

Life Lens-AI: Advanced AI-Driven Framework for Predicting and Preventing Kidney Stone Recurrence with Personalized Care

Ankur Singh¹, Sumit Kumar Singh², Anjali Mathur³, Ms. Neha Goyal⁴

Department of Computer Science Engineering (Artificial Intelligence) Bansal Institute of Engineering and Technology Lucknow, India

DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150300108>

Received: 28 March 2026; 03 April 2026; Published: 22 April 2026

ABSTRACT

Kidney stone disease continues to be a major global health challenge, largely due to its high recurrence rate even after successful surgical treatment. This study introduces LIFE Lens-AI, an intelligent framework designed to support both prediction and long-term prevention of kidney stone recurrence through the use of artificial intelligence.

The proposed system combines predictive analytics, medical image analysis, and personalized recommendation techniques within a single integrated platform. It leverages diverse data sources, including patient demographics, clinical history, lifestyle patterns, and medical imaging, to generate accurate and clinically meaningful insights.

The predictive module operates in two stages: recurrence risk prediction using XGBoost and surgical intervention prediction using a Random Forest classifier. The latter is modeled as a binary classification task, where labels are derived from established clinical treatment guidelines and historical decision patterns. Experimental results show that the system achieves an accuracy of 87.9% for recurrence prediction and 90.5% for surgical decision classification, supported by strong performance across precision, recall, F1-score, and AUC-ROC metrics.

Beyond prediction, the framework emphasizes patient-centric care by offering personalized dietary suggestions, specialist recommendations, and continuous monitoring support. The system is implemented as a secure web-based application with modern encryption and authentication mechanisms. Overall, LIFE Lens-AI provides a practical step toward proactive, AI-enabled healthcare and improved long-term patient outcomes.

Keywords— Kidney stone analysis, prediction models, personalized treatment planning, machine learning, deep learning, artificial intelligence, clinical decision support, healthcare informatics, computer-aided diagnosis, medical imaging, preventive nephrology, precision medicine, telemedicine, patient care optimization.

INTRODUCTION

Nephrolithiasis, commonly known as kidney stone disease, is a widespread health issue affecting nearly 12% of the global population. One of the major concerns is its high recurrence rate, with almost half of the patients experiencing it again within five to ten years after treatment. The economic burden is also significant, with costs exceeding \$10 billion annually in the United States alone. In addition to direct medical expenses, there are indirect impacts such as reduced productivity, long-term pain management, and complications including kidney dysfunction and cardiovascular issues. Over the past two decades, the number of cases has increased by around 30% across both developed and developing countries. This rise is especially noticeable among young and middle-aged individuals, where it directly affects their quality of life and work efficiency.

Current clinical practices mainly focus on treating the immediate problem rather than preventing future occurrences. Most treatments, such as extracorporeal shock wave lithotripsy (ESWL), ureteroscopy, and percutaneous nephrolithotomy, are effective in removing existing stones but do not address the root causes behind their formation. As a result, many patients develop stones again after treatment. This gap in long-term

care becomes more serious considering that patients with recurring stones contribute to nearly 75% of the total treatment cost. These observations highlight the need for better strategies that focus on prevention and continuous patient management instead of only short-term solutions.

Preventing kidney stone recurrence is challenging because it involves multiple interconnected factors. These include metabolic conditions, dietary habits, genetic factors, and overall lifestyle. For example, conditions like hypercalciuria, hyperoxaluria, and low citrate levels can increase the risk of stone formation. Similarly, dietary habits such as low water intake, high salt consumption, excessive protein intake, and foods rich in oxalates also contribute to the problem. Genetic factors play a role as well, with certain gene variations affecting calcium and oxalate regulation in the body. Recent studies have also pointed to the role of the gut microbiome, especially the presence of *Oxalobacter formigenes*, in influencing stone formation risk.

Traditional patient education and general dietary advice often do not produce effective long-term results. One major reason is that these recommendations are usually not tailored to individual needs. They often ignore factors such as a patient's metabolic condition, cultural eating habits, and financial limitations, making them difficult to follow in real life. As a result, adherence to dietary guidelines remains low, with studies showing that less than 35% of patients continue these practices over time without proper support. In addition, follow-up systems are often weak and do not include regular monitoring of important health indicators, which limits the chances of early intervention.

Another challenge is the difficulty in accurately predicting recurrence due to the complex interaction between different risk factors. Traditional statistical methods often fail to capture these relationships because they rely on limited variables and do not adapt to changes over time. This is where artificial intelligence can play an important role. AI-based systems can analyze large and diverse datasets, identify hidden patterns, and provide more accurate predictions. However, most existing solutions focus only on specific tasks such as imaging or prediction and do not provide a complete system for patient care. This highlights the need for an integrated approach that combines prediction, prevention, and continuous monitoring into a single framework.

Furthermore, the relationship between different risk factors makes it difficult to accurately predict kidney stone recurrence without proper computational methods. Stone formation is influenced by multiple variables that interact in complex and nonlinear ways, which traditional statistical approaches often fail to capture. These methods usually rely on a limited number of measurable factors and do not consider how risk changes over time. As a result, existing clinical prediction models show only moderate performance, with Cstatistic values typically ranging from 0.65 to 0.75. This indicates the need for more advanced techniques that can handle complex data and provide better prediction accuracy.

In recent years, artificial intelligence and machine learning have shown strong potential in healthcare, especially in diagnostics and predictive analysis. Several studies have explored their use in urology, particularly for detecting kidney stones and analyzing their composition. Deep learning models, for instance, have been successfully applied to CT scan analysis, achieving performance levels comparable to radiologists in tasks such as stone detection, size estimation, and composition analysis. In addition, natural language processing techniques have been used to extract useful information from clinical reports, while reinforcement learning approaches are being explored to support personalized treatment decisions based on patient-specific data. Despite these advancements, there is still a lack of a complete system that integrates prediction, prevention, and long-term patient management. Most existing solutions focus only on individual components, such as imaging or diet tracking, without connecting them into a unified workflow. They often do not provide end-to-end support from diagnosis to prevention, and many lack the ability to generate personalized recommendations and track patient progress over time. This fragmented approach reduces their effectiveness in real-world clinical settings and highlights the need for a more integrated and practical solution.

In this work, we present LIFE Lens-AI, a system designed to address these limitations through the following key contributions:

- **Advanced Predictive Analytics:** A combined approach that uses medical images, clinical data, and lifestyle information to estimate recurrence risk and support treatment decisions with improved accuracy.

- **Personalized Care Recommendations:** A recommendation module that provides diet plans, hydration advice, and specialist suggestions based on individual patient profiles, helping improve adherence and outcomes.
- **Secure Patient Management Platform:** A web-based system that supports continuous monitoring, secure data sharing, and communication between patients and doctors, ensuring both usability and data protection.

System Architecture

The LIFE Lens-AI framework is designed as a modular and scalable system, where multiple components work together to support kidney stone prediction and personalized healthcare. Each module performs a specific function, and together they form an integrated pipeline for efficient data processing and decision-making.

Overall Framework:

The architecture is divided into four main modules, each responsible for a particular task:

- **Data Acquisition and Preprocessing:** This module gathers both structured and unstructured patient data from different sources such as Electronic Health Records (EHRs), laboratory reports, and medical imaging systems.
- **Predictive Analytics Engine:** This component applies machine learning and deep learning models to estimate recurrence risk, predict the need for surgery, and analyze medical images.
- **Recommendation System:** It generates personalized suggestions related to diet, lifestyle, and clinical care based on medical guidelines and similarity-based techniques.
- **Patient Management Interface:** A secure platform that allows patients and doctors to access results, communicate effectively, and view predictions in a clear format.

Life Lens-AI System Architecture:

[Patient Data → Data Acquisition → Preprocessing → Predictive Analytics Engine → Recommendation System → Patient Interface].

This structured pipeline ensures smooth data flow between modules and allows easy integration with hospital systems. It also supports scalability, making it suitable for deployment in different clinical environments.

Data Collection and Preprocessing

The system works with multiple types of patient data, which are grouped as follows:

- **Demographics:** Includes age, gender, BMI, occupation, and family history related to kidney stones.
- **Clinical History:** Covers previous treatments, existing health conditions such as diabetes or hypertension, and medication records.
- **Lifestyle Factors:** Includes daily water intake, dietary habits (oxalate, calcium, sodium), physical activity, and smoking or alcohol use.
- **Medical Imaging:** CT scans, X-rays, and ultrasound images used for detecting and measuring kidney stones.
- **Laboratory Results:** Test values such as urine pH, calcium, uric acid, citrate levels, and serum creatinine.

A dataset containing 15,000 records with 42 features was created using statistically valid distributions. This dataset was further supported by annotated imaging data collected from publicly available sources.

Preprocessing Pipeline:

- Normalization: Continuous data values are scaled using Z-score normalization to maintain consistency.
- Encoding: Categorical variables are converted into numerical form using one-hot encoding.
- Missing Data Handling: Missing values are filled using mean or mode to avoid data loss.
- Image Preprocessing: Images are resized to 256×256, converted to grayscale, and augmented using techniques such as rotation, flipping, and noise addition to improve model performance.

These steps ensure that the collected data is clean, consistent, and suitable for further processing by AI models.

Predictive Modeling:

The predictive engine uses a hybrid ensemble approach to improve overall performance:

- Recurrence Risk Prediction: Implemented using XGBoost, along with SHAP analysis to identify important risk factors such as high sodium intake and family history.
- Surgical Intervention Prediction: The surgical intervention prediction module was designed as a binary classification task to determine whether a patient requires surgical treatment or can be managed through conservative approaches. To ensure clinical relevance, each patient record was labeled using guideline-based decision criteria derived from standard urological treatment protocols and documented clinical practices. The labeling process incorporated multiple medically significant factors, including stone size, anatomical location, degree of obstruction, recurrence of symptoms, and the patient's response to prior conservative treatment. Specifically, cases involving stones larger than 10 mm, obstructive stones associated with hydronephrosis, and patients experiencing recurrent symptomatic episodes were labeled as requiring surgical intervention, while smaller, non-obstructive, and asymptomatic stones were categorized under conservative management. A Random Forest classifier was trained using a combination of clinical attributes, laboratory findings, and imaging-derived features. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure robust model generalization and avoid overfitting.

Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. The proposed model achieved an accuracy of 90.5%, with a precision of 0.893, recall of 0.912, and F1-score of 0.902. Additionally, the AUC-ROC value of 0.94 indicates strong discriminative capability. These results demonstrate a high level of agreement between model predictions and clinically established decision-making criteria, supporting the reliability of the system for assisting surgical decisionmaking in real-world scenarios.

Image Analysis Module: A modified U-Net convolutional neural network with attention mechanisms is used for segmenting kidney stones and measuring their size and density from CT and ultrasound images.

Recommendation Systems:

The recommendation module supports personalized treatment planning through two main components:

- Dietary Recommendation Engine: A knowledge-based system that uses medical guidelines, nutrition data, and patient-specific information to suggest suitable diet plans.
- Doctor Matching System: based approach that connects patients with the most appropriate specialists, considering feedback and case complexity.

Security and Privacy Considerations:

Since healthcare data is sensitive, the system includes multiple security layers:

Encryption: AES-256 is used for data storage, while TLS

Ensures secure data transmission.

- Authentication: Multi-factor authentication with bcrypt-based password hashing is implemented.
- Access Control: Role-based access ensures separation between patient and doctor permissions.
- Regulatory Compliance: The system design follows standards such as GDPR and HIPAA.
- Audit Logging: All system activities are recorded to detect and prevent unauthorized access.

AI Integration

Artificial Intelligence (AI) has played an important role in improving modern healthcare by enabling systems that can process complex medical data, support clinical decisions, and adapt treatment to individual patients. Unlike traditional rule-based approaches, AI models can learn from large and diverse datasets, including medical images, lab reports, patient history, and behavioral patterns. This capability allows healthcare systems to shift from reactive treatment to more proactive and preventive care. In urology, especially in kidney stone management, AI makes it possible to combine imaging, prediction, personalized recommendations, and continuous monitoring into a single system. Such integration not only improves prediction accuracy but also helps patients follow long-term treatment plans more effectively, reducing the chances of recurrence.

AI-Driven Medical Imaging Analysis:

AI has become widely used in medical imaging, particularly in radiology and urological diagnosis. Deep learning methods, especially Convolutional Neural Networks (CNNs), have made it possible to automatically detect abnormalities with accuracy close to that of medical experts. In kidney stone diagnosis, AI-based techniques are commonly used to analyze CT scans and locate stones in ultrasound images. The introduction of the U-Net architecture was a key development in this area and is still widely used for biomedical image segmentation. Recent work has also explored combining CNNs with transformer-based models and self-supervised learning to improve performance further. In our system, imaging analysis is not used alone; instead, it is combined with clinical and biochemical data to form a multimodal system that supports both detection and risk prediction.

AI-Powered Predictive Analytics in Healthcare

AI-based prediction models are increasingly used to estimate disease risk, progression, and recurrence. Traditional methods like logistic regression and random forests are still useful, but newer techniques such as ensemble learning, deep neural networks, and gradient boosting provide better performance when dealing with complex and mixed data. Another advantage of modern AI is its ability to combine different types of data, including structured records, clinical notes, and imaging data, into a single predictive model. However, many existing systems are designed for only one task, such as classification or prediction. In contrast, our approach uses a combination of multi-task learning and multimodal data integration to predict recurrence, monitor dietary adherence, and evaluate treatment response. This makes the system more suitable for continuous patient care rather than isolated predictions.

AI-Enhanced Personalized Recommendation Systems:

Recommendation systems in healthcare have improved significantly over time. Earlier systems were mostly rule-based, but now they use AI techniques that can adapt based on patient behavior and feedback. Methods such as collaborative filtering, content-based filtering, and reinforcement learning are used to provide better recommendations. In nephrology, most systems focus on chronic kidney disease, while personalized solutions for kidney stone prevention are still limited. By using real-time patient data, lifestyle inputs, and predictive insights, AI can generate personalized suggestions for diet, hydration, and daily habits. In our framework, the

recommendation engine continuously updates its suggestions based on imaging results, clinical data, and patient compliance, making it more practical for long-term preventive care.

AI-Integrated Patient Management Platforms:

The use of telemedicine has increased significantly after the COVID-19 pandemic, highlighting the importance of remote healthcare solutions. Although many digital platforms are available, most of them focus only on general monitoring and do not provide condition-specific insights. In the case of kidney stones, where recurrence is common, patient care requires continuous monitoring and personalized support. AI improves these platforms by enabling features such as risk alerts, smart scheduling, personalized feedback, and real-time tracking through wearable devices and mobile applications. LIFE Lens-AI integrates all these components into a single platform, combining prediction, recommendation, and followup mechanisms. This ensures that patients receive not only treatment but also ongoing support to prevent recurrence and maintain long-term health.

Implementation and Evaluation

The implementation of the LIFE Lens-AI framework involved combining several AI-based modules, including predictive models, medical image analysis, recommendation systems, and performance optimization for real-time use. Each component was developed carefully and tested to ensure that the system works reliably in practical healthcare scenarios. Along with measuring prediction accuracy, the evaluation also considered clinical usefulness, system efficiency, and feedback from domain experts. A detailed validation approach was followed to test the framework across different aspects, ensuring that it performs well for both diagnosis and long-term prevention. The following subsections describe the dataset preparation, model performance, imaging results, recommendation evaluation, and system efficiency in detail.

Dataset Composition and Evaluation Protocol:

The dataset used in this study was divided into three parts to ensure proper training and testing of the models. Around 70% of the data was used for training, 15% for validation, and the remaining 15% for testing. This split helps in preventing overfitting and ensures that the model performs well on unseen data. To evaluate the performance of the models, standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC were used. These metrics help in understanding not only how accurate the model is but also how well it performs in identifying true positive cases and maintaining overall balance in predictions. In addition, this evaluation approach provides a clearer understanding of model consistency and reliability across different data samples.

Predictive Model Performance:

The performance comparison between baseline models and the proposed system shows noticeable improvements. Logistic Regression achieved an accuracy of 0.769, with precision of 0.752, recall of 0.781, F1-score of 0.766, and an AUC-ROC value of 0.832. The Support Vector Machine (SVM) model performed slightly better, with an accuracy of 0.802, precision of 0.784, recall of 0.806, F1-score of 0.795, and an AUC-ROC of 0.863. The Random Forest model showed further improvement, achieving 0.831 accuracy, 0.813 precision, 0.837 recall, 0.825 F1-score, and an AUCROC of 0.891.

In comparison, the LIFE Lens-AI framework performed better than all baseline models, achieving an accuracy of 0.879, precision of 0.862, recall of 0.885, and an F1-score of 0.873, along with the highest AUC-ROC value of 0.931. These results indicate that combining multiple data types and using an ensemble-based approach leads to more reliable and accurate predictions. The improvement can also be attributed to better feature representation and the ability of the model to capture complex relationships within the data, which are often missed by individual models.

Model Performance Comparison

To provide a clearer comparison between baseline models and the proposed framework, performance metrics are summarized in Table 1.

Table 1: Performance Comparison of Prediction Models:

Model	Accuracy	Precision	Recall	F1score	AUC-ROC
Logistic Regression	0.769	0.752	0.781	0.766	0.832
Support Vector Machine	0.802	0.784	0.806	0.795	0.863
Random Forest	0.831	0.813	0.837	0.825	0.891
LIFE Lens-AI	0.879	0.862	0.885	0.873	0.931

The results show that the proposed LIFE Lens-AI framework outperforms baseline models across all evaluation metrics. The improvement can be attributed to the integration of multimodal data, ensemble learning, and optimized feature representation.

Image Segmentation and Analysis:

The imaging module was developed using the U-Net architecture, which is widely used for biomedical image segmentation. The model achieved a Dice coefficient of 0.87, showing a strong match with expert annotations. In addition, the system achieved 92.4% accuracy in estimating stone size within a margin of ± 1.2 mm when compared with measurements provided by radiologists. These results show that the imaging module is capable of providing accurate and clinically useful outputs.

Recommendation System Evaluation:

The recommendation module was evaluated with the help of four urologists and three certified nutritionists. Each expert independently reviewed the system's dietary and lifestyle recommendations using a five-point Likert scale. The evaluation focused on important aspects such as clinical relevance, level of personalization, clarity, and practical usefulness.

The system achieved an average score of 4.4 out of 5, indicating that the recommendations were generally wellaccepted and considered useful by the experts. To further check the consistency of their evaluations, Fleiss' kappa statistic was calculated, which resulted in a value of 0.71. This indicates a substantial level of agreement among the experts, showing that the recommendations were consistently judged as appropriate.

However, since the evaluation involved a relatively small number of experts, the results may have some limitations in terms of generalizability. In future work, a larger group of specialists will be included to further validate and improve the recommendation system.

System Responsiveness and Computational Performance:

To check the practical usability of the system, its computational performance was also evaluated. The framework was tested on a system with an Intel i7 processor and 16 GB RAM. The average time taken for prediction was around 2.7 seconds per case, which is suitable for real-time applications. For better scalability, the model was deployed using TensorFlow Serving, which helps in faster and more efficient execution without affecting performance.

SUMMARY OF FINDINGS:

Overall, the evaluation results show that the proposed framework performs well across multiple aspects, including prediction accuracy, imaging analysis, recommendation quality, and system efficiency. The combination of these results suggests that LIFE Lens-AI can be used as a reliable tool for supporting kidney stone diagnosis, prevention, and long-term patient care in a practical setting. It also demonstrates consistent performance across different test scenarios and varying data conditions.

Deployment in Resource-Constrained Environments:

To ensure practical usability, the computational requirements of the LIFE Lens-AI framework were evaluated. The complete system was tested on a machine with an Intel i7 processor and 16 GB RAM, achieving an average

prediction time of approximately 2.7 seconds per case. This performance is suitable for real-time clinical decision support.

For deployment in resource-limited settings such as rural hospitals, a lightweight inference version of the model was developed. This version uses reduced feature dimensions and optimized model parameters, enabling operation on systems with 8 GB RAM without significant loss in prediction accuracy. Additionally, cloud-based deployment can be used to offload computation, allowing healthcare centers with limited hardware resources to access predictions through a secure web interface.

This flexible deployment strategy makes the system suitable for both advanced hospitals and low-resource healthcare environments.

Study Limitations:

Although the proposed LIFE Lens-AI framework demonstrates promising performance, several limitations should be acknowledged. The structured dataset used for training the predictive models was synthetically generated using statistically modeled distributions rather than collected directly from real patient populations. While this approach helps maintain balanced data and controlled experimentation, it may not fully capture the variability present in real-world clinical environments.

In addition, imaging data were obtained from publicly available datasets that may differ in acquisition protocols, scanner types, and patient demographics. These variations may influence model performance when deployed in different hospital settings. Furthermore, the recommendation system evaluation was conducted using a limited number of domain experts, which may restrict generalizability.

Future work will focus on validating the framework using prospectively collected multi-center clinical datasets, expanding expert evaluation, and improving robustness across diverse patient populations. These steps will help improve the clinical reliability and real-world applicability of the proposed system.

Future Work

The LIFE Lens-AI framework shows strong potential in applying artificial intelligence to improve postoperative kidney stone care. Although the system has produced promising results in prediction, imaging, and personalized recommendations, there is still work to be done before it can be widely used in real clinical environments. For broader adoption and long-term impact, the framework needs further validation, better integration with modern technologies, and improvements in scalability. In addition, factors such as ethical use, patient involvement, and compatibility with existing healthcare systems must be carefully addressed. The following areas highlight possible directions for future development and improvement of LIFE Lens-AI as a complete and practical healthcare solution.

Clinical Validation through Trials:

- Conduct multi-center clinical trials to test the system across different patient groups, imaging setups, and hospital environments.
- Compare key outcomes such as recurrence rates, recovery duration, and patient satisfaction with existing treatment methods.

Integration of Real-Time Sensor Data:

- Use wearable devices and IoT-based sensors to monitor hydration, diet, urinary pH, and physical activity in real time.
- Develop feedback systems that can provide timely alerts and preventive suggestions based on changes in patient health data.

Electronic Health Record (EHR) Interoperability:

- Create secure methods for seamless data exchange between LIFE Lens-AI and hospital EHR systems.
- Support collaborative care by enabling doctors and specialists to access and share a unified patient profile for better decision-making.

Ethical and Fairness Auditing:

- Introduce mechanisms to regularly check for bias in model predictions across different demographic groups.
- Incorporate explainable AI techniques so that both patients and clinicians can better understand how decisions are made by the system.

Patient Education and Engagement:

- Develop user-friendly dashboards and AI-based assistants to present medical information in a simple and understandable way.
- Include features like progress tracking and motivation tools to help patients maintain healthy habits over time.

Longitudinal and Scalability Studies:

- Perform long-term studies to evaluate the impact of the system on recurrence rates, patient well-being, and healthcare costs.
- Explore cloud-based solutions to make the system scalable and accessible across both urban hospitals and rural healthcare centers.

CONCLUSION

The LIFE Lens-AI framework represents an important step toward improving the use of artificial intelligence in the postsurgical management of kidney stone patients. By combining predictive models, medical image segmentation, and personalized recommendation features, the system focuses on addressing the major issue of stone recurrence. The evaluation results show that the integrated model achieved an accuracy of 87.9%, which is higher than traditional methods such as Logistic Regression (76.9%), Support Vector Machine (80.2%), and Random Forest (83.1%). The model also achieved a precision of 86.2%, recall of 88.5%, and an F1-score of 87.3%, indicating stable and reliable performance. In addition, the AUC-ROC value of 0.931 highlights its effectiveness in clinical prediction tasks. The imaging module, based on the U-Net architecture, achieved a Dice coefficient of 0.87 and provided 92.4% accuracy in stone size estimation within a margin of ± 1.2 mm when compared with expert measurements. The dietary recommendation system was also evaluated by experts and received an average score of 4.4 out of 5, confirming its practical usefulness. From a computational perspective, the system maintained good efficiency, with an average response time of 2.7 seconds per case, making it suitable for real-time applications.

Looking forward, LIFE Lens-AI provides a flexible and scalable framework that can be extended beyond kidney stone management to other chronic health conditions. Studies indicate that nearly 50% of kidney stone patients experience recurrence within 5 to 10 years, which creates both medical and financial challenges. By supporting continuous monitoring, combining multiple data sources, and offering personalized lifestyle recommendations, the system has the potential to reduce recurrence rates and improve overall patient outcomes. Its modular design allows easy integration with hospital systems, wearable devices, and cloud platforms, making it usable in both advanced and resource-limited healthcare settings. In addition, the inclusion of fairness checks and explainable AI features supports responsible and transparent use of the system. Overall, LIFE Lens-AI not only improves

prediction accuracy but also shows how AI-based, patient-focused solutions can contribute to the future of personalized healthcare in a practical and scalable way.

ACKNOWLEDGMENT

The authors would like to thank the urology specialists and certified nutritionists who provided valuable feedback during the evaluation of the recommendation system. Their insights helped improve the clinical relevance of the LIFE Lens-AI framework. The authors also acknowledge the guidance and support provided by faculty members and peers from the Department of Computer Science Engineering (Artificial Intelligence), Bansal Institute of Engineering and Technology, Lucknow, which contributed to the successful completion of this work.

Declaration

The authors declare that this manuscript represents original research work and has not been submitted or published elsewhere. All authors contributed to the conceptualization, system design, methodology development, implementation, analysis, and manuscript preparation.

The study was conducted following standard research practices. No personally identifiable patient data were used in this work. Structured data were generated using statistical modelling, and imaging data were obtained from publicly available datasets.

The authors declare no conflict of interest related to this research. All authors have reviewed and approved the final version of the manuscript and take responsibility for its content.

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