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Performance Evaluation of an Artificial Intelligence-Assisted Mobile Application for Dietary Oxalate Assessment in Kidney Stone Prevention

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Olumide A. Ojo [1], Ferdinand Anokwuru [1], Jessica Javaherforoush [2], Andersen Teoh [3], Janelly Jimenez [4], Bhushan Suryavanshi [5], Kymora B. Scotland [4], Robert Chan [3]

1. Urology, Charles R. Drew University College of Medicine, Los Angeles, USA 2. Urology, University of California, Los Angeles (UCLA), Los Angeles, USA 3. Urology, MarinHealth Urology, Greenbrae, USA 4. Urology, David Geffen School of Medicine, University of California, Los Angeles (UCLA), Los Angeles, USA 5. Applied Artificial Intelligence, StoneFree AI Inc, San Francisco, USA

Corresponding author: Robert Chan, cardinalrcc@gmail.com

Abstract

Background and objective

Calcium oxalate nephrolithiasis is the most common type of kidney stone disease. Dietary oxalate intake is an important modifiable factor. Assessing dietary oxalate exposure in clinical practice poses challenges due to limitations of traditional dietary recall tools and variability in food composition data. Artificial intelligence (AI) applications in mobile health may offer scalable solutions for better dietary monitoring and kidney stone prevention. We examined the ability of StoneFree AI (StoneFree AI Inc., San Francisco, CA) to estimate dietary oxalate from natural-language text and image-based food inputs.

Methodology

StoneFree AI uses Google Gemini 2.5 Flash to interpret food inputs. Performance was evaluated using 804 researcher-generated text descriptions containing explicit food and portion-size information and 275 food images from the Automated Self-Administered 24-Hour Dietary Assessment Tool (ASA24) portion-size image database. Text-based oxalate estimates were compared with Harvard Oxalate Database reference values using absolute error, agreement within ±1, ±5, and ±10 mg, and the concordance correlation coefficient (CCC). Image outputs were assessed using recorded error categories covering food identification, portion size, ingredient recognition, oxalate reference selection, inability to analyze, and other errors.

Results

Among the 804 text entries, 660 (82.1%) estimates were within ±1 mg of the reference values, 736 (91.5%) were within ±5 mg, and 760 (94.5%) were within ±10 mg. The mean absolute error was 3.32 mg, the median absolute error was 0.10 mg, and the CCC was 0.860. Among the 275 image entries, 161 (58.5%) had a recorded error. Error categories included food identification in 91 (33.1%) entries, portion size in 30 (10.9%), ingredient recognition in 14 (5.1%), inability to analyze in 14 (5.1%), other errors in 11 (4.0%), and oxalate reference selection in 1 (0.4%). The remaining 114 (41.5%) entries had no recorded error code; absence of a code was not treated as independently verified correctness.

Conclusions

StoneFree AI showed favorable agreement with reference oxalate values for controlled, researcher-generated text descriptions. Image assessment identified substantial food-identification, portion-size, and ingredient-recognition errors. These findings describe internal benchmark performance and do not establish accuracy for patient-generated dietary reports or clinical outcomes. Independent evaluation and prospective clinical validation are needed before clinical implementation.

Categories: Urology
Keywords: artificial intelligence, calcium oxalate, dietary assessment, dietary oxalate, food recognition, kidney stones, large language models, mobile health

Introduction

Calcium oxalate nephrolithiasis is the most prevalent type of kidney stone disease and a significant health problem worldwide. Nutrition-related factors play a key role in the formation of calcium oxalate stones, and dietary oxalate intake is a direct factor in urinary oxalate excretion and calcium oxalate supersaturation [1-3]. There is evidence that targeted oxalate management along with sufficient dietary calcium, hydration, and reduction of sodium decreases the risk of recurrence. Secondary prevention, however, depends on the correct

assessment of diet and patient education that can be applied in everyday life [4,5].

Accurate assessment of dietary oxalate intake is difficult in routine clinical practice. Furthermore, there is significant variation in the oxalate content of plants, processing methods, and analytical techniques, and common tools like food frequency questionnaires and 24-hour dietary recalls are subject to recall bias, underreporting, and variability in food composition [5-7]. There are many patient resources available, and many of them have outdated or overly simplified oxalate lists, which can lead to confusion and inconsistent advice for patients. These barriers restrict individual counseling and the effectiveness of dietary prevention strategies.

Mobile health apps with artificial intelligence (AI) capabilities could be the answer, as they enable real-time, personalized feedback and allow for ongoing dietary tracking. While mobile apps can help with kidney stone prevention, AI-based dietary oxalate estimation methods need further validation before they can be widely used in clinical practice [8-10]. In this study, an AI-based mobile app to estimate dietary oxalate intake and important nutritional parameters for kidney stone prevention is evaluated.

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Materials And Methods

Ethical considerations

This study was a preclinical performance evaluation using reference food data and standardized food images. No human participants were enrolled, and no patient information was collected. Thus, institutional review board approval was not necessary.

Application development

StoneFree AI (StoneFree AI Inc., San Francisco, CA) was developed as a cross-platform mobile application to help patients at risk of calcium oxalate nephrolithiasis with dietary oxalate tracking. The application used the Flutter framework and Dart programming language for iOS and Android.

The development was done using an iterative product design methodology, which combines Agile software development and AI-assisted product design. Early prototypes were used to determine whether real food inputs could be converted into structured nutritional data for the estimation of oxalate.

The StoneFree AI workflow is shown in Figure *1*.

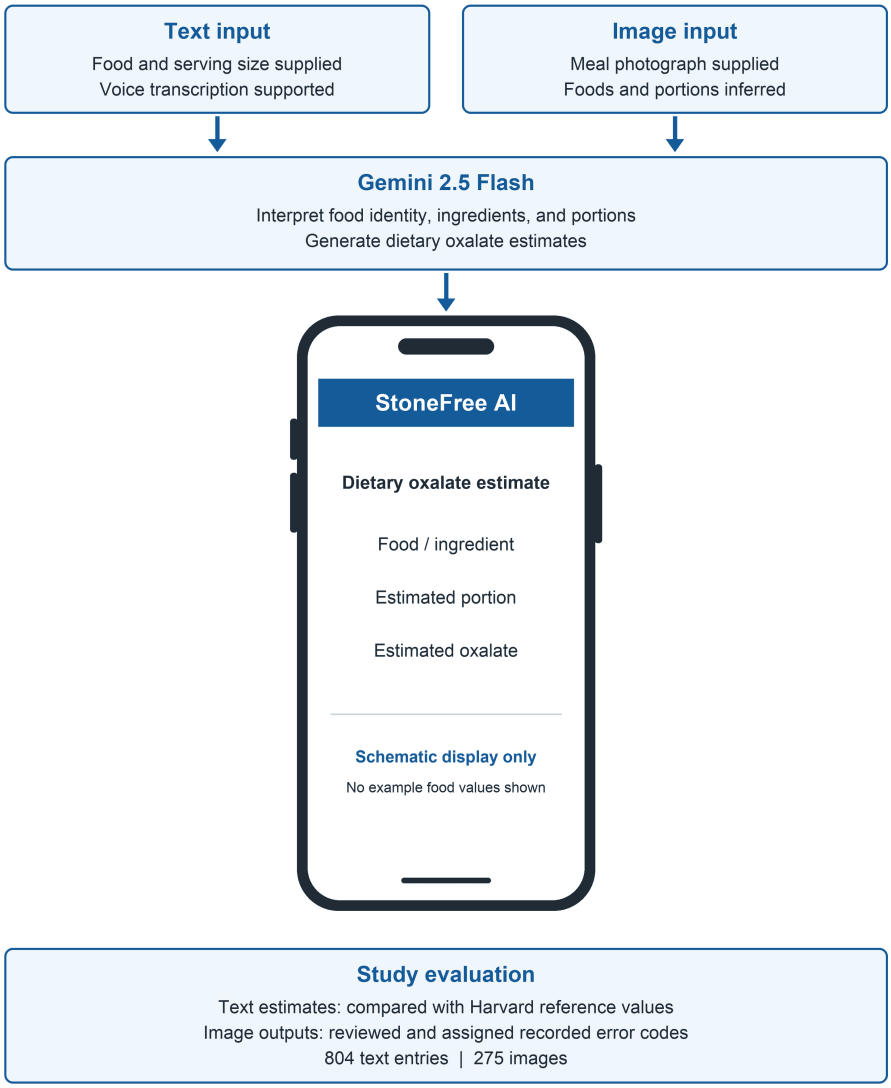

FIGURE 1: StoneFree AI workflow.

Schematic workflow, not an application screenshot. The phone display contains no measured results or example food-specific oxalate values. Voice recognition and transcription accuracy were not evaluated. Harvard reference values were used for evaluation; a separate application database-lookup step is not established by the supplied prompt. Figure created by the authors using Microsoft PowerPoint (Microsoft Corp., Redmond, WA).

AI, artificial intelligence

User Input Modalities

The application supports text food descriptions, voice transcription, and meal photographs. The present study evaluated researcher-generated text descriptions and standardized food images. Speech recognition and speech-to-text transcription accuracy were not evaluated. The inputs represented controlled benchmark conditions rather than patient-generated dietary records.

AI Processing and Prompts

The Google Gemini 2.5 Flash model was used to interpret food inputs. Natural-language text entries used the template “I had one (serving size) of (food item),” with the food and serving size specified for each entry. For image inputs, the supplied system prompt instructed the model to identify distinct foods or ingredients, estimate their portions, and provide per-item nutritional information and a confidence level. Requested nutritional information included calories, protein, carbohydrates, fats, sodium, calcium, and oxalate content. The prompt requested oxalate output as low, moderate, high, or very high, with approximate milligram values if reliable data were available. The prompt referred generally to standard nutritional databases and established urological dietary guidelines. It did not explicitly name the Harvard Oxalate

Database. The verbal-entry template and full image system prompt are reproduced in the Appendix.

Dataset and Performance Evaluation

The evaluation included 804 researcher-generated natural-language food descriptions containing explicit food and portion information and 275 food images from the Automated Self-Administered 24-Hour Dietary Assessment Tool (ASA24) portion-size image database [11]. The text descriptions were not obtained from patients, and the study did not evaluate the full variability, ambiguity, or incompleteness of real-world dietary reporting.

Text-based oxalate estimates were compared with reference values from the Harvard Oxalate Database. Performance was summarized using the proportions of estimates within ±1, ±5, and ±10 mg of the reference value. Additional measures included mean absolute error (MAE), median absolute error, interquartile range (IQR), mean and median signed error, and the CCC. Signed error was defined as the AI estimate minus the reference value.

Because the error distribution contained many exact-zero values and was markedly skewed, threshold-based and distribution-free summaries were emphasized. A percentile bootstrap with 20,000 resamples was used to estimate a 95% confidence interval for the MAE. A sensitivity analysis calculated the MAE and median absolute error after excluding the 354 entries with exact agreement. The 20 entries with the largest absolute differences were ranked in an exploratory analysis.

The histogram displayed nonzero signed errors between -20 and +20 mg. The 354 exact-zero entries and 24 observations outside this range were omitted from the histogram only and retained in the full-dataset calculations. The empirical cumulative distribution included all 804 entries, although its horizontal axis was limited to 20 mg for readability.

Image Error Assessment

Image-based outputs were reviewed and recorded with error codes in the shared spreadsheet. Error categories covered food identification, portion size, ingredient recognition, oxalate reference selection, inability to analyze an image, and other errors.

Image outcomes were summarized using the final corrected category totals supplied by the study team. Each image with a recorded error code was counted once in the overall error rate and the corresponding food category error rate. Entries without an error code were described as having no recorded error rather than being assumed to be independently verified as correct.

Food-category error rates were calculated as the number of images with a recorded error code divided by the number evaluated in that category. Eight food categories were presented individually. These included meat, poultry, and seafood; vegetables; mixed dishes; grains; baked goods; fruit; nuts and seeds; and candy. These categories included 230 images. The remaining 45 images belonged to other categories or had no food category label.

Development and Evaluation Overlap

The benchmark sources contributed to application development and prompt refinement as well as performance evaluation. The findings were therefore interpreted as internal benchmark performance rather than independent external validation.

Results

Performance of natural-language text entries

Using the Harvard Oxalate Database as the reference, 804 natural-language food entries were evaluated. Overall, 660 (82.1%) of estimates were within ±1 mg, 736 (91.5%) were within ±5 mg, and 760 (94.5%) were within ±10 mg. The MAE was 3.32 mg (bootstrap 95% confidence interval (CI) 2.10-4.83), and the median absolute error was 0.10 mg (IQR 0.00-0.70). Exact agreement occurred in 354 (44.0%) entries. The mean signed error was +0.03 mg, the median signed error was 0.00 mg (IQR -0.10 to 0.23), and the CCC was 0.860. Among the 450 entries with nonzero errors, the MAE was 5.93 mg, and the median absolute error was 0.50 mg. The difference between the mean and median indicates that a small number of large discrepancies disproportionately increased the mean error. Figure *2* shows the distribution of nonzero signed errors within ±20 mg.

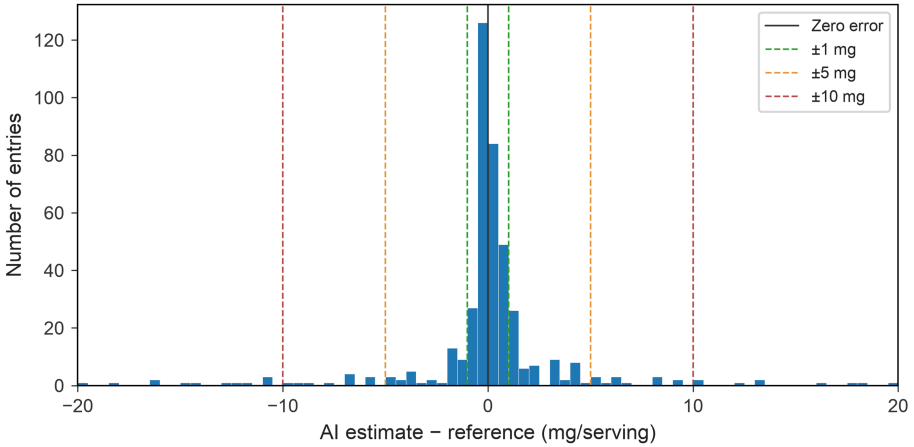

FIGURE 2: Distribution of nonzero text estimation errors.

Signed error is the AI estimate minus the reference oxalate value in mg per serving. The histogram displays 426 nonzero errors between −20 and +20 mg, using 0.5-mg bins. The 354 exact-zero errors and 24 observations outside this range are omitted from this plot only; all 804 entries remain in the full-dataset calculations. Dashed lines mark ±1, ±5, and ±10 mg.

AI, artificial intelligence

Distribution of natural-language text errors

The empirical cumulative distribution confirms that most absolute errors were small despite a long right tail: among 804 entries, 660 (82.1%) had absolute errors ⩽1 mg, 736 (91.5%) had absolute errors ⩽5 mg, and 760 (94.5%) had absolute errors ⩽10 mg (Figure *3*). The zero-inflated, skewed distribution and the gap between the median absolute error (0.10 mg) and MAE (3.32 mg) show why threshold-based and distribution-free summaries are informative for this benchmark.

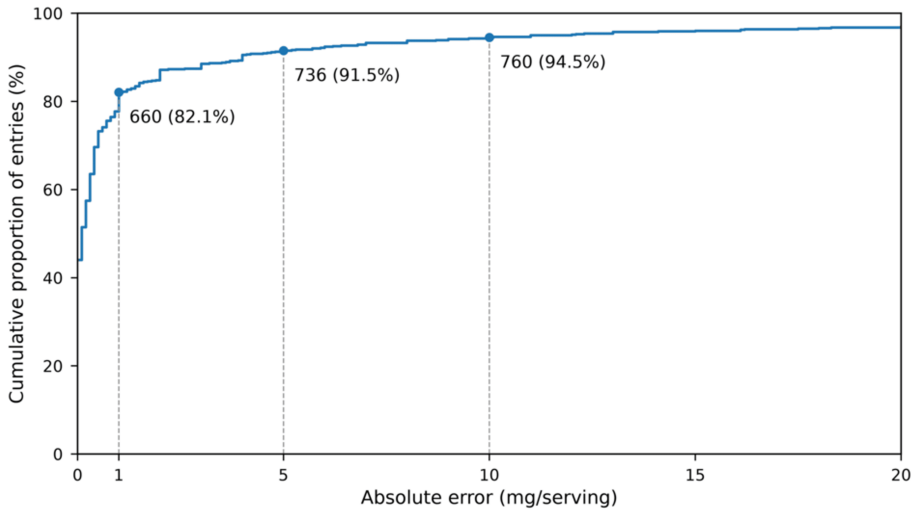

FIGURE 3: Cumulative distribution of absolute text estimation errors.

Empirical cumulative distribution of absolute errors for all 804 text entries. Exact agreement occurred in 354 (44.0%) entries; 660 (82.1%), 736 (91.5%), and 760 (94.5%) entries had absolute errors of at most 1, 5, and 10 mg per serving, respectively. The horizontal axis is limited to 20 mg; all 804 entries remain in the denominator.

Oxalate discrepancies

A small subset of foods accounted for the largest absolute errors, and the largest error observed was 377 mg. High-discrepancy items included high-oxalate vegetables and certain prepared foods. Examples included cooked spinach (reference 755 mg vs. AI 378 mg; absolute error 377 mg), rhubarb (reference 541 mg vs. AI 271 mg; absolute error 270 mg), mashed potatoes (reference 29 mg vs. AI 205 mg; absolute error 176 mg),

and boiled, drained, unsalted spinach (reference 547.4 mg vs. AI 378 mg; absolute error 169.4 mg). Figure 4 presents the 20 entries with the largest absolute discrepancies.

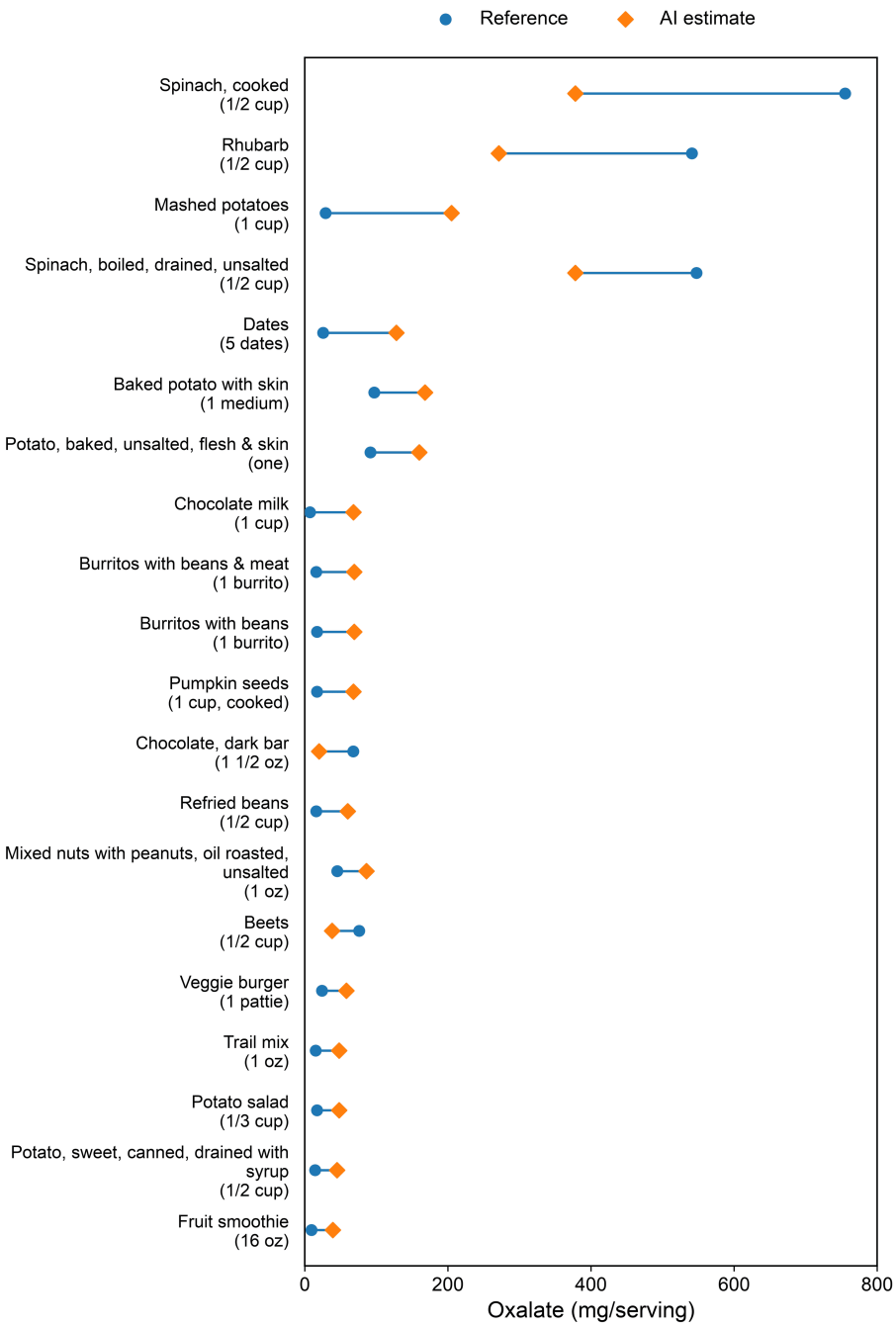

FIGURE 4: Largest absolute discrepancies in text-based oxalate estimates.

The 20 text entries with the largest absolute differences between AI estimates and reference oxalate values are shown in descending order of absolute error. Blue circles denote reference values and orange diamonds denote AI estimates, in mg per serving. Lines connect paired values. This is an exploratory display of the largest discrepancies, not a prespecified subgroup.

AI, artificial intelligence

Performance of image-based entries

Among 275 image-based entries, 161 (58.5%) had a recorded error, and 114 (41.5%) had no recorded error code. The final aggregate counts included food identification errors in 91 (33.1%) entries, portion-size errors

in 30 (10.9%), ingredient errors in 14 (5.1%), inability to analyze in 14 (5.1%), other errors in 11 (4.0%), and oxalate reference errors in 1 (0.4%). These recorded outcomes are shown in Figure 5. The absence of a recorded error code does not establish that an output was correct.

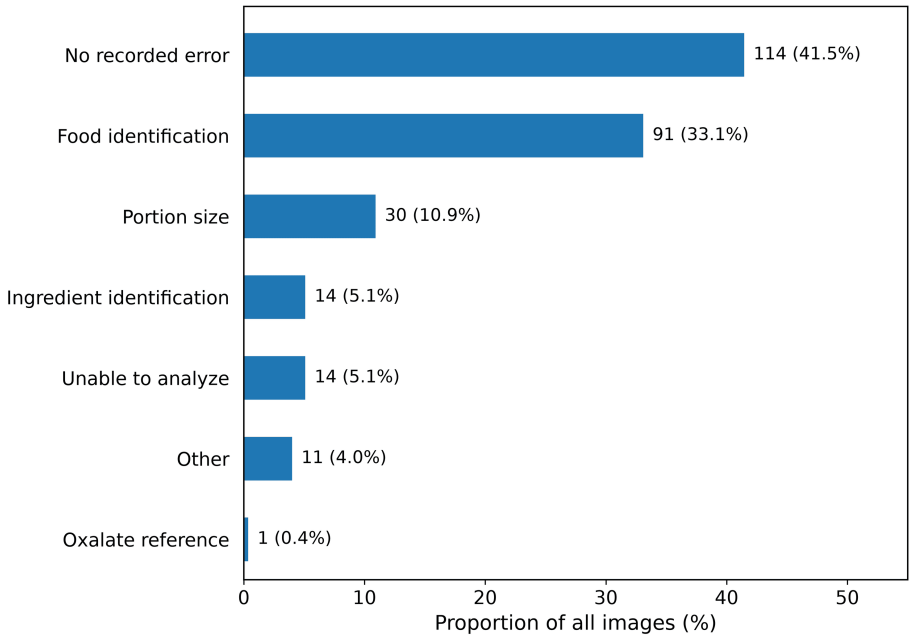

FIGURE 5: Recorded image assessment outcomes.

Recorded outcomes for 275 images, using the study team's final aggregate error-category counts. Percentages use all 275 images as the denominator. Of these, 161 (58.5%) had a recorded error and 114 (41.5%) had no recorded error code. "No recorded error" does not establish that every such output was correct.

Error rates differed across ASA24 food categories. Recorded errors occurred in 10 (71.4%) of 14 candy images, 26 (68.4%) of 38 mixed-dish images, 23 (62.2%) of 37 grain images, 19 (59.4%) of 32 baked-goods images, and 25 (56.8%) of 44 meat/poultry/seafood images. Recorded errors also occurred in 15 (44.1%) of 34 vegetable images, 7 (33.3%) of 21 fruit images, and 4 (40.0%) of 10 nuts/seeds images. These eight categories comprise 230 of the 275 images and are shown in Figure 6. The remaining 45 images, which represent small categories such as baby food and condiments, as well as two images without a food-category label, are not included in the graph. Category-specific estimates should be interpreted cautiously due to limited sample sizes.

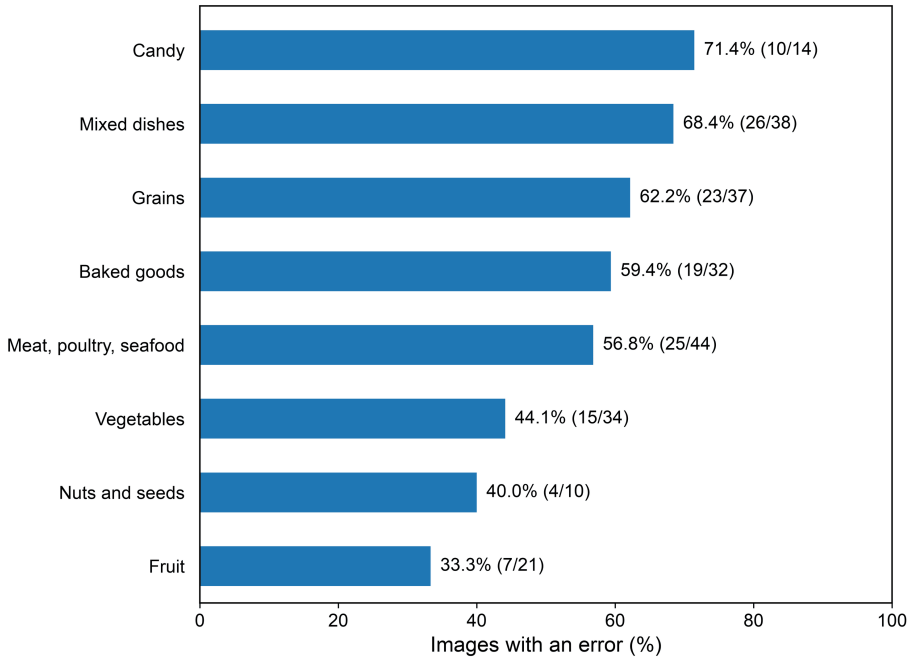

FIGURE 6: Recorded image error rates by food category.

Bars show the percentage of images with a recorded error within each food category. Labels give percentages and counts of images with errors divided by the number assessed. The eight categories comprise 230 of 275 images; 45 images in other or unspecified categories are not shown. Category-specific estimates should be interpreted cautiously because sample sizes were limited.

ASA24, Automated Self-Administered 24-Hour Dietary Assessment Tool

Discussion

The primary finding of this study was that StoneFree AI demonstrated favorable agreement with reference oxalate values for controlled, researcher-generated natural-language text descriptions containing explicit food and portion information. Image-based analysis by StoneFree AI showed frequent recorded errors. Of 804 text estimates, 760 (94.5%) were within ±10 mg of the reference value (Figure *3*), while 161 (58.5%) of 275 image-based entries had a recorded error code (Figure *5*). These findings suggest that natural-language text input currently provides more consistent benchmark performance than image-based analysis. However, these results do not establish accuracy for patient-generated dietary logs or independent clinical use. Text agreement thresholds and image error classifications assess different outcomes, and no formal inferential comparison between modalities was performed.

The observed agreement for natural-language text entries may be due to the fact that the dataset was carefully constructed. Descriptions explicitly specified the food and amount. These conditions minimized the linguistic variability and ambiguity that can be found in patient-generated dietary reports, such as incomplete portions, colloquial food names, misspellings, omitted preparation methods, and descriptions with multiple foods. If the user explicitly specifies the food item and quantity, the model can more easily match the input to the appropriate reference value. The error distribution was right-skewed for natural-language inputs (Figure *2*). The median absolute error was smaller than the mean, indicating that most estimates had small absolute errors under the controlled benchmark conditions and that a few large discrepancies increased the mean. Further development could include guided prompts, follow-up questions to clarify ambiguity, and more standardized handling of mixed dishes and composite foods.

Image-based analysis involves estimating multiple variables, including food type, ingredients, and portion size. These steps add uncertainty and may contribute to the recorded errors. Mixed dishes and grain-based foods had relatively high recorded error rates (Figure *6*). Structured text inputs provide information about food identity and portion size, while image-based estimates depend on visual information. The final summary also included 11 entries in the other-error category. The available category totals alone do not establish the specific mechanism for each of those errors.

Dietary oxalate remains an important consideration in calcium oxalate stone prevention [12]. Accurate estimation of dietary oxalate intake remains challenging in routine clinical practice. Food frequency questionnaires and dietary recalls are time-consuming and susceptible to recall bias and underreporting.

The agreement observed for natural-language text estimates indicates that mobile platforms such as this warrant further study as a potential approach to scalable dietary feedback. The broader role of nutrition in stone prevention is well established [1], but this study did not measure changes in urinary oxalate, dietary adherence, or stone recurrence.

Patient engagement is also a key consideration. Internet-based dietary programs have been studied as a means of facilitating dietary modifications in patients at risk of kidney stones and have also demonstrated decreases in urinary oxalate excretion and increases in adherence to dietary recommendations [13]. This suggests that digital tools could play a role in kidney stone prevention. Whether StoneFree AI improves engagement or adherence requires prospective evaluation. The recorded errors in image-based outputs suggest that fully automated photo-based logging should not be assumed suitable for independent clinical use. Structured approaches with support from images might be a viable middle ground and warrant further study.

A small number of foods had particularly large discrepancies (Figure *4*), including high-oxalate foods and prepared dishes. For high-oxalate foods, a small proportional error could create a large absolute difference in estimated oxalate. The true causes of the observed discrepancies were not fully established. These outliers may reflect difficulties in portion standardization, food mapping, or variation in reference oxalate content. Although overall benchmark agreement for natural-language entries was favorable, these discrepancies require further investigation and validation.

Performance estimates used predefined food entries and standardized image datasets. The finding that 760 of 804 text estimates (94.5%) were within ±10 mg of the Harvard reference values strictly applies to these conditions, not in a real-world clinical setting. Prospective studies using generated descriptions and meal photographs are needed to evaluate whether performance is maintained with routine usage. Finally, the reference database itself contains variability in reported oxalate values, which may contribute to some observed differences.

Because paired text errors were substantially zero-inflated and right-skewed, with 354 (44.0%) of 804 entries showing exact agreement, the analysis emphasized absolute-error thresholds, medians, IQRs, an empirical cumulative distribution, and a bootstrap confidence interval for the MAE. Future external validation should include biostatistical review and prospectively specified methods appropriate for zero-inflated and skewed error distributions.

Several of the largest discrepancies occurred in high-oxalate foods such as spinach and rhubarb, and performance was not stratified by oxalate level. Future studies should assess performance across clinically relevant oxalate ranges, improve recognition of mixed dishes, use multiple independent reviewers, and evaluate patient-generated inputs on held-out datasets. Prospective studies of usability, adherence, workflow integration, urinary oxalate excretion, and stone recurrence are needed before clinical implementation.

Limitations

There are multiple limitations to this study. First, the evaluation used database reference values rather than physiologic measurements such as urinary oxalate excretion. Second, the natural-language descriptions were researcher-generated and contained explicit food and portion information. The study did not assess patient-generated descriptions, inter-speaker or inter-writer variation, ambiguous or incomplete entries, repeated alternative phrasings, transcription errors, or audio-input performance. Third, the benchmark sources contributed to prompt refinement and performance evaluation; the findings should therefore be interpreted as internal benchmark performance rather than independent external validation. Fourth, the available coding record does not establish independent duplicate review or provide an inter-rater reliability estimate. Some entries without error codes contain evaluative notes; absence of a recorded code should not be interpreted as verified correctness. Fifth, standardized food images may not reflect the lighting, angles, plating styles, and visual complexity of everyday use. Sixth, the company operating StoneFree AI is no longer active and the application is inaccessible, so we could not determine whether the system's performance changed with additional training over time. The results therefore represent the application's performance at a single point in its development. Seventh, reference oxalate values vary with food type, preparation, and analytical method. Finally, the text and image analyses used different outcome definitions, limiting direct comparison.

Conclusions

StoneFree AI showed favorable agreement with reference oxalate values for researcher-generated natural language descriptions containing explicit food and portion information under controlled benchmark conditions. Image-based assessment remained constrained by food-identification, ingredient-recognition, and portion-estimation errors. These findings represent internal benchmark performance and do not establish accuracy for patient-generated dietary records or clinical benefit. Independent evaluation using held-out datasets, prospective patient-generated inputs, and clinically relevant outcomes is necessary before clinical implementation.

Appendices

Appendix

The following template and image prompt were supplied by the study team. The meal-entry template describes the user input; it is not a separate text-analysis system prompt.

Meal-entry template

"I had one (serving size) of (food item)"

Image system prompt

You are a highly accurate, multimodal nutritional AI engine specializing in computer vision food analysis and kidney stone dietary tracking.
Analyze the attached image of a meal and provide a structured breakdown. If multiple food items or distinct ingredients are present, analyze each one separately before providing a meal total.
For your analysis, utilize standard nutritional databases and established urological dietary guidelines to estimate values. Follow this exact format:

Food Identification & Visual Breakdown

Provide a bulleted list of each distinct food item or ingredient you detect in the image, including an estimated weight (in grams) or volume (e.g., cups, tablespoons) based on standard serving sizes.

- [Food Item Name]: [Estimated portion size/weight]

Nutritional Breakdown (Per Item)

For each identified food item, provide the following metrics:

- **[Food Item Name]**
  - Calories: [kcal]
  - Protein: [g]
  - Carbohydrates: [g]
  - Fats: [g]
  - Sodium: [mg]
  - Calcium: [mg]
  - Oxalate Content: [Low / Moderate / High / Very High] (Estimate approximate mg if reliable data exists)

Confidence Level: [High / Medium / Low based on image clarity and ingredient visibility]

FIGURE 7: Supplied meal-entry template and image system prompt.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Jessica Javaherforoush, Olumide A. Ojo, Ferdinand Anokwuru, Andersen Teoh, Kymora B. Scotland, Robert Chan, Bhushan Suryavanshi

Acquisition, analysis, or interpretation of data: Jessica Javaherforoush, Olumide A. Ojo, Ferdinand Anokwuru, Janelly Jimenez, Andersen Teoh, Kymora B. Scotland, Robert Chan

Drafting of the manuscript: Jessica Javaherforoush, Olumide A. Ojo, Ferdinand Anokwuru, Janelly Jimenez, Andersen Teoh, Kymora B. Scotland, Robert Chan, Bhushan Suryavanshi

Critical review of the manuscript for important intellectual content: Jessica Javaherforoush, Olumide A. Ojo, Ferdinand Anokwuru, Andersen Teoh, Kymora B. Scotland, Robert Chan

Supervision: Jessica Javaherforoush, Olumide A. Ojo, Kymora B. Scotland, Robert Chan

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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