Salutogenic Approach to Early Kidney Health Promotion: Comparing Deep Learning Facial Analysis and Questionnaire Screening in Adolescents

Uun Nurjanah✉[1)], Erlena Erlena[1)], Wahyudi[2)], Iham Suryana[1)]

[1] Department of Nursing, Faculty of Science, Horizon University, Karawang, West Java, Indonesia 41316
[2] Department of Information Systems, Faculty of Computer Science, Horizon University, Karawang, West Java, Indonesia 41316
✉Email: erlenstikeskharisma@gmail.com

ABSTRACT

***Background**: Chronic kidney disease (CKD) is increasingly reported in adolescents and is driven by modifiable lifestyle factors such as inadequate hydration, frequent consumption of processed foods, obesity, and poor sleep quality. Because early CKD is typically asymptomatic, routine laboratory screening is often impractical in school or community settings. Self-reported questionnaires can help estimate lifestyle-related risk but rely on subjective recall. **Objective**: To compare the effectiveness of a DL-based facial analysis model with self-reported questionnaire screening for early CKD risk in adolescents. **Methods**: A cross-sectional study was conducted among 100 adolescents aged 16–19 in Karawang, Indonesia. Participants completed validated questionnaires assessing hydration, dietary habits, and sleep quality using the Pittsburgh Sleep Quality Index (PSQI). Standardized facial photographs were analyzed using a convolutional neural network (CNN) trained to detect CKD-related facial markers. Agreement between methods was assessed using Cohen's kappa, and diagnostic performance was evaluated using ROC analysis. **Results**: Questionnaire screening classified 88% of adolescents as low-risk, 10% moderate-risk, and 2% high-risk, while the AI model classified 95%, 4%, and 1%, respectively, demonstrating moderate agreement ($\kappa = 0.61$, $p < 0.001$). The AI model achieved 91.0% accuracy, 88.0% sensitivity, 92.0% specificity, and an AUC of 0.904. Overweight adolescents had higher odds of being at risk (OR = 2.35). **Conclusion**: Combining AI-based facial analysis with questionnaire assessment provides a rapid, scalable, and non-invasive strategy for early CKD risk screening in adolescents, particularly in resource-limited settings.*

***Keywords**: Adolescents, Artificial Intelligence, Deep Learning, Early Detection, Non-Invasive Screening*

INTRODUCTION

Chronic kidney disease (CKD) is an escalating global health problem that often remains undetected until renal function is irreversibly compromised and morbidity has increased substantially (Levey *et al.*, 2007). Early identification is critical to preventing progression to end-stage renal disease (ESRD) and reducing long-term healthcare costs (Adenwalla *et al.*, 2024). However, commonly used screening methods, including proteinuria testing, serum creatinine measurement, and estimated glomerular filtration rate (eGFR), are invasive, costly, and frequently unavailable in community-based or resource-limited settings (Yeo *et al.*, 2024); Cordero and Ortiz, 2025).

To address these challenges, non-invasive and readily accessible screening innovations are urgently needed (Wu *et al.*, 2025). Self-reported questionnaires are widely used to assess lifestyle and behavioural risk factors (Schrauben, Apple and Chang, 2022). Nevertheless, these tools are susceptible to response bias and may fail to capture early physiological indicators associated with CKD, such as hydration status, sleep duration, and physical activity.

Recent advancements in artificial intelligence (AI) have enabled the

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

development of computer vision models capable of identifying subtle facial cues such as periorbital oedema, facial asymmetry, and changes in skin tone (Bhatt and Muduli, 2022); (Vacarel, Barbulescu Sgiea and Cristache, 2025). These features may serve as potential indicators of fluid imbalance and early kidney impairment, including paleness and oedema (Alkahlout *et al.*, 2021).

Building on these advancements, the SIGAGA (Smart Innovation for Early Kidney Disease Detection) program was developed as an integrated AI-based platform that combines facial image analysis with digital self-assessment questionnaires. The system is designed for use among adolescents in school and community health settings and provides real-time, non-invasive risk assessment.

The purpose of this study was to assess the diagnostic accuracy and agreement between questionnaire-based risk assessment and AI-based facial feature classification within the SIGAGA framework. This approach uniquely integrates behavioural risk profiling with visual biomarker identification, offering a youth-focused, scalable, and non-invasive model for early chronic kidney disease (CKD) screening in resource-constrained settings. Unlike previous studies, which have typically applied questionnaire-based screening or AI-driven facial analysis in isolation, the present research integrates both methods within a single platform.

To our knowledge, this is the first study to evaluate and compare the diagnostic accuracy and agreement between questionnaire-based screening and deep-learning facial feature analysis specifically for early kidney health promotion in adolescents. Through a salutogenic lens, this work shifts the focus from disease detection toward the upstream promotion of kidney health in young populations.

METHODS

Study Design and Participants

In Karawang, Indonesia, a cross-sectional study was conducted among 100 adolescents aged 16 to 19 years. Participants were recruited through school-based and community health initiatives. The inclusion criteria included willingness to participate in facial imaging and questionnaire completion, as well as the absence of a prior diagnosis of chronic kidney disease (CKD).

The minimum required sample size was calculated as 85 adolescents, providing 80% statistical power to detect an area under the receiver operating characteristic (ROC) curve (AUC) of 0.85 (Pendrill *et al.*, 2023), assuming a two-sided significance level (α) of 0.05 and a null hypothesis AUC of 0.70 (Al-Mekhlafi, Becker and Klawonn, 2022). To account for potential missing data or poor-quality responses, the sample size was increased to 100 participants. A stratified random sampling approach was used to recruit adolescents from urban and semi-urban schools in Karawang, Indonesia, ensuring representation across diverse residential contexts.

Study Outcomes

The primary outcome of this study was the level of agreement between questionnaire-based CKD risk classification and AI-based facial analysis, assessed using Cohen's kappa coefficient.

Secondary outcomes included the diagnostic performance of the AI facial analysis model, as measured by the area under the curve (AUC), sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV); the distribution of CKD risk levels (low, moderate, and high) among adolescents; and the associations between participant characteristics, including sleep quality, hydration habits, lifestyle behaviours, and demographic factors, with CKD risk levels.

Data Collection

To identify the early risk of chronic kidney disease (CKD) among adolescents, this cross-sectional study employed a dual-screening framework integrating self-reported behavioural assessments with deep learning–based facial feature analysis. Participants completed a structured questionnaire that included the Pittsburgh Sleep Quality Index (PSQI) to assess sleep quality (Setyowati and Chung, 2021), along with validated instruments measuring lifestyle behaviours (Ahn, Lee and Seo, 2022), hydration habits (Radić *et al.*, 2023), medical history (Petzke *et al.*, 2025), and demographic characteristics (Alobaidi, 2021). All questionnaires had been previously validated, demonstrating acceptable Cronbach's alpha reliability

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

coefficients, and permission for their use was obtained from the original authors.

Facial Image Acquisition and Pre-processing

Facial images were captured using smartphone cameras under standardized conditions with uniform lighting. Participants were instructed to maintain a neutral facial expression, remove glasses and jewellery, and ensure that the camera was positioned at eye level. Each image was captured at a resolution of 1080 × 1080 pixels and saved in JPEG format. Prior to analysis, all images were resized to 224 × 224 pixels, brightness-adjusted, and cropped to include only the facial region, following standard pre-processing protocols for convolutional neural network (CNN)–based image recognition models (Kang *et al.*, 2021); (Soekarta and Ku-Mahamud, 2024). These steps ensured consistency of input data and optimized model performance.

A CNN model fine-tuned from a pre-trained facial recognition network was subsequently used to identify early facial indicators potentially associated with CKD, including pallor, periorbital swelling, and facial puffiness. Each facial image was automatically classified as normal, mild, or abnormal, which were then mapped to low, moderate, or high CKD risk levels. The model employed transfer learning and feature optimization techniques to enhance detection accuracy and reduce overfitting, in accordance with current best practices in AI-based medical facial analysis (Wasilewski, Kamysz and Gębicki, 2024).

Statistical Analysis

Cohen's kappa coefficient was calculated to assess the level of agreement between questionnaire-based and AI-based CKD risk classifications. Receiver operating characteristic (ROC) curve analysis was conducted to evaluate the discriminatory accuracy and diagnostic performance of the AI model, including the area under the curve (AUC), sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). Chi-square tests were performed to examine associations between participant characteristics and CKD risk levels. A p-value of less than 0.05 was considered statistically significant for all analyses (Lee *et al.*, 2022).

Statistical analyses were conducted using SPSS version 28 (IBM Corp., Armonk, NY, USA), while deep learning model development and ROC computations were performed using Python version 3.10 with the TensorFlow framework (Hamad Ismail, 2024). A schematic representation of the integrated workflow combining the validated self-report questionnaire and AI-based facial analysis is presented in Supplementary Figure 1, illustrating the SIGAGA (Smart Innovation for Early Kidney Disease) detection process from data acquisition to risk stratification and output interpretation.

Ethical Approval

The study was approved by the Institutional Review Board of Horizon University (Ref. No: DP.04.03/F.XXVI.20/KEPK/841/2025). Written informed consent was obtained from all participants.

RESULTS AND DISCUSSION

Participant Characteristics

A total of 100 adolescents participated in this study, the majority of whom were female (88%). Most participants were 18 years old (58%), followed by those aged 19 years (28%). More than half of the respondents identified as Sundanese (55%), while 32% reported Indonesian ethnicity; the remainder identified as Javanese or Betawi, or did not specify their ethnicity.

Regarding nutritional status, 46% of participants had a normal body mass index (BMI), while 34% were overweight and 20% were underweight. Only 5% reported a history of smoking, and none reported alcohol consumption. Most adolescents reported no family history of disease (81%) and no personal medical history (96%). Routine health check-ups were uncommon, with 46% indicating they had never undergone one.

Nearly all participants reported no current clinical symptoms (95%), whereas a small proportion experienced unusual fatigue (3%) or swelling (2%). High-salt food consumption was common, with 40% consuming salty foods one to two times per week and 14% consuming them daily. Most participants reported a daily water intake of 1–2 liters (69%). The majority indicated no smoking habits (96%) and low levels of physical activity, with only 2% exercising

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

daily and 18% reporting no physical activity at all.

The use of over-the-counter medications was notably high (93%). Most participants reported moderate stress levels (64%), and nearly all had inadequate sleep duration, with only 2% reporting more than eight hours of sleep per night. More than half of the participants were categorized as having a low risk of kidney disease (58%). Sleep quality, as measured by the Pittsburgh Sleep Quality Index (PSQI), was predominantly poor, with 82% classified as having mildly poor sleep quality and 4% as having severely poor sleep quality (Table 1).

Table 1. Demographic and health characteristics of participants (n = 100).

Variable	Category	Frequency (n)	Percentage (%)
Sex	Male	12	12.0
	Female	88	88.0
Age (years)	16	1	1.0
	17	13	13.0
	18	58	58.0
	19	28	28.0
Ethnicity	Not specified	3	3.0
	Indonesian	32	32.0
	Sundanese	55	55.0
	Javanese	8	8.0
	Betawi	2	2.0
Body Mass Index (BMI)	Underweight	20	20.0
	Normal	46	46.0
	Overweight	34	34.0
Smoking History	Yes	5	5.0
	No	95	95.0
Alcohol Consumption	Yes	0	0.0
	No	100	100.0
Family Disease History	None	81	81.0
	One disease	18	18.0
	More than one disease	1	1.0
Personal Medical History	None	96	96.0
	One disease	3	3.0
	More than one disease	1	1.0
Routine Health Check-up	Every 6 months	2	2.0
	Yes, but irregular	52	52.0
	Never	46	46.0
Clinical Symptoms	None	95	95.0
	Unusual fatigue	3	3.0
	Swelling	2	2.0
Salty Food Consumption	Rare/Never	19	19.0
	1–2 times/week	40	40.0
	3–5 times/week	27	27.0
	Daily	14	14.0
Sugary/Carbonated Drinks	Rare/Never	86	86.0
	1–2 times/week	12	12.0

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

Variable	Category	Frequency (n)	Percentage (%)
	3–5 times/week	2	2.0
Water Intake	> 2 liters/day	13	13.0
	1–2 liters/day	69	69.0
	< 1 liter/day	18	18.0
Smoking Habit	No	96	96.0
	Yes, occasionally	3	3.0
	Yes, frequently	1	1.0
Physical Activity	Daily	2	2.0
	3–5 times/week	13	13.0
	1–2 times/week	67	67.0
	Never	18	18.0
Use of Over-the-Counter Medication	Yes	93	93.0
	No	7	7.0
Stress Level	Low	28	28.0
	Moderate	64	64.0
	High	6	6.0
	Very high	2	2.0
Sleep Duration	> 8 hours	2	2.0
	7–8 hours	46	46.0
	5–6 hours	45	45.0
	< 5 hours	7	7.0
Kidney Disease Risk Screening	Low	58	58.0
	Moderate	42	42.0
Sleep Quality (PSQI)	Good	14	14.0
	Mild poor	82	82.0
	Severe poor	4	4.0

AI-Based Facial Feature Classification

The SIGAGA AI model analyzed facial regions associated with fluid retention, periorbital puffiness, and skin tone variation. Table 2 summarizes the distribution of classified facial features. Most participants exhibited normal characteristics, 20–25% showed mild deviations, and 8–10% had more pronounced abnormalities.

Table 2. AI-Based Facial Feature Classification (n = 100)

Facial Feature	Normal n (%)	Mild n (%)	Abnormal n (%)
Facial swelling	72 (72.0)	20 (20.0)	8 (8.0)
Skin tone	70 (70.0)	25 (25.0)	5 (5.0)
Periorbital (eye area)	68 (68.0)	22 (22.0)	10 (10.0)
Overall facial condition	74 (74.0)	19 (19.0)	7 (7.0)

The majority of participants exhibited typical facial features, while approximately 20–25% showed minor abnormalities, primarily periorbital puffiness and variations in skin tone. A smaller proportion (around 8–10%) presented with more pronounced facial anomalies, which are consistent with previously documented signs suggestive of potential early kidney involvement.

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

AI and Questionnaire-Based CKD Risk Classification

Participants were classified as having low, moderate, or high CKD risk using both screening approaches. Based on the questionnaire, 88% of respondents were categorized as low risk, whereas the AI-based facial analysis classified 95% as low risk. A moderate level of agreement was observed between the two methods (κ = 0.61, p < 0.001) (Table 3).

Table 3. Comparison of CKD Risk Classification Between AI-Based and Questionnaire Methods (n = 100)

Risk Category	AI-Based n (%)	Questionnaire n (%)	Agreement (n)	κ	*p*-value
Low	95 (95.0)	88 (88.0)	85		
Moderate	4 (4.0)	10 (10.0)	2		
High	1 (1.0)	2 (2.0)	0		
Total	**100 (100)**	**100 (100)**	—	**0.61**	**< 0.001**

Diagnostic Performance

According to the AI-based facial analysis, the overall accuracy was 91.0%, with a sensitivity of 88.0% and a specificity of 92.0%. The area under the receiver operating characteristic curve (AUC) was 0.904 (95% CI: 0.86–0.96) (Table 4). The output of the SIGAGA system is illustrated in Figure 1. Panel A presents a sample AI-based facial analysis highlighting periorbital puffiness, facial pallor, and oedema, while Panel B displays the ROC curve, demonstrating the high discriminative performance of the questionnaire-based screening.

Table 4. Diagnostic Performance of AI-Based Facial Feature Model Compared to the Questionnaire (n = 100)

Metric	**Value (95% CI)**
Accuracy	91.0% (85.4–96.6)
Sensitivity	88.0% (79.4–96.6)
Specificity	92.0% (86.1–97.9)
Positive Predictive Value	80.0% (70.3–89.7)
Negative Predictive Value	94.7% (90.1–99.3)
AUC	0.904 (0.86–0.96)
p-value	< 0.001

Table 4 summarizes the diagnostic effectiveness of the AI-based facial feature model, which demonstrated an AUC of 0.904 (95% CI, 0.86–0.96) and high accuracy (91.0%), sensitivity (88.0%), and specificity (92.0%). These indicators reflect a strong ability to differentiate between high- and low-risk CKD populations. Figure 1 presents the model's ROC curve along with the graphical output of the SIGAGA system. Representative examples of AI-based facial analysis results are shown in panel A, highlighting facial pallor, periorbital puffiness, and oedema. The ROC curve in panel B illustrates the AI model's superior predictive performance compared with the questionnaire-based risk assessment.

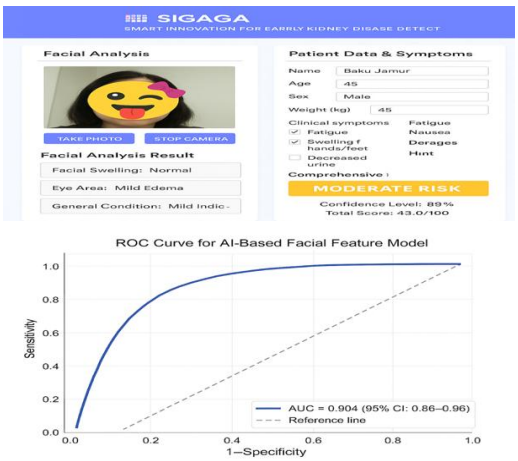

Figure 1. SIGAGA (Smart Innovation for Early Kidney Disease Detection) system output for early CKD risk assessment. Panel

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

A shows the AI-based facial analysis output, highlighting periorbital puffiness, facial pallor, and overall swelling. Panel B shows the receiver operating characteristic (ROC) curve comparing the AI model with the self-reported questionnaire, demonstrating high discriminative performance (AUC = 0.904, 95% CI 0.86–0.96; $p < 0.001$). All data are anonymized and used solely for illustration.

This study demonstrates that the SIGAGA AI-based facial analysis system is a reliable and non-invasive screening tool for identifying early CKD risk among adolescents. As illustrated in Figure 1, Panel A, the model detects subtle facial cues such as facial pallor, periorbital puffiness, and swelling, which may reflect underlying physiological changes associated with impaired kidney function. By identifying these visual biomarkers before the onset of overt clinical symptoms, the AI system supports secondary prevention through earlier risk recognition.

Figure 1 further illustrates the diagnostic performance of the AI model, showing a receiver operating characteristic (ROC) curve with excellent discriminative accuracy (AUC = 0.904) and a strong balance between sensitivity (88.0%) and specificity (92.0%). These findings indicate that AI-based facial analysis complements traditional behavioral assessments by providing direct physiological insights. The moderate agreement between AI- and questionnaire-based classifications ($\kappa = 0.61$, $p < 0.001$) highlights the complementary nature of the two approaches. While the AI model captures biophysical cues derived from facial morphology, the questionnaire reflects behavioral and lifestyle factors, such as hydration, sleep, and physical activity, that are associated with CKD risk. Together, these dual modalities enhance early detection accuracy and offer a feasible screening framework for school and community settings.

These findings are consistent with earlier research on facial analytics in metabolic and renal conditions (Peng *et al.*, 2025), suggesting that subtle variations in facial features may provide meaningful insights into systemic metabolic and renal health. Changes in skin tone and facial morphology may represent early signs of physiological dysregulation. Integrating AI-driven facial assessment into routine adolescent health monitoring could therefore enable timely interventions, particularly in resource-constrained environments where access to laboratory testing is limited.

Several limitations should be acknowledged. The sample size was relatively small and drawn from a single geographic area, which limits the generalizability of the findings. In addition, laboratory confirmation of kidney function, such as estimated glomerular filtration rate (eGFR) and proteinuria, was not performed, restricting direct clinical validation of the early CKD risk classifications. The AI facial analysis model was also trained on a limited dataset, underscoring the need for larger, multi-center studies to enhance accuracy, fairness, and population representativeness (Pavan *et al.*, 2024).

Beyond its diagnostic utility, the SIGAGA system aligns closely with health promotion principles and the salutogenic approach, which emphasize strengthening individuals' capacity to maintain health rather than focusing solely on disease detection. From a salutogenic perspective, health exists along a continuum, and effective interventions enhance adolescents' sense of coherence by improving their ability to understand health information, manage risks, and find meaning in adopting healthy behaviors. By offering a rapid, non-invasive, and youth-friendly screening tool, SIGAGA promotes early awareness of kidney health and supports proactive self-care. The integration of behavioral questionnaires with AI-based physiological assessment enables tailored feedback on modifiable lifestyle factors, including hydration, sleep, stress, and physical activity. This dual-assessment framework not only identifies risk but also empowers adolescents to engage in health-promoting actions, in line with the World Health Organization's adolescent health promotion strategies. In school and community settings, SIGAGA may serve as a catalyst for preventive education, fostering healthy routines well before clinical manifestations of CKD emerge. Consequently, this study contributes to the operationalization of salutogenic principles in digital adolescent health screening by shifting the focus from

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

disease surveillance to the development of health assets and resilience.

CONCLUSION

The integration of AI-based facial analysis and behavioral self-assessment within the SIGAGA system provides a practical, low-burden approach for early CKD risk screening among adolescents. This dual-method framework enhances detection accuracy while simultaneously promoting awareness of key modifiable factors such as hydration, diet, sleep, and physical activity. As a health promotion strategy, SIGAGA can be feasibly implemented in school and community settings to strengthen preventive behaviors and improve health literacy. Further validation using larger and more diverse populations is necessary to ensure clinical reliability and broader applicability. Overall, SIGAGA supports a paradigm shift from curative to preventive kidney health management at the community level.

Conflict of Interest

The authors have no conflicts of interest associated with the material presented in this paper.

Funding

This research was supported by a grant from the Directorate General of Higher Education, Research, and Technology (DIKTI), Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia (Contract No. 125/C3/DT.05.00/PL/2025).

Acknowledgements

This study was supported by the Directorate General of Higher Education, Research, and Technology (DIKTI), Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia, and Horizon University, Indonesia. The authors sincerely thank the participating schools and adolescents for their cooperation and valuable contribution to this research.

REFERENCES

Adenwalla, S. F. *et al*. (2024) 'Advance care planning for patients with end-stage kidney disease on dialysis: narrative review of the current evidence, and future considerations.', *Journal of nephrology*, 37(3), pp. 547–560. doi: 10.1007/s40620-023-01841-3.

Ahn, J.-W., Lee, S. M. and Seo, Y. H. (2022) 'Factors associated with self-care behavior in patients with pre-dialysis or dialysis-dependent chronic kidney disease.', *PloS one*, 17(10), p. e0274454. doi: 10.1371/journal.pone.0274454.

Al-Mekhlafi, A., Becker, T. and Klawonn, F. (2022) 'Sample size and performance estimation for biomarker combinations based on pilot studies with small sample sizes', *Communications in Statistics - Theory and Methods*, 51(16), pp. 5534–5548. doi: 10.1080/03610926.2020.1843053.

Alkahlout, M. *et al*. (2021) 'An Expert System for Diagnosing Facial-Swelling Using CLIPS', *International Journal of Academic Information Systems Research (IJAISR)*, 5(5), pp. 29–36.

Alobaidi, S. (2021) 'Knowledge of Chronic Kidney Disease Among the Population of Saudi Arabia Evaluated Using a Validated Questionnaire: A Cross-Sectional Study.', *Patient preference and adherence*, 15, pp. 1281–1288. doi: 10.2147/PPA.S315369.

Bhatt, P. and Muduli, A. (2022) 'Artificial intelligence in learning and development: a systematic literature review', *European Journal of Training and Development*, 47(7–8), pp. 677–694. doi: 10.1108/EJTD-09-2021-0143.

Hamad Ismail (2024) 'Performance Evaluation of AI-Based Healthcare Systems in the United Arab Emirates: A Comparative Analysis of Diagnostic Accuracy and Predictive Capability Using SPSS', *RIT Digital Institutional Repository*.

Kang, M.-K. *et al*. (2021) 'Facial Depth and Normal Estimation using Single Dual-Pixel Camera', *ArXiv*, abs/2111.12928.

Lee, S. *et al*. (2022) 'Machine Learning-Aided Chronic Kidney Disease Diagnosis Based on Ultrasound Imaging Integrated with Computer-Extracted Measurable Features.', *Journal of digital imaging*, 35(5), pp. 1091–1100. doi: 10.1007/s10278-022-00625-8.

Levey, A. S. *et al*. (2007) 'Chronic kidney disease as a global public health problem: Approaches and initiatives – a position statement from Kidney Disease Improving Global Outcomes', *Kidney International*, 72(3), pp. 247–259. doi: https://doi.org/10.1038/sj.ki.5002343.

Pavan, J. *et al*. (2024) 'A strategy based on integer programming for optimal dosing

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026

and timing of preventive hypoglycemic treatments in type 1 diabetes management', *Computer Methods and Programs in Biomedicine*, 250, p. 108179. doi: https://doi.org/10.1016/j.cmpb.2024.108179.

Pendrill, L. R. *et al*. (2023) 'Modernising Receiver Operating Characteristic (ROC) Curves', *Algorithm*, 16(253). doi: https://doi.org/10.3390/ a16050253.

Peng, Q. *et al*. (2025) '3D facial imaging: a novel approach for metabolic abnormalities risk profiling', *Science China Life Sciences*, 68(6), pp. 1786–1800. doi: 10.1007/s11427-024-2726-8.

Petzke, D. *et al*. (2025) 'Exploration of chronic kidney disease screening, diagnosis and management in Australian general practice using electronic medical record data.', *BMC nephrology*, 26(1), p. 405. doi: 10.1186/s12882-025-04345-3.

Radić, J. *et al*. (2023) 'Assessment of Hydration, Nutritional Status and Arterial Stiffness in Hypertensive Chronic Kidney Disease Patients.', *Nutrients*, 15(9). doi: 10.3390/nu15092045.

Schrauben, S. J., Apple, B. J. and Chang, A. R. (2022) 'Modifiable Lifestyle Behaviors and CKD Progression: A Narrative Review.', *Kidney360*, 3(4), pp. 752–778. doi: 10.34067/KID.0003122021.

Setyowati, A. and Chung, M.-H. (2021) 'Validity and reliability of the Indonesian version of the Pittsburgh Sleep Quality Index in adolescents.', *International journal of nursing practice*, 27(5), p. e12856. doi: 10.1111/ijn.12856.

Soekarta, R. and Ku-Mahamud, R. (2024) 'Recent Facial Image Preprocessing Techniques: A Review', *Engineering Proceedings*, 84(1), p. 39. doi: https://doi.org/10.3390/engproc2025084039.

Vacarel, E. V., Barbulescu Sgiea, E. D. and Cristache, C. M. (2025) 'From Saliva to Diagnosis: A Scoping Review of Conventional and Biosensor-Based Methods for Salivary Biomarkers in Chronic Kidney Disease.', *Diagnostics (Basel, Switzerland)*, 15(17). doi: 10.3390/diagnostics15172226.

Wasilewski, T., Kamysz, W. and Gębicki, J. (2024) 'AI-Assisted Detection of Biomarkers by Sensors and Biosensors for Early Diagnosis and Monitoring.', *Biosensors*, 14(7). doi: 10.3390/bios14070356.

Wu, Q. *et al*. (2025) 'A noninvasive model for chronic kidney disease screening and common pathological type identification from retinal images.', *Nature communications*, 16(1), p. 6962. doi: 10.1038/s41467-025-62273-0.

Yeo, S. C. *et al*. (2024) 'Cost-effectiveness of screening for chronic kidney disease in the general adult population: a systematic review.', *Clinical kidney journal*, 17(1), p. sfad137. doi: 10.1093/ckj/sfad137.

Received: 08-11-2025, Accepted: 08-12-2025, Published Online: 09-01-2026