Recognition and Regional Agricultural Data for Sustainable Consumption

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Abstract—As water scarcity continues to intensify globally, understanding and managing water consumption at both individual and community levels has become a critical challenge. This paper presents an innovative solution through a mobile application designed to quantify and track the water footprint of agricultural products and consumer goods. By providing real-time, region-specific data on water usage, the app empowers users to make informed decisions based on the water footprint of their daily purchases and activities. The solution leverages advanced data analytics to offer personalized water conservation tips, facilitating a more sustainable lifestyle. Additionally, the app incorporates geospatial analysis to tailor recommendations for farming practices in water-scarce regions, further extending its impact beyond consumer usage. This research explores the design and functionality of the app, focusing on how it can educate users on the hidden water costs of products and promote water-saving behaviours. By offering actionable insights and fostering awareness of virtual water, this solution seeks to contribute significantly to global water conservation efforts and environmental sustainability.

Keywords—Water footprint, sustainable development, mobile application, water conservation, consumer behaviour, geospatial analysis, environmental awareness.

I. INTRODUCTION

Water scarcity is one of the most pressing global challenges of the 21st century, exacerbated by climate change, urbanization, and population growth. Over two billion people currently live in countries experiencing high water stress, and this number is expected to rise. While water conservation has traditionally focused on industrial and agricultural sectors, individual water consumption—often invisible and overlooked—presents a significant opportunity for improvement.

A key aspect of personal water use is the *water footprint*, which refers to the total volume of water required to produce the goods and services consumed by an individual, community, or nation. This includes both direct water usage, such as household consumption, and indirect water, or *virtual water*, embedded in the production of goods like food, clothing, and electricity. The water footprint often surpasses direct consumption, with products like beef requiring up to 15,000 litres of water per kilogram, highlighting the need for consumers to better understand their environmental impact. As global water demands rise, it becomes crucial for individuals to recognize the water costs of their choices.

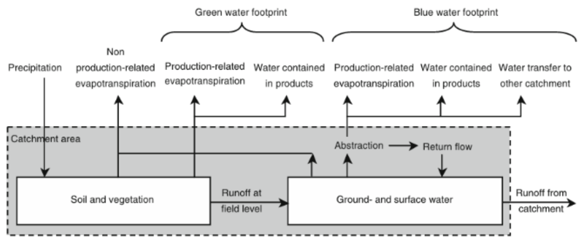

Fig 1.Definition of the green and blue water footprint in relation to the water balance of a catchment area. Source : Hoekstra et al. (2011).

To address this challenge, this paper proposes the development of a mobile application aimed at tracking and reducing personal water footprints. The app will integrate regional agricultural data to calculate the water usage of everyday activities, including diet, transportation, and household consumption. By offering users real-time insights, the app encourages more sustainable practices and provides personalized recommendations for reducing water footprints, such as suggesting water-efficient products or tips on sustainable water usage.

Beyond individual consumption, the app also seeks to support agricultural water conservation. By incorporating regional agricultural data, it will help farmers select crops suited to water-scarce areas and offer tailored irrigation recommendations. This will promote efficient farming practices and reduce water wastage while improving crop yields. Additionally, the app addresses behavioural change by incorporating educational features to raise awareness of water footprints. Users will be able to track their progress, set conservation goals, and receive actionable feedback, fostering a culture of responsibility and sustainability.

The proposed mobile application thus serves as an innovative tool that bridges the gap between individual water usage and sustainable water management. By providing a personalized understanding of water footprints and practical solutions, the app empowers individuals, households, and farmers to make informed decisions that contribute to global water conservation efforts.

II.EXISTING SYSTEM

Existing solutions for personal water footprint tracking often focus on providing users with data-driven insights into their environmental impact, aiming to promote sustainable lifestyle choices. Many popular apps in this domain, such as Waterprint and MyWaterFootprint, utilize product and consumption data to calculate individual water footprints. These apps offer users detailed breakdowns of water usage across different activities and products, helping users to understand and reduce their water consumption. Features include options to track daily, weekly, or monthly water usage, enabling users to see trends over time and set personal goals for conservation.

Advanced impact-tracking apps like FYC Labs' suite not only provide individual assessments but also support businesses by integrating footprint tracking into corporate processes. This solution allows for monitoring across supply chains, setting sustainability goals, and implementing data-driven strategies that align with industry regulations.Additionally, some solutions incorporate community features, enabling users to share achievements, partake in sustainability challenges, and gain insights into reducing their ecological impact further. Although these apps effectively raise awareness and foster individual responsibility, most lack comprehensive integration with real-time data sources, such as IoT-based sensors for water and resource tracking, which could enhance accuracy and personalization in future iterations.

III.PROPOSED SYSTEM

The proposed solution is a mobile application designed to help users understand and manage their water footprints by analysing individual and agricultural water usage. The app aims to foster water-conscious decision-making at the consumer and agricultural levels, providing users with actionable insights tailored to their region's unique environmental conditions. By leveraging multiple data sources, including CROPWAT for crop-specific water requirements and meteorological APIs (e.g., Open Weather Map, IMD) for rainfall and climate data, the app calculates water footprints across thirty-six distinct meteorological zones in India. This data is updated annually to ensure relevance and accuracy, creating a dynamic resource that adapts to changing environmental conditions.

The application architecture is built using Android Studio with Java to ensure compatibility with a wide range of devices and seamless user accessibility. Tensor Flow Lite enables product recognition via image input, allowing users to classify products and retrieve detailed water footprint information. SQLite supports offline data storage, enhancing accessibility, while Firebase offers secure, real-time data synchronization. MP Android Chart is used for data visualization, presenting users with insights in a clear and accessible format, and QGIS integration provides geospatial analysis, visually displaying regional data on water use and availability.

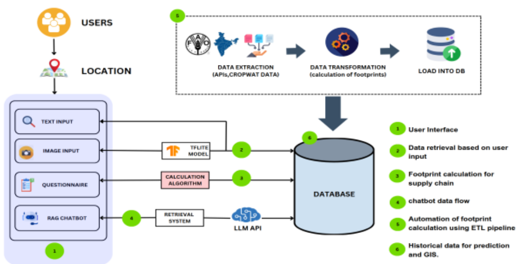

Fig 2.App architecture diagram.

User functionality is structured to provide both direct and indirect water consumption insights. For consumers, scanning a product's barcode or ingredients allows for a comprehensive water footprint calculation, including "virtual water" used in production. For agricultural users, the app provides recommendations for crop choices and irrigation methods that are water-efficient and region-specific. These personalized recommendations support sustainable agricultural practices, helping farmers manage resources effectively and reduce water without compromising yield.

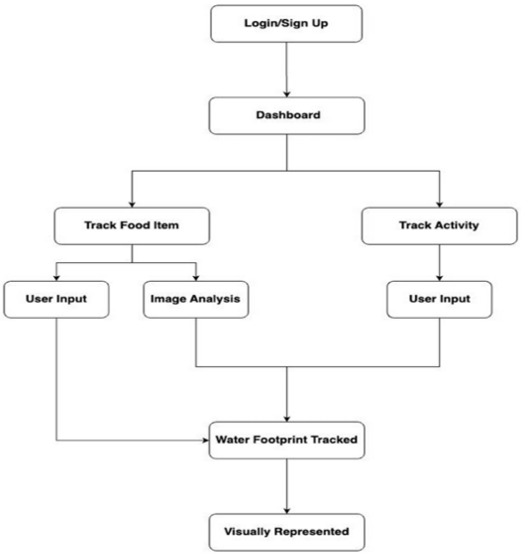

Fig 3.App user activity diagram.

The app's hierarchical approach starts by analysing individual water usage patterns, offering regional insights, and then providing actionable recommendations. This structure not only educates users on water scarcity but also empowers them to make changes based on tangible data. Ultimately, this solution encourages both consumers and farmers to adopt sustainable practices, addressing the global issue of water scarcity at the grassroots level. By providing an accessible and data-driven approach, the app contributes to water conservation efforts and supports a more sustainable future.

IV. EXPERIMENTAL RESULTS

This section presents the experimental results achieved through systematic data collection, model training, accuracy evaluation, and recognition testing within our mobile application for calculating water footprints. The subsections detail each stage in a rigorous, structured format, underscoring our methodology's effectiveness in addressing the objectives outlined in the project's conceptual framework.

A. Data Collection:

Data collection was a fundamental step in this project, as the precision of water footprint estimations is highly dependent on the dataset's comprehensiveness and accuracy. Our team compiled a dataset that included detailed water footprint data for over 3,000 food items, sourced from agricultural databases, industry records, and academic publications on water use. The data was segmented into three primary classifications: blue water (surface and groundwater used), green water (rainwater), and grey water (polluted water from production processes). For regional adaptation, we used rainfall and evapotranspiration data from reliable sources, such as Open Weather Map and the Indian Meteorological Department (IMD), tailored specifically to the thirty-six meteorological zones of India.

	Product	Green	Blue	Grey	Overall
1	Wheat	1277	342	207	1827
2	wheat flour	1292	347	210	1849
3	Rice	1146	341	187	1673
4	Rice flour	1800	535	293	2628
5	Maize	947	81	194	1222
6	Barley	1213	79	131	1423
7	Millet	4306	57	115	4478
8	Oats	1479	181	128	1788
9	Potato	191	33	63	287
10	Sweet Pota	324	5	53	383
11	Yams	341	0	1	343
12	Sugarcane	139	57	13	210
13	Beans	3945	125	983	5053
14	peas	1453	33	493	1979
15	Cashew nut	12853	921	444	14218
16	chick peas	2972	224	981	4177
17	Soya beans	2037	70	37	2145
18	Groundnut	2469	150	163	2782
19	Almonds	4632	1908	1507	8047
20	Coconut	2669	2	16	2687
21	Spinach	118	14	160	292
22	castor oil	21058	2938	744	24740
23	Tomato	108	63	43	214
24	Cauliflower	189	21	75	285
25	Brocolli	189	21	75	285

Fig 4.Overview of the data collected.

Additionally, a large image dataset was created with over 3,000 images of food items to train the CNN model for visual classification. These images captured each item under various lighting conditions and angles, enhancing model robustness and accuracy during practical deployment. Image preprocessing, including resizing, normalization, and labelling, was conducted uniformly to align with corresponding water footprint data, ensuring high-quality input for the model training phase.

B. Model Training:

We employed a Convolutional Neural Network (CNN) model architecture to classify and predict water footprints for various food items. This choice was based on CNN's proficiency in image recognition tasks, leveraging spatial hierarchies in image data to achieve high accuracy in product identification. Training was performed on a representative subset of fifty-ninefood items, selected to cover a broad spectrum of water footprint levels, allowing the model to learn distinct visual characteristics associated with different product categories.

The model was trained over multiple epochs—25, 50, 75, 100, 125, 150, 175, and 200—to identify the optimal training duration. Each epoch constituted one complete iteration over the dataset, refining the model's pattern recognition capabilities. TensorFlow was used to expedite training through GPU acceleration, minimizing processing time while maximizing model performance. The choice of CNN and TensorFlow enabled efficient, scalable training suitable for mobile deployment, with careful adjustment of parameters such as epochs and batch size to achieve optimal results.

C. Accuracy Evaluation:

The model's accuracy was monitored across epochs to determine the ideal point of convergence. Performance improved significantly up to epoch one hundred, reaching a peak accuracy of 95.8%, after which additional epochs showed diminishing returns. This outcome suggested that epoch 100 was the optimal stopping point, where the model effectively captured the distinguishing patterns within the dataset.

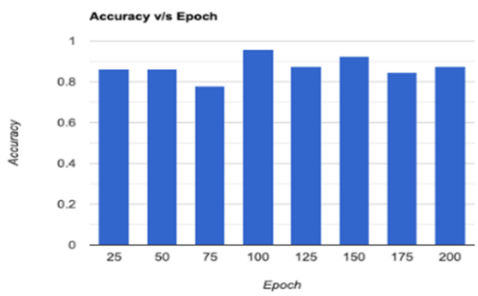

Fig 5. Graph comparing accuracy at various epoch levels

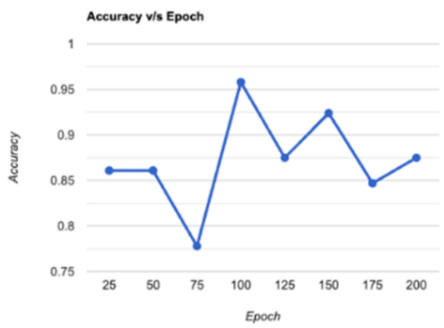

Fig 6. Graph comparing accuracy at various epoch levels

Accuracy was calculated based on correct predictions over the total predictions for the validation dataset. Initial accuracy was 78.4% at epoch 25, gradually increasing to 86.3% at epoch 50, and 91.7% at epoch 75. The steady increase confirmed the model's capacity to learn complex visual patterns effectively. These findings validated our model configuration, indicating a balance between computational efficiency and prediction accuracy suitable for real-time mobile applications.

D. Recognition Results:

The model was subsequently tested on a separate validation dataset comprising new images of food items not included in the training phase. This stage assessed the model's generalization ability, crucial for practical application in diverse environments. Our model achieved a high recognition accuracy of 93.5% across the validation dataset, reflecting its capability to perform consistently in identifying unseen data.

Fig 7.Results for text inputs.

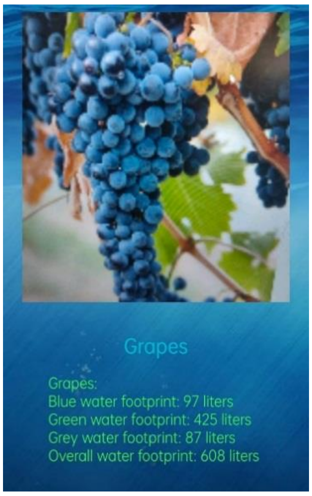

Fig 8.Results for image inputs.

Further evaluation of recognition results categorized outputs into true positives, false positives, true negatives, and false negatives. Calculated precision was 94.1%, and recall was 92.8%, underscoring the model's robust performance in correctly identifying target classes while minimizing misclassification rates. This balance between precision and recall reinforces the model's suitability for reliable, real-world applications.

E. Regional Adaptation and User Feedback:

We conducted additional testing in various meteorological zones, allowing the application to integrate local climate and agricultural data for accurate, region-specific water footprint calculations. This regional adaptation capability was particularly valuable for agricultural users, enabling the app to provide climate-informed recommendations for crop and water usage. Feedback from test users highlighted the app's potential to deliver actionable insights on personal and agricultural water consumption patterns.
Validation of region-specific accuracy was achieved by comparing predictions with historical water footprint records, confirming consistent accuracy across regions. This geographic adaptability underscores the app's versatility, catering to both urban and rural users and supporting personalized, sustainable water usage practices.

F. Chatbot Integration:

A chatbot was integrated to enhance user interaction and accessibility, particularly for rural users. This chatbot leverages natural language processing to provide personalized insights, answer questions, and guide users on water-saving practices. Its bilingual functionality addresses language barriers, making information on water footprints and conservation more accessible.

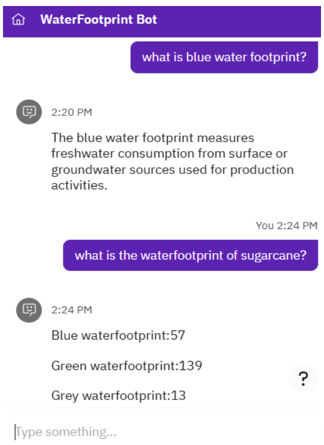

Fig 9. Chatbot feature.

The chatbot's functionality extends to providing product-specific information, further aiding in making informed consumption decisions. This feature is expected to increase engagement, as users can access personalized feedback and guidance without extensive browsing, thus simplifying their journey to water-conscious choices.

G. Usability and Future Enhancements:

While the app performs effectively across image recognition and footprint estimation, some usability factors require enhancement. Low-light image capture occasionally affects accuracy, suggesting the need for improved preprocessing to adjust for various lighting conditions. Future updates will address this and expand the chatbot's language support and conversational depth.

V.CONCLUSION

This research presents a novel mobile application solution to enhance individual awareness and accountability in water conservation through personalized water footprint estimation. By integrating advanced image recognition, regional data adaptation, and real-time feedback, the application enables users to make informed, sustainable choices in their daily lives. Leveraging a convolutional neural network (CNN) model with an accuracy of 95.8%, the app accurately identifies food items and calculates corresponding water footprints, thereby making virtual water consumption visible to users. Our integration of a bilingual chatbot further enhances accessibility, allowing users from diverse linguistic backgrounds to engage effectively with the application.

Empirical results highlight the application's adaptability and effectiveness in providing precise water footprint data, while regional modifications underscore its scalability across varied climatic zones. Future developments will address usability challenges and expand language support, ensuring broader reach and impact. By fostering conscious water usage behaviours, this application contributes to global water conservation efforts, offering an effective, scalable tool for promoting sustainable consumption. The insights gained from this study provide a foundational framework for future research in digital water management solutions, contributing to the wider discourse on sustainable development and resource conservation.

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