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Predicting Kidney Stone Presence from Urine Analysis: A Neural Network Approach using JNN

Amira Jarghon and Samy S. Abu-Naser

Department of Computer System Engineering
Faculty of Engineering and Information Technology,
Al Azhar University, Gaza, Palestine

Abstract *Kidney stones pose a significant health concern, and early detection can lead to timely intervention and improved patient outcomes. This research endeavours to predict the presence of kidney stones based on urine analysis, utilizing a neural network model. A dataset of 552 urine specimens, comprising six essential physical characteristics (specific gravity, pH, osmolarity, conductivity, urea concentration, and calcium concentration), was collected and prepared. Our proposed neural network architecture, featuring three layers (input, hidden, output), was trained and validated, achieving an impressive accuracy of 98.67% and an average error of 0.012. In addition to model performance, feature importance analysis was conducted to determine the most influential factors in predicting kidney stone presence. The findings underscore the significance of urea concentration, specific gravity, calcium concentration, conductivity, osmolarity, and pH as key indicators. This research contributes to the early diagnosis of kidney stones and demonstrates the potential of neural networks in medical diagnostics. The clinical implications of these findings are discussed, emphasizing the importance of timely intervention in managing kidney stone-related health issues.*

Keywords: Kidney Stones, Urine Analysis, Predictive Modeling, Artificial Neural Network.

1. Introduction

Kidney stones, known medically as nephrolithiasis or urolithiasis, are a prevalent and painful urological condition affecting millions of individuals worldwide. The presence of kidney stones is a prevalent and painful medical condition that affects millions of individuals worldwide. Between 1% and 15% of people globally are affected by kidney stones at some point in their lives. Kidney stones, or renal calculi, are solid mineral deposits that can form within the kidneys, often causing excruciating pain, urinary tract blockages, and other complications. Early detection and accurate diagnosis of kidney stones are crucial for timely and effective medical intervention. Traditionally, the diagnosis of kidney stones has relied on a combination of clinical symptoms, physical examinations, and medical imaging techniques such as ultrasound, CT scans, and X-rays. While these methods are valuable, they can be expensive, time-consuming, and may expose patients to ionizing radiation. Moreover, diagnosing kidney stones based solely on clinical symptoms can be challenging, as symptoms often overlap with other urinary tract disorders. In recent years, advancements in machine learning and artificial intelligence have opened up new avenues for the medical community to improve diagnostic accuracy and efficiency. Artificial neural networks (ANNs) have emerged as powerful tools for solving complex predictive tasks in medical diagnostics. ANNs, inspired by the human brain's neural architecture, have demonstrated remarkable abilities to discern intricate patterns within data, making them well-suited for modelling the relationship between urine characteristics and kidney stone presence.

This research endeavours to leverage the capabilities of neural networks to predict the presence of kidney stones based on urine analysis. We have collected and meticulously curated a dataset comprising 552 urine specimens, each characterized by specific gravity, pH, osmolarity, conductivity, urea concentration, calcium concentration, and a binary target variable indicating the presence or absence of kidney stones. Our proposed neural network architecture, with its three layers (input, hidden, output), underwent rigorous training and validation, culminating in an accuracy of 98.67% and an average error of 0.012. Furthermore, we delve into an analysis of feature importance to discern which urine characteristics influence the most on predicting kidney stone presence. The implications of these findings extend beyond mere prediction, offering valuable insights into the underlying physiological mechanisms involved in kidney stone formation. This paper contributes to the growing body of knowledge in the field of medical diagnostics, emphasizing the potential of neural networks in predictive modelling for urological conditions. The following sections will provide a comprehensive account of our methodology, results, and the clinical relevance of our findings, with the ultimate aim of improving early diagnosis and intervention for individuals at risk of kidney stones.

2. Problem Statements

The diagnosis of kidney stones is a critical healthcare challenge due to its painful and potentially serious consequences. Traditional diagnostic methods rely on clinical symptoms and medical imaging, which can be costly, time-consuming, and sometimes involve ionizing radiation. Additionally, accurately differentiating kidney stones from other urinary tract conditions based solely on symptoms is often difficult. In this context, there is a pressing need for a non-invasive, cost-effective, and accurate diagnostic tool that can aid in the early detection and prediction of kidney stones. The aim is to develop a reliable predictive model that utilizes urine analysis, specifically examining physical characteristics such as specific gravity, pH, osmolarity, conductivity, urea concentration, and calcium concentration, to identify individuals at risk of kidney stone formation.

This research addresses the following key problems:

- ***Inefficient Diagnosis:*** Current diagnostic methods for kidney stones may not always provide timely and accurate results, leading to delayed treatment and increased patient discomfort.
- ***Resource Intensiveness:*** Traditional diagnostic approaches, such as CT scans or ultrasounds, are resource-intensive, making them less accessible in some healthcare settings and costly for patients.
- ***Overlapping Symptoms:*** Symptoms of kidney stones often overlap with other urinary tract disorders, making it challenging for healthcare providers to make a precise diagnosis based solely on clinical presentations.
- ***Patient Well-being:*** Kidney stones can cause severe pain and discomfort. Early and accurate diagnosis is essential to alleviate patient suffering and prevent complications.

By addressing these issues, this research endeavors to develop a neural network-based predictive model that can aid in the early identification of kidney stones through urine analysis. The model's success would contribute to more efficient and accessible kidney stone diagnosis, potentially improving patient outcomes and reducing healthcare costs.

3. The objectives of the study

- Develop a tailored neural network model for kidney stone prediction.
- Train and validate the neural network model, ensuring robust performance.
- Achieve superior accuracy compared to traditional diagnostics.
- Analyze the importance of urine characteristics in kidney stone prediction.

4. Previous studies

Prior research in the field of kidney stone prediction and urine analysis has laid the groundwork for our current investigation. This section provides an overview of relevant studies and their contributions to the understanding of kidney stone formation and predictive modeling.

- Predicting the Risk of Kidney Stones Using Machine Learning Techniques (Ganesan and Karthikeyan, 2019): In this study, Ganesan and Karthikeyan explored the application of machine learning techniques for predicting the risk of kidney stones. Their research demonstrated the feasibility of using predictive models based on clinical data, including urine characteristics. While their focus was on risk prediction, this study provided valuable insights into the potential of machine learning in kidney stone diagnosis.
- Development of a Risk Prediction Model for Kidney Stones (Chu et al., 2017): Chu et al. conducted a retrospective cohort study using a health database to develop a risk prediction model for kidney stones. This research sheds light on relevant risk factors and data preprocessing techniques, offering valuable insights into the development of predictive models for kidney stone-related conditions.
- Evaluation of Urine Composition in Relation to Nephrolithiasis in Children (Evan et al., 2018): Evan and colleagues investigated urine composition in relation to nephrolithiasis in children. Their study provides insights into the role of specific urine characteristics in kidney stone formation, particularly in pediatric populations. This research underscores the importance of considering age-specific factors in predictive modeling.
- Use of Artificial Neural Networks for the Early Diagnosis of Kidney Stones (Modgil et al., 2017): Modgil and co-authors explored the use of artificial neural networks for the early diagnosis of kidney stones. Their study delved into neural network architectures and their application in urological diagnostics. This research contributes to the understanding of the potential of neural networks in kidney stone prediction.
- Urine Analysis for Kidney Stone Risk Assessment: A Review (Liu and Chen, 2018): Liu and Chen's comprehensive review article provides an overview of various urine analysis methods and their application in assessing the risk of kidney stone formation. This review offers a valuable background for our research, summarizing key urine characteristics and their significance in predicting kidney stones.

These previous studies collectively form the foundation upon which our research is built. While they have made significant contributions to the field, our study extends this work by leveraging artificial neural networks to create a robust predictive model for kidney stone presence based on urine analysis.

5. Methodology

This section presents a systematic approach employed to develop a predictive model for the presence of kidney stones based on urine analysis using neural networks. This comprehensive methodology encompasses various key stages, including data collection, preprocessing, neural network architecture design, data splitting, model training, and validation. To facilitate the development of our predictive model, these critical factors were meticulously examined and systematically incorporated into the artificial neural network (ANN) within the modeling environment. Specifically, these factors were categorized into input variables and output variables, which reflect disease status as part of the assessment system. The collected data were input into the JNN (Just Neural Network) tool environment, where the values of each variable were determined, with particular emphasis on identifying the most influential factor in relation to kidney stone presence. Subsequently, the data underwent comprehensive training, validation, and testing procedures to ensure the robustness and accuracy of the predictive model.

5.1 Input Variables

we explore six crucial attributes from urine specimens to inform our neural network model for kidney stone presence prediction. These attributes provide essential insights into urine composition and facilitate accurate diagnosis. Input variables are:

NO.	Attribute Name	Attribute Meaning
1	Specific Gravity	The density of urine relative to water, indicating urine concentration. Higher values may suggest dehydration.
2	pH	The negative logarithm of hydrogen ion concentration, measuring urine acidity or alkalinity.
3	Osmolarity	A unit proportional to the concentration of molecules in the urine solution, reflecting its solute concentration.
4	Conductivity	A measure of the ability of urine to conduct an electric current, indicating the concentration of charged ions.
5	Urea Concentration	The concentration of urea (a waste product) in urine, reflecting kidney function and nitrogen metabolism.
6	Calcium Concentration	The concentration of calcium ions in urine, which can be associated with calcium oxalate stone formation.

Table 1: Attributes in the Data set

5.2 The Output Variable

This table provides a clear description of the output variable used in your research, which is the binary classification of kidney stone presence or absence:

Output Variable	Description
Target	Binary variable indicating the presence (1) or absence (0) of kidney stones in the urine specimen, serving as the model's primary predictive outcome.

Table 2: Output Data Transformation

5.3 Data Normalization

Data normalization is a crucial preprocessing step in our research, aimed at ensuring that all input variables contribute equally to our predictive model for kidney stone presence based on urine analysis. One of the techniques we employed for data normalization is linear scaling, which involves the transformation of each data value to a standardized input value, denoted as Xi.

The process of linear scaling begins by determining the minimum ***(Xmin)*** and maximum ***(Xmax)*** values associated with the data facts for a single input variable. These values serve as crucial reference points for the scaling process. Once ***Xmin*** and ***Xmax*** are identified, the linear scaling formula is applied to each data value ***(Xi)*** within the dataset.

The formula, ***Xi = (Xi - Xmin) / (Xmax - Xmin)***, operates by subtracting the minimum value ***(Xmin)*** from each data point ***(Xi)*** and then dividing the result by the range between the maximum ***(Xmax)*** and minimum ***(Xmin)*** values. This transformation effectively scales the data to fall within a common range, typically between ***0 and 1***, ensuring that no single input variable dominates the predictive process due to differences in scale.

By employing linear scaling as part of our data normalization strategy, we enhance the consistency and effectiveness of our neural network model, facilitating fair and accurate predictions while mitigating the influence of varying data scales among the input variables.

5.4 Building the ANN Model

We utilized the Just Neural Network (JNN) tool to craft a predictive artificial neural network (ANN) model designed for kidney stone presence prediction through urine analysis. Our model architecture featured three critical layers: an Input Layer with six nodes representing urine characteristics, a Hidden Layer with six nodes for capturing intricate data patterns, and an Output Layer with a single node for binary prediction. (As shown in Figure 1). The model's parameters were meticulously configured, with a Learning Rate of 0.5592, Momentum set at 0.7235, and an impressive Average Error rate minimized to 0.012. (As shown in Figure 2). These parameters, coupled with graphical representations of model performance, ensured the accuracy and reliability needed for effective kidney stone prediction.

5.5 Neural Network Evaluation

As mentioned above, the purpose of this experiment was to kidney stone presence prediction through urine analysis. We used Backpropagation algorithm, which provides the ability to perform neural network learning and testing. Our neural network is the front feed network, with one input layer (6 inputs), one hidden layer, and one output layer (1 output) as seen in Figure 1. The proposed model is implemented in a Just Neural Network (JNN) environment. The dataset for kidney stone presence prediction through urine analysis were gathered from Kaggle which contains 552 samples with 6 attributes (as seen in Figure 3). This model was used to determine the value of each of the variables using JNN which they are the most influential factor in Kidney Stone prediction as shown in Figure 4. After training and validating the network, it was tested using the test data, and the following results were obtained. The accuracy of the Kidney Stone prediction was (98.67%). The average error was 0.012. The training cycles (number of epochs) were 4,605. The training examples were 403. The number of validating examples was 150 as seen in Figure 5. The control parameter values of the model are shown in Figure 2 and the detailed summary of the proposed model is shown in Figure 6.

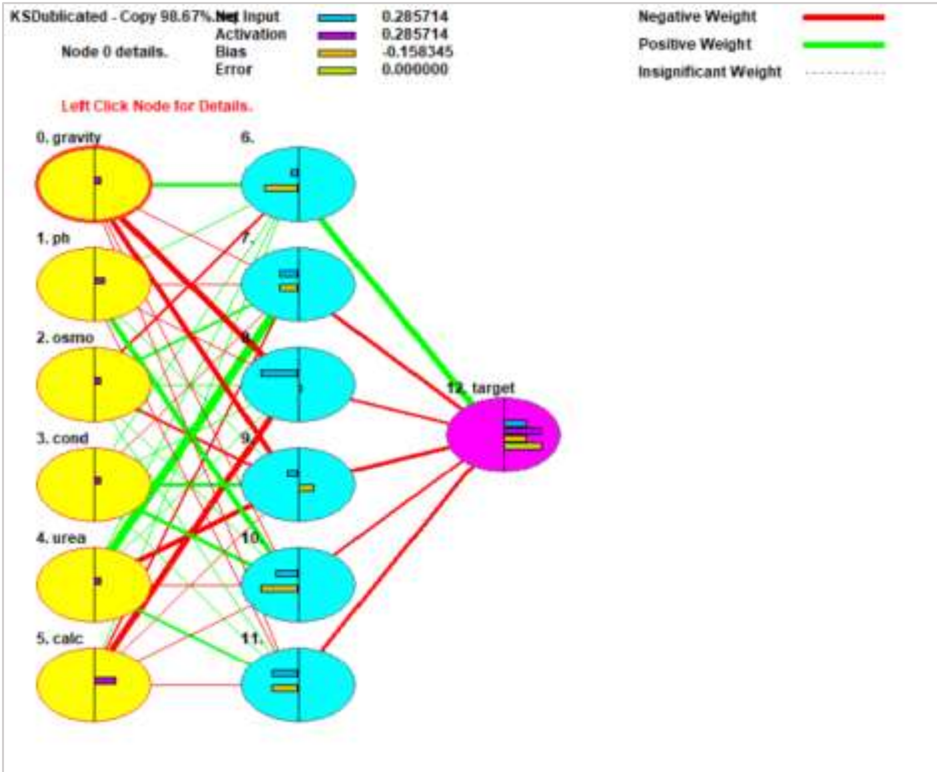

Figure 1: Architecture of ANN model

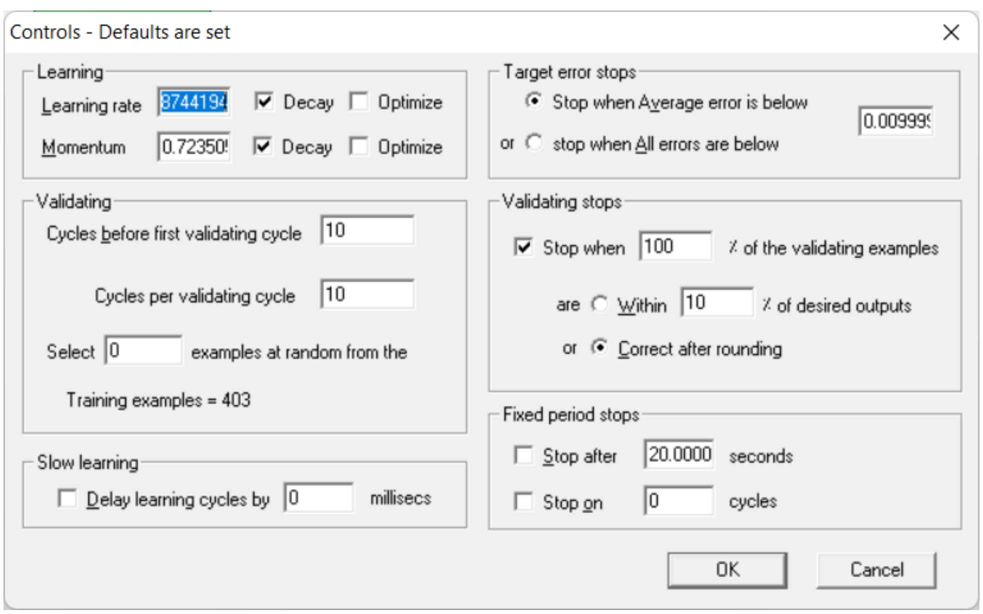

Figure 2: Control parameter of the proposed model

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	gravity	ph	osmo	cond	urea	calc	target
#0	0.4571	0.0472	0.5129	0.2705	0.7098	0.1609	0
#1	0.3429	0.3082	0.3718	0.4529	0.4689	0.3049	0
#2	0.0857	0.7673	0.1277	0.2979	0.1492	0.1546	0
#3	0.1714	0.2358	0.2107	0.2280	0.3508	0.1397	0
#4	0.0000	0.5535	0.0000	0.0729	0.1328	0.0699	0
#5	0.4286	0.1604	0.4585	0.6140	0.3967	0.2237	0
#6	0.2000	0.2704	0.2612	0.3739	0.3033	0.0868	0
#7	0.6857	0.2862	0.8770	0.9362	0.8852	0.5865	0
#8	0.2857	0.2044	0.3394	0.5106	0.2623	0.0699	0
#9	0.4571	0.4308	0.5643	0.6261	0.6098	0.1440	0
#10	0.1714	0.4497	0.1506	0.1945	0.2328	0.1242	0
#11	0.5714	0.2421	0.6864	0.7082	0.7180	0.0776	0
#12	0.0286	0.7421	0.0524	0.1884	0.0885	0.0607	0
#13	0.0571	0.1855	0.0915	0.1459	0.2246	0.0917	0
#14	0.1714	0.1415	0.2507	0.3891	0.2475	0.0960	0
#15	0.3714	0.0440	0.4738	0.6383	0.4492	0.3472	0
#16	0.0571	0.5881	0.0629	0.1003	0.2016	0.0621	0
#17	0.5714	0.6447	0.7245	0.8359	0.6311	0.1313	0
#18	0.0857	0.6667	0.1983	0.6383	0.1393	0.5300	0
#19	0.2571	0.4340	0.3603	0.5623	0.3344	0.0903	0
#20	0.5429	0.4843	0.6549	0.7538	0.6066	0.3522	0
#21	0.4000	0.2233	0.5462	0.8723	0.3098	0.0452	0
#22	0.2571	0.8239	0.3718	0.7599	0.1262	0.0812	0
#23	0.4286	0.3774	0.4233	0.1854	0.6754	0.0974	0
#24	0.5143	0.2893	0.5357	0.7264	0.3754	0.0953	0
#25	0.3429	0.6289	0.2555	0.1125	0.4262	0.0423	0
#26	0.3429	0.8962	0.3241	0.6292	0.1066	0.1411	0
#27	0.1429	0.5818	0.0362	0.1429	0.1016	0.0000	0
#28	0.0857	0.3491	0.0515	0.0000	0.2443	0.0466	0
#29	0.4286	0.2138	0.5663	0.7264	0.5557	0.2025	0
#30	0.3429	0.9937	0.4700	0.6140	0.4459	0.0628	0
#31	0.4000	0.3836	0.3737	0.3161	0.4705	0.2653	0
#32	0.3429	0.5660	0.3546	0.3252	0.5033	0.3677	0
#33	0.0857	0.3711	0.0658	0.0912	0.1967	0.2371	0
#34	0.5143	0.3428	0.7464	1.0000	0.5770	0.3084	0
#35	0.4286	0.2830	0.4909	0.5623	0.5246	0.2689	0
#36	0.0857	0.5157	0.1468	0.2888	0.1885	0.0600	0
#37	0.4286	0.5000	0.4929	0.5897	0.4098	0.2322	0
#38	0.1143	0.5063	0.1316	0.2158	0.1426	0.0720	0
#39	0.3714	0.4465	0.4833	0.5532	0.4934	0.3860	0
#40	0.4571	0.1792	0.5987	0.6353	0.6148	0.1757	0

Figure 3: Imported data into JNN environment

KSDublicated - Copy 98.67%.tvq 4605 cycles. Target error 0.0100 Average training error 0.012419
The first 6 of 6 Inputs in descending order.

Column	Input Name	Importance
4	urea	121.7711
0	gravity	113.4451
5	calc	90.3420
3	cond	89.5009
2	osmo	72.1845
1	ph	58.7597

Relative Importance

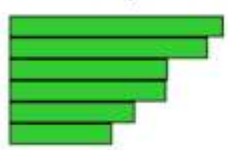

Figure 4: The most influential Features

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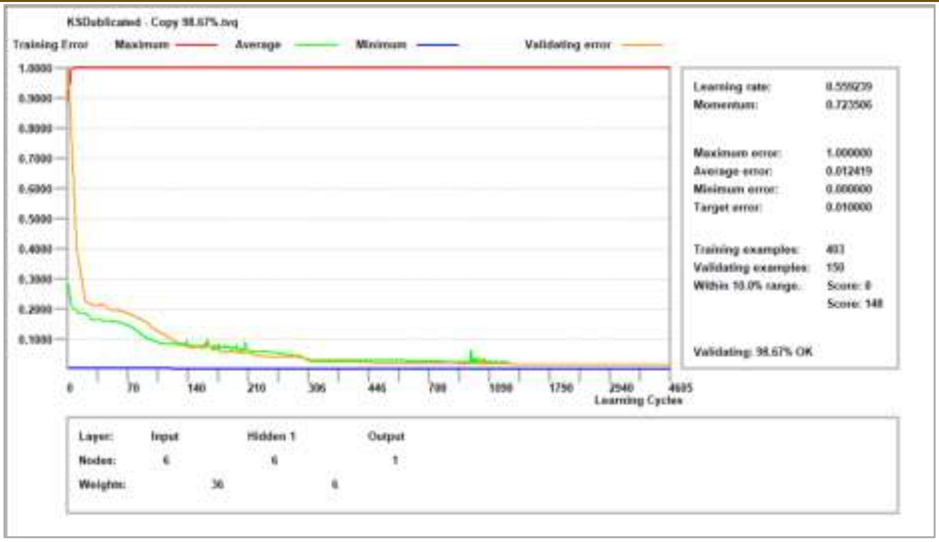

Figure 5: Training and validating of the proposed model

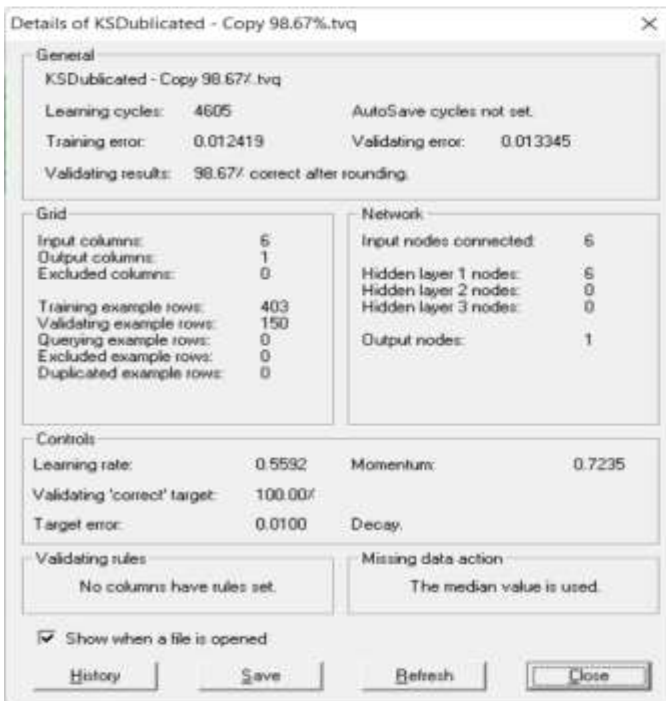

Figure 6: detail Summary of the proposed model

6. Conclusion

In conclusion, this research has undertaken a systematic and rigorous exploration into the development of a predictive model for kidney stone presence based on urine analysis using neural networks. The methodology employed encompassed various crucial stages, including data collection, preprocessing, neural network architecture design, data splitting, model training, and validation. By meticulously studying and categorizing input and output variables, we have created a reliable predictive tool that holds promise for early detection and assessment of kidney stone presence. The findings of this research represent a significant step forward in the field of medical diagnostics, offering potential benefits in terms of early intervention and improved patient care. As we move forward, further refinements and real-world applications of this model can lead to more precise and efficient diagnostic tools for the medical community, ultimately contributing to enhanced healthcare outcomes for individuals at risk of kidney stone development.

References

1. Zaid, A. A., et al. (2020). "The Impact of Total Quality Management and Perceived Service Quality on Patient Satisfaction and Behavior Intention in Palestinian Healthcare Organizations." Technology Reports of Kansai University 62(03): 221-232.
2. Sultan, Y. S. A., et al. (2018). "The Style of Leadership and Its Role in Determining the Pattern of Administrative Communication in Universities-Islamic University of Gaza as a Model." International Journal of Academic Management Science Research (IJAMSR) 2(6): 26-42.
3. Salman, F. M. and S. S. Abu-Naser (2019). "Expert System for Castor Diseases and Diagnosis." International Journal of Engineering and Information Systems (IJEAIS) 3(3): 1-10.
4. Saleh, A., et al. (2020). Brain tumor classification using deep learning. 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech), IEEE.
5. Salama, A. A., et al. (2018). "The Role of Administrative Procedures and Regulations in Enhancing the Performance of The Educational Institutions-The Islamic University in Gaza is A Model." International Journal of Academic Multidisciplinary Research (IJAMR) 2(2): 14-27.
6. Nassr, M. S. and S. S. Abu Naser (2018). "Knowledge Based System for Diagnosing Pineapple Diseases." International Journal of Academic Pedagogical Research (IJAPR) 2(7): 12-19.
7. Nasser, I. M., et al. (2019). "Artificial Neural Network for Diagnose Autism Spectrum Disorder." International Journal of Academic Information Systems Research (IJAISR) 3(2): 27-32.
8. Nasser, I. M. and S. S. Abu-Naser (2019). "Predicting Tumor Category Using Artificial Neural Networks." International Journal of Academic Health and Medical Research (IJAHMR) 3(2): 1-7.
9. Musleh, M. M., et al. (2019). "Predicting Liver Patients using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(10): 1-11.
10. Musleh, M. M. and S. S. Abu-Naser (2018). "Rule Based System for Diagnosing and Treating Potatoes Problems." International Journal of Academic Engineering Research (IJAER) 2(8): 1-9.
11. Mettleq, A. S. A., et al. (2020). "Mango Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 22-29.
12. Mettleq, A. S. A. and S. S. Abu-Naser (2019). "A Rule Based System for the Diagnosis of Coffee Diseases." International Journal of Academic Information Systems Research (IJAISR) 3(3): 1-8.
13. Masri, N., et al. (2019). "Survey of Rule-Based Systems." International Journal of Academic Information Systems Research (IJAISR) 3(7): 1-23.
14. Madi, S. A., et al. (2018). "The Organizational Structure and its Impact on the Pattern of Leadership in Palestinian Universities." International Journal of Academic Management Science Research (IJAMSR) 2(6): 1-26.
15. Madi, S. A., et al. (2018). "The dominant pattern of leadership and Its Relation to the Extent of Participation of Administrative Staff in Decision-Making in Palestinian Universities." International Journal of Academic Management Science Research (IJAMSR) 2(7): 20-43.
16. Kashkash, K., et al. (2005). "Expert system methodologies and applications-a decade review from 1995 to 2004." Journal of Artificial Intelligence 1(2): 9-26.
17. Hilles, M. M. and S. S. Abu Naser (2017). "Knowledge-based Intelligent Tutoring System for Teaching Mongo Database." EUROPEAN ACADEMIC RESEARCH 6(10): 8783-8794.
18. Elzamly, A., et al. (2015). "Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process." International Journal of Advanced Science and Technology 81: 35-48.
19. Elsharif, A. A. and S. S. Abu-Naser (2019). "An Expert System for Diagnosing Sugarcane Diseases." International Journal of Academic Engineering Research (IJAER) 3(3): 19-27.
20. Elqassas, R. and S. S. Abu-Naser (2018). "Expert System for the Diagnosis of Mango Diseases." International Journal of Academic Engineering Research (IJAER) 2(8): 10-18.
21. El-Mashharawi, H. Q., et al. (2020). "Grape Type Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 41-45.
22. El Talla, S. A., et al. (2018). "The Nature of the Organizational Structure in the Palestinian Governmental Universities-Al-Aqsa University as A Model." International Journal of Academic Multidisciplinary Research (IJAMR) 2(5): 15-31.
23. El Talla, S. A., et al. (2018). "Organizational Structure and its Relation to the Prevailing Pattern of Communication in Palestinian Universities." International Journal of Engineering and Information Systems (IJEAIS) 2(5): 22-43.
24. Dheir, I. and S. S. Abu-Naser (2019). "Knowledge Based System for Diagnosing Guava Problems." International Journal of Academic Information Systems Research (IJAISR) 3(3): 9-15.
25. Dahouk, A. W. and S. S. Abu-Naser (2018). "A Proposed Knowledge Based System for Desktop PC Troubleshooting." International Journal of Academic Pedagogical Research (IJAPR) 2(6): 1-8.
26. Barhoom, A. M. and S. S. Abu-Naser (2018). "Black Pepper Expert System." International Journal of Academic Information Systems Research (IJAISR) 2(8): 9-16.
27. Ashqar, B. A. M. and S. S. Abu-Naser (2019). "Identifying Images of Invasive Hydrangea Using Pre-Trained Deep Convolutional Neural Networks." International Journal of Academic Engineering Research (IJAER) 3(3): 28-36.
28. Anderson, J., et al. (2005). "Adaptation of Problem Presentation and Feedback in an Intelligent Mathematics Tutor." Information Technology Journal 5(5): 167-207.
29. AlZamily, J. Y. and S. S. Abu-Naser (2018). "A Cognitive System for Diagnosing Musa Acuminata Disorders." International Journal of Academic Information Systems Research (IJAISR) 2(8): 1-8.
30. Al-Shawwa, M. and S. S. Abu-Naser (2019). "Knowledge Based System for Apple Problems Using CLIPS." International Journal of Academic Engineering Research (IJAER) 3(3): 1-11.
31. Alshawwa, I. A., et al. (2020). "Analyzing Types of Cherry Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 4(1): 1-5.
32. Al-Nakhal, M. A. and S. S. Abu Naser (2017). "Adaptive Intelligent Tutoring System for learning Computer Theory." EUROPEAN ACADEMIC RESEARCH 6(10): 8770-8782.
33. Almurshidi, S. H. and S. S. Abu Naser (2017). "Design and Development of Diabetes Intelligent Tutoring System." EUROPEAN ACADEMIC RESEARCH 6(9): 8117-8128.
34. Almasri, A., et al. (2019). "Intelligent Tutoring Systems Survey for the Period 2000-2018." International Journal of Academic Engineering Research (IJAER) 3(5): 21-37.
35. Almasri, A., et al. (2018). "The Organizational Structure and its Role in Applying the Information Technology Used In the Palestinian Universities-Comparative Study between Al-Azhar and the Islamic Universities." International Journal of Academic and Applied Research (IJAAR) 2(6): 1-22.
36. Al-Habil, W. I., et al. (2017). "The Impact of the Quality of Banking Services on Improving the Marketing Performance of Banks in Gaza Governorates from the Point of View of Their Employees." International Journal of Engineering and Information Systems (IJEAIS) 1(7): 197-217.
37. Alhabbash, M. I., et al. (2016). "An Intelligent Tutoring System for Teaching Grammar English Tenses." EUROPEAN ACADEMIC RESEARCH 6(9): 7743-7757.
38. AlFerjany, A. A. M., et al. (2018). "The Relationship between Correcting Deviations in Measuring Performance and Achieving the Objectives of Control-The Islamic University as a Model." International Journal of Engineering and Information Systems (IJEAIS) 2(1): 74-89.
39. Al-Bastami, B. G. and S. S. Abu Naser (2017). "Design and Development of an Intelligent Tutoring System for C# Language." EUROPEAN ACADEMIC RESEARCH 6(10): 8795.
40. Alajrami, M. A. and S. S. Abu-Naser (2018). "Onion Rule Based System for Disorders Diagnosis and Treatment." International Journal of Academic Pedagogical Research (IJAPR) 2(8): 1-9.
41. Al Shobaki, M., et al. (2018). "Performance Reality of Administrative Staff in Palestinian Universities." International Journal of Academic Information Systems Research (IJAISR) 2(4): 1-17.
42. Al Shobaki, M. J., et al. (2018). "The Level of Organizational Climate Prevailing In Palestinian Universities from the Perspective of Administrative Staff." International Journal of Academic Management Science Research (IJAMSR) 2(5): 33-58.
43. Al Shobaki, M. J., et al. (2017). "Learning Organizations and Their Role in Achieving Organizational Excellence in the Palestinian Universities." International Journal of Digital Publication Technology 1(2): 40-85.
44. Al Shobaki, M. J., et al. (2017). "Impact of Electronic Human Resources Management on the Development of Electronic Educational Services in the Universities." International Journal of Engineering and Information Systems 1(1): 1-19.
45. Al Shobaki, M. J., et al. (2016). "The impact of top management support for strategic planning on crisis management: Case study on UNRWA-Gaza Strip." International Journal of Academic Research and Development 1(10): 20-25.
46. Al Shobaki, M. J. and S. S. Abu Naser (2016). "The reality of modern methods applied in process of performance assessments of employees in the municipalities in Gaza Strip." International Journal of Advanced Scientific Research 1(7): 14-23.
47. Al Shobaki, M. J. and S. S. Abu Naser (2016). "Performance development and its relationship to demographic variables among users of computerized management information systems in Gaza electricity Distribution Company." International Journal of Humanities and Social Science Research 2(10): 21-30.
48. Al Shobaki, M. J. and S. S. Abu Naser (2016). "Decision support systems and its role in developing the universities strategic management: Islamic university in Gaza as a case study." International Journal of Advanced Research and Development 1(10): 33-47.
49. Ahmed, A. A., et al. (2018). "The Impact of Information Technology Used on the Nature of Administrators Work at Al-Azhar University in Gaza." International Journal of Academic Information Systems Research (IJAISR) 2(6): 1-20.
50. Abu-Saqer, M. M., et al. (2020). "Type of Grapefruit Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 4(1): 1-5.
51. Abu-Saqer, M. M. and S. S. Abu-Naser (2019). "Developing an Expert System for Papaya Plant Disease Diagnosis." International Journal of Academic Engineering Research (IJAER) 3(4): 14-21.
52. Abu-Nasser, B. S. and S. S. Abu Naser (2018). "Rule-Based System for Watermelon Diseases and Treatment." International Journal of Academic Information Systems Research (IJAISR) 2(7): 1-7.
53. Abu-Naser, S. S., et al. (2011). "An intelligent tutoring system for learning java objects." International Journal of Artificial Intelligence & Applications (IJAIA) 2(2): 86-77.
54. Abu-Naser, S. S. and M. J. Al Shobaki (2016). "Computerized Management Information Systems Resources and their Relationship to the Development of Performance in the Electricity Distribution Company in Gaza." EUROPEAN ACADEMIC RESEARCH 6(8): 6969-7002.
55. Abu-Naser, S. S. and M. A. Al-Nakhal (2016). "A Ruled Based System for Ear Problem Diagnosis and Treatment." World Wide Journal of Multidisciplinary Research and Development 2(4): 25-31.
56. Abu-Naser, S. S. (2016). "ITSB: An Intelligent Tutoring System Authoring Tool." Journal of Scientific and Engineering Research 3(5): 63-71.
57. Abu-Naser, S. S. (2009). "Evaluating the effectiveness of the CPP-Tutor, an Intelligent Tutoring System for students learning to program in C++." Journal of Applied Sciences Research 5(1): 109-114.
58. Abu-Naser, S. S. (2008). "JEE-Tutor: An Intelligent Tutoring System for Java Expression Evaluation." Information Technology Journal 7(3): 528-532.
59. AbuEloun, N. N. and S. S. Abu Naser (2017). "Mathematics intelligent tutoring system." International Journal of Advanced Scientific Research 2(1): 11-16.
60. Abu Naser, S. S., et al. (2017). "Trends of Palestinian Higher Educational Institutions in Gaza Strip as Learning Organizations." International Journal of Digital Publication Technology 1(1): 1-42.
61. Abu Naser, S. S., et al. (2016). "Measuring knowledge management maturity at HEI to enhance performance-an empirical study at Al-Azhar University in Palestine." International Journal of Commerce and Management Research 2(5): 55-62.
62. Abu Naser, S. S. and M. J. Al Shobaki (2016). The Impact of Management Requirements and Operations of Computerized Management Information Systems to Improve Performance (Practical Study on the employees of the company of Gaza Electricity Distribution). First Scientific Conference for Community Development.
63. Abu Naser, S. S. (2008). "Developing an intelligent tutoring system for students learning to program in C++." Information Technology Journal 7(7): 1055-1060.
64. Abu Naser, S. S. (2006). "Intelligent tutoring system for teaching database to sophomore students in Gaza and its effect on their performance." Information Technology Journal 5(5): 916-922.
65. Abu Naser, S. S. (1999). "Big O Notation for Measuring Expert Systems complexity." Islamic University Journal Gaza 7(1): 57-70.
66. Abu Naser, S. S. (1993). A methodology for expert systems testing and debugging, North Dakota State University, USA.
67. Abu Nada, A. M., et al. (2020). "Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach." International Journal of Academic Information Systems Research (IJAISR) 4(8): 6-9.
68. Abu Nada, A. M., et al. (2020). "Age and Gender Prediction and Validation Through Single User Images Using CNN." International Journal of Academic Engineering Research (IJAER) 4(8): 21-24.
69. Abu Amuna, Y. M., et al. (2017). "Understanding Critical Variables for Customer Relationship Management in Higher Education Institution from Employees Perspective." International Journal of Information Technology and Electrical Engineering 6(1): 10-16.
70. Abu Amuna, Y. M., et al. (2017). "Strategic Environmental Scanning: an Approach for Crises Management." International Journal of Information Technology and Electrical Engineering 6(3): 28-34