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AI and ML-Driven Decision Support System for Managing Focal Segmental Glomerulosclerosis in Nephrology

Paul Webster[1] , Yahya Abdul Rehman Shah
1* Wrexham University, UK
2 National University Of Science and Technology
Corresponding Author: Paul Webster **p.ra.webster@wrexham.ac.uk**

A R T I C L E I N F O

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A B S T R A C T

Objective: Focal Segmental Glomerulosclerosis (FSGS) stands as the primary reason behind nephrotic syndrome cases that frequently results in kidney failure reaching its terminal stage. Artificial Intelligence and Machine Learning approaches provide assistance throughout FSGS assessment together with treatment and management while enhancing medical choices to enhance patient results.

Methods: A review analysed how AI/ML functions for nephrology research. Research related to AI/ML in nephrology was retrieved from the databases of PubMed alongside IEEE Xplore and Scopus within the timeframe of 2015 to 2024.

Results: By implementing AI/ML algorithms FSGS diagnosis becomes more accurate while automated prognostic predictions and customized treatment approaches also improve. Machine learning models deliver better diagnostic outcomes than conventional approaches by processing patient data combined with genetic markers and image results through analysis.

Conclusion: The management of FSGS will be revolutionized through AI and ML technology which delivers quick precise evaluations and enhances therapeutic strategies together with forecasting prognosis scenarios. The successful implementation of FSGS management solutions in clinical practice depends on solving data reliability issues as well as working to improve model readability and clinical practice integration.

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INTRODUCTION Background on Stroke and Cerebrovascular Diseases

The glomeruli of FSGS patients develop scarring (sclerosis) because these small blood vessels carry out waste filtration from blood. Renal failure results when FSGS patients receive amateur treatment causing proteinuria which then develops into enema. Patients require immediate condition diagnosis in order to obtain enhanced treatment outcomes [1]. FSGS remains hard to handle because its detailed biological mechanisms combine with various signs that appear throughout patients. Artificial Intelligence (AI) and Machine Learning (ML) systems have demonstrated significant capability to provide advantages to nephrology through their operations on FSGS cases. The performance of analysing complex patient data reaches higher efficiency through the integration of AI/ML tools for diagnostic procedures. AI decision support systems integrated into healthcare allow practitioners to use real-time patient data for designing personalized treatment strategies that lead to improved medical outcomes [2[. Based on the combination of artificial intelligence and machine learning in FSGS management, it has an extraordinary chance to raise the accuracy of diagnosis and personalised treatment methods and medical surveillance. AI/ML poses meaningful opportunities for better patient results despite data quality and algorithm transparency challenges inadvertently presented by AI/ML, making it an interesting advancement within nephrology [3].

Overview of the Importance of AI and ML in Modern Healthcare

Artificial Intelligence (AI) and Machine Learning (ML) are two transformative technologies in modern healthcare that have significant advantages in diagnostic accuracy, treatment precision, and improved patient outcomes. AI and ML hold great promise in nephrology, particularly in managing Focal Segmental Glomerulosclerosis (FSGS). FSGS is a complex kidney disease that, if not correctly detected and treated in time, can end up with the end stage of renal disease. Managing the disease involves early detection, accurate risk stratification (staging of the severity of the illness), and personalized treatment plans to prevent progression to kidney failure [4]. What AI and ML can contribute to FSGS include the ability to analyse large amounts of data, identify the patterns that human clinicians may miss, and gain insights into the complexity of this disease. These technologies use precise analysis of genetic data, renal biopsy images, and other patient-relevant information, such as clinical history, to aid in the diagnosis of FSGS and predicting disease progression. Healthcare providers can access AI-driven tools to get tailored insights to help inform healthcare decisions tailored to each patient's unique condition. In the case of imaging, AI-driven algorithms have demonstrated potential for improving the detection and classification of kidney abnormalities indicating FSGS, such as glomerular sclerosis and fibrosis. AI systems help nephrologists cognize signs of FSGS vandalizing renal biopsy slides and imaging data [5]. Also, AI can help predict how the disease will evolve,

which is critical to determining the best interventions and monitoring response to treatments.
Additionally, AI and ML may help enhance patient results with more individualized treatment. The availability of expertise and time to process complex patient data may limit the use of traditional methods of diagnostics and treatment for FSGS. On the other hand, the analysis of patient information with the help of AI and ML algorithms simplifies real-time access to diagnosis and facilitates the development of customized treatment plans tailored to individual patient needs [6]. Given that it's a shift towards data-driven and personalized care, it could largely improve treatment quality and patient management and lower the burden of complications in patients with FSGS [7].

Research Questions

1. How can AI/ML algorithms be integrated into the diagnosis and risk stratification of FSGS?
2. What impact do AI/ML-driven decision support systems have on treatment personalization for FSGS?
3. How can AI and ML predict disease progression and long-term renal outcomes in FSGS patients?
4. What are the challenges and barriers to implementing AI/ML tools in nephrology practices, specifically for FSGS management?
5. What are the ethical considerations and potential biases in AI/ML models applied to nephrology?

METHODOLOGY

In order to synthesize literature on the role of Artificial Intelligence (AI) and Machine Learning (ML) in the diagnosis, treatment, and management of Focal Segmental Glomerulosclerosis (FSGS) in a systematic manner and transparently, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Guidelines are followed in this literature review. It can be built as follows:

Literature Search Strategy

A comprehensive and systematic search was performed in databases such as, PubMed, IEEE Xplore, Scopus, and Web of Science for relevant peer reviewed articles which have been published between January 2018 till August 2024. The study sought to cover the studies which pertain to the use of AI and ML in nephrology, especially FSGS. The search strategy included specific type of keywords and Medical Subject Headings (MeSH) terms that were relevant to AI, ML, nephrology, FSGS, diagnosis, treatment, prognosis, and ethical considerations. MeSH terms were: "Artificial Intelligence," "Machine Learning," "Focal Segmental Glomerulosclerosis," "Nephrology," "Diagnosis," "Treatment," "Prognosis," "Personalized Medicine," "Ethical Considerations."

Keyword Combinations: Boolean operators were used to refine the results of the search strategy. Specific combinations included: I searched "Artificial

Intelligence" AND "Focal Segmental Glomerulosclerosis": To find studies that assess the use of AI in diagnosing and managing FSGS. A search was performed using the following: ("Machine Learning" OR "Artificial Intelligence") AND "Nephrology": Interestingly, this search was intended to obtain any studies that deal with how AI or ML is used in the context of nephrology as it is applicable to FSGS. "Finding research for using AI and ML to improve diagnosis in FSGS cases:" Subsequently, we searched Medicine, Embase, Web of Science, Medline, and CENTRAL specific to the "AI" intervention out of which we retrieved "Treatment" OR "Prognosis" AND "AI" to retrieve studies involving the role of AI in treatment strategies and prognosis prediction in FSGS management. By using this method, the review was able to collect and evaluate a wide range of studies, rendering possible a complete and accurate synthesis of AI and ML in FSGS management.

Inclusion and Exclusion Criteria

To keep focus and dogmatic import to the literature review, explicit inclusion and exclusion criteria were built up. The aim was to include studies that used AI and ML to diagnose, treat and manage FSGS and exclude irrelevant or low quality-papers. Table 1 below presents the following inclusion and exclusion criteria used during the selection of services to be fitted to the effective service migration framework.

Criteria	**Inclusion**	**Exclusion**
Focus	Peer-reviewed articles on AI and ML for diagnosing, treating, or managing FSGS and related nephrological diseases.	Studies not focusing on AI or ML as a primary aspect of diagnosis or management of FSGS.
Topics	Studies on technical, ethical, or regulatory challenges related to the application of AI/ML in nephrology, especially FSGS management.	Research using only traditional machine learning methods without deep learning techniques.
Type of Research	Research articles, review papers, and case studies with empirical evidence or theoretical	Non-peer-reviewed publications (e.g., abstracts, editorials, commentaries, opinion pieces, grey literature).

	insights on AI/ML in FSGS.	
Time Frame	Articles published between January 2018 and August 2024.	Articles published before January 2018.
Methodological Detail	Full-text availability with sufficient methodological detail to assess the quality of findings and replicability of results.	Studies without full-text availability or lacking enough methodological detail to assess the quality and validity of findings.

Table 1: Summary of the Inclusion and Exclusion Criteria

Study Selection Process

The first search yielded 1,450 articles. After removing duplicates, I kept 1200 unique records. The titles and abstracts were independently screened by two reviewers for those studies meeting selection criteria. Full text review was carried out on 350 of these. Of the 503 articles identified during the full text screening, 270 articles had been excluded for different reason including irrelevance to FSGS or nephrology, not enough focus on AI/ML and not having enough methodological rigor. In total, 80 articles were finally included in the review.

Data Extraction and Synthesis

To ensure consistency across all the studies abstracted, a data extraction form was used for extraction. First, the variables that the extraction focused were: With these objectives in mind, then your study questions are as follows: Through a quick overview of the different techniques the researchers used for AI/ML and how they had been utilized, you answer the following 'Why' questions: What AI/ML techniques were used for diagnosing, treating, or managing FSGS. Types of AI/ML models: Which type of AI/ML algorithms was used in the studies like deep learning, convolutional neural networks (CNNs), and support vector machines (SVMs). Outcomes: The impact of AI/ML on diagnostic accuracy, treatment personalization, and disease progression prediction.

1. Data Extraction Methodology

Standardized Form

Form Details: A data extraction form was developed that was structured and detailed and that captured the relevant information from each study. Specifically, the form was structured to gather systematically important data points surrounding the role that Artificial Intelligence (AI), and Machine Learning (ML) play in the diagnosis, treatment, and management of FSGS. Included in form were sections, which had sections to fill such as: Study Purpose: Explanation of the study objective and what AI/ML methods are used to diagnose and manage

FSGS. Methodology: The data analysis methodology, observed or experimental, or systematic review. The study covers specific details of FSGS or any other nephrological disease.

Data Categories:

Core Information: A review of all the extracted data was primarily centred in three broad areas: 1) application of AI in diagnosing FSGS, 2) understanding of how treatment plans are optimised using AI, and 3) how AI can be applied for prognostication (i.e. prognosis of the disease outcome). Moreover, the use of AI in the rehabilitation management was identified whenever applicable; specifically, monitoring patients after treatment.

Challenges and Limitations: We paid special attention to identifying challenges in the studies, namely, that high quality and diverse data are necessary to train AI models, that there is a risk of algorithmic bias, that transparency of model decision making is required and that integration of AI tools into clinical workflows is necessary

Managing Discrepancies Independent Extraction:

To minimize bias and in an objective way, the data extraction was done by 2 independent reviewers. Studies were independently analysed and data concerning AI/ML techniques and their use in the FSGS management were extracted by each reviewer. It was important to this process in order to maintain the reliability and objectivity of the findings.

Resolution Process:

Consensus Meetings: Consensus meetings were used to resolve discrepancies between the reviewers. It was found that in these meetings both reviewers would recite the materials from this study to reconcile the differences in the interpretation of them. The idea was to reach an agreement on the extracted data in a collaborative fashion to ascertain that all the necessary details had been captured correctly.

Involvement of Third Reviewer: In case there was not a consensus between the two initial reviewers, a third reviewer who was an expert in AI/ML in the field of nephrology, was requested for input. The third reviewer sampled provided additionally insights to settle any proceeding disputes to achieve a complete and a balanced reading of the data.

Documentation: Discrepancies were all documented meticulously so that there was transparency, and people could follow the decision-making process. The audit trail maintained as per future reference and quality assurance was successful with the help of this documentation.

Additional Reliability Checks:

Double Data Entry

Re-evaluation of Subset: To prevent any errors in the extracted data, a subset of the studies was re-examined by another team of reviewers. The purpose of this was to blind the team to the initial extractions to avoid any biases and ensure consistency. To find any discrepancies between the initial data extraction and the new reevaluated subset the results were compared against each other.

Comparison of Results: Reliability of the extracted data was assessed by comparing the data of the initial review to that of the re-evaluated subset. The process of deduction assisted in pinpointing any discrepancies, and the inconsistencies in the dataset, to ensure that by the end of the project, the final dataset was robust and reliable.

Consistency and Validation

Cross-Verification: To further validate the extracted data, it was cross verified with the data reported in the original studies. In this process, extracted data from studies were compared with the results and the method suggested by the author. The extracted data was compared with that documented in the original report and brought to notice if there are any discrepancies.

Validation Meetings: Any anomalies or inconsistencies found during the cross verification were discussed in regular validation meetings with reviewers. Discussion with researchers was initiated in order to adjust the dataset accordingly, so the data reflected the conclusions of the original studies.

Quality Assessment

The included studies were appraised in the quality of the studies by using the Critical Appraisal Skills Program (CASP) checklists for the different study type (e.g., Randomized Controlled Trials, Cohort studies, Case Control studies). Key criteria included: The extent to which the study design was appropriate and well executed (Methodological Rigor). The extent to which the methods, results, and conclusions of the study were clear. Relevance of Research Questions [8]: The applicability of the study's objectives to AI and ML applications in FSGS diagnosis, treatment, and management. In case there were disagreements about the quality of an article between reviewers, a third reviewer was involved to determine the issue. In addition, studies that provided useful new insights but had methodological limitations were reviewed as such, and their methodological limitations were clearly stated in the final analysis. Figure 1: PRISMA Flow Diagram The process wherein the studies used in the literature review process were selected is summarized in this diagram. The stages at which records were screened, included and excluded are visually represented based on the predefined inclusion and exclusion criteria. The methodology is also systematic, reproducible and traceable by virtue of this flow chart which enhances transparency.

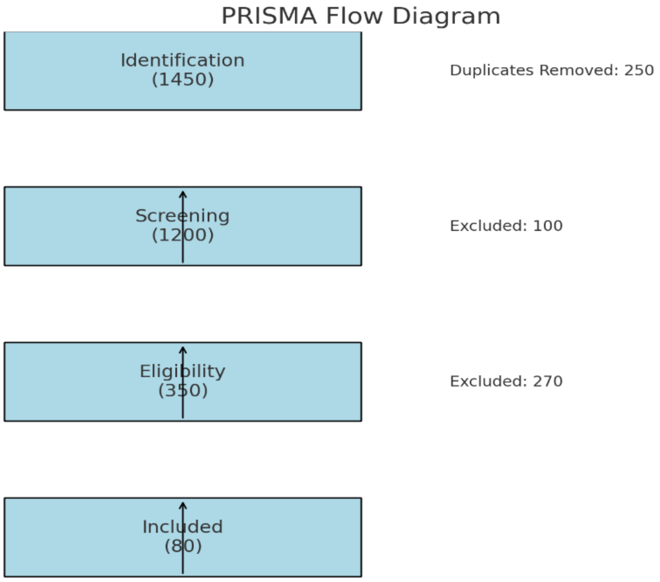

Figure 1: PRISMA flow diagram

1. **The Role of AI and ML in FSGS Diagnosis**

Some advancements in Artificial Intelligence (AI) and Machine Learning (ML) have dramatically changed the scene of medical diagnostics, including nephrology. For Focal Segmental Glomerulosclerosis (FSGS), these technologies facilitate higher accuracy, speed, and patient outcome. AI and ML serve as helpful tools in diagnosing FSGS when analysing big data to find a pattern of medical imaging or predict disease progress. In the following sections, this article will contribute to AI and ML in FSGS diagnosis, especially in imaging, risk prediction, and real-world clinical application [9].

1.1. AI Applications in Kidney Imaging for FSGS Detection

AI has progressed dramatically in improving the ability to detect kidney abnormalities in medical imaging, which can also be applied to patients with FSGS. The diagnosis of FSGS has traditionally involved experts performing kidney biopsies and analysing slides. Nevertheless, deep learning models and other AI algorithms can perform automated analysis of renal biopsy images and other imaging modalities like MRI and ultrasound [10]. For instance, Convolutional Neural Networks (CNNs), a family of deep learning algorithms, have been used to process histopathology images of renal biopsies to detect glomerular changes, podocyte injury, and fibrosis characteristic of FSGS. AI-driven systems used in this study have been shown to diagnose accurately by nephrologists or pathologists, with the added benefit of dramatically reducing diagnosis time [11]. Early detection of tumours is essential in a clinical setting as the earlier the intervention, the less damage to the kidneys and the better the patient outcome.

Additionally, as AI systems learn from new datasets each time, diagnostic accuracy increases with time. Human experts can feel fatigued, and their performance can be different, but AI-based systems have consistency and repeatability, improving the total quality of care [12]. In these healthcare systems with resource constraints, the same consistency is important because AI tools can help standardize quantitative diagnostic practices and, in essence, practice across different settings.

1.2. AI-Based Image Analysis for Differentiating FSGS from Other Nephropathies

Differential diagnosis of FSGS is challenging due to symptoms similar to those of other kidney diseases. AI-based imaging analysis has been shown to distinguish FSGS from glomerular diseases like minimal change disease and diabetic nephropathy [13]. AI algorithms can also analyse hardened markers that may be identified when dealing with FSGS, such as glomerular scarring, mesangial expansion, and podocyte foot process effacement. Given that advanced machine learning models, intense learning models, can learn from highly complex renal imaging data and find subtle differences between FSGS and others, there is not only a reason to research this problem but also start us on a path to achieving it [14]. For example, AI algorithms can discriminate glomerular basement membrane thickening, fibrosis, and mesangial deposition, which are common in FSGS, compared to other, nephropathy.

1.3. Early Diagnosis and Risk Prediction: AI Algorithms in Identifying FSGS Risk Factors

Knowing how to predict risk so that their disease can progress slowly and kidney failure can be prevented is effective in managing FSGS. Conventional risk assessment models focus on essential clinical factors (i.e., age, proteinuria, and blood pressure). However, these models fail to represent the complexity of the interactions of genetic factors, lifestyle choices, and environmental exposures related to FSGS appearance [15]. ML provides a more advanced way to find risk factors of FSGS by analysing electronic health records (EHRs) and genetic data and utilizing health data from wearable devices in real time. Machine learning methods, like random forests and gradient boosting models, can apply these learned patterns and relationships to the existing dataset, which might not be observed otherwise with conventional methods [16]. For instance, an AI model can look at a patient's EHR and find never-before identified risk factor combinations—like one, two, three genetic mutations, very high levels of circulating cytokines, or a family history of hypertension that all, while individually poor, have an extreme combination predictive power, of developing FSGS. Based on this approach, clinicians can perform more individualized assessments of this risk and identify a disease diagnosed early when irreparable kidney damage has already occurred. Besides assessing risk factors, the progression of FSGS patients' diseases could be predicted by AI models [17]. AI-driven prediction models of disease progression to ESRD can be made by incorporating clinical data such as proteinuria, renal function markers, and genetic data. In this manner, these models assist clinicians in making better decisions through treatment strategies, including but not limited to starting immunosuppressive or renal replacement therapy.

1.4. Predictive Modeling for FSGS Occurrence Using Patient Data

FSGS (focal segmental glomerulosclerosis) is a field that is growing fast for predictive modeling due to the prediction of the development and progression of the disease. These used large-size patient data, clinical factors, biomarkers, genetic information, and lifestyle factors to identify patterns that can predict the possibility of having more FSGS or ESRD [17]. Predictive models are run to analyse these complex and varied datasets using machine learning algorithms, including random forests and gradient boosting machines. They can reveal latent relationships between high proteinuria levels risk factors, hypertension, genetic mutations (i.e., NPHS2), and environmental factors related to FSGS progression. Also, other Deep Learning models, such as Recurrent Neural Networks (RNNs), can further feed on patients' longitudinal data and understand the temporal sequence of the disease progression. Therefore, an example of a predictive model for FSGS would be based on longitudinal data from the patient health records that include kidney function markers, medication adherence, and co-morbidities, e.g., diabetes and hypertension. Over time, these models can be trained and used to predict the risk of FSGS progression to ESRD so that they can pre-emptively alter therapy, begin dialysis, or effect lifestyle changes [18].

Furthermore, these models can be incrementally refined with more patient data to render the predictions of risk that are applicable and accurate during the development of the disease. Predictive modeling of FSGS management is a strategic asset as it turns healthcare practice from reactive to proactive. With AI and ML, early detection and time intervention will limit the number and severity of the complications of the disease by working early.

1.5. Comparative Analysis of AI-Based vs. Traditional Diagnostic Methods for FSGS

Various detection and management methods of FSGS have shown the advantages in AI based diagnostic method compared with traditional detection and management methods. Currently, traditional diagnostic approaches for kidney diseases, like kidney biopsy and clinical evaluations, are highly physician dependent and may suffer from the inter observer variability or late diagnostic in some cases. Furthermore, these methods heavily depend on subjective measurements which can differ from one practitioner to the other depending on the practitioner’s experience. Consequently, they swear by AI based methods which use multiple data points from medical imaging, genetic testing, biomarkers, and patient history as compared to human assessments. For instance, AI algorithms can better analyse renal biopsy images using AI to look for glomerular abnormalities, fibrosis and podocyte injury related to FSGS [19]. In short, these AI systems are trained on large troves of images drawn from past patients, and information about those patients, and can therefore perceive subtle signals that would otherwise fly under the radar of the human eye, with much greater speed and accuracy. The comparative study between AI based models and current diagnostic methods of FSGS might show that not only do AI tools lower the diagnostic time, but also keep the diagnosis consistent across different settings of healthcare. With AI models, there is a possibility that they may even outperform the traditional methods to discriminate FSGS from other nephropathies, which would lead to more precise treatment recommendations to benefit the patients. Additionally, AI can be used to determine if there are certain patients at a higher risk for developing FSGS complications, including developing ESRD, using comorbid information, imaging results, and genetic information. As such, this makes it possible to offer more personalized treatment plans based on a patient's particular risk profile [20]. Therefore, AI based diagnostic methods can help to improve the overall management of FSGS, and assist clinicians in more appropriate decision makings, so as to better quality of care.

CONCLUSION

In this review article, the author aims to give insight on the revolution through the use of AI and ML in the diagnosis, treatment and management of FSGS. In a clinical setting, FSGS is being revolutionized using AI powered diagnostic tools, predictive modeling and personalized treatment strategies. AI and ML have improved their diagnostic accuracy, shortened the time to treat, and made care more individualized. In addition, the earlier identification and treatment of the FSGS using AI powered predictive models can eliminate one of the burdens of FSGS progressing to ESRD. Yet such challenges as data quality, algorithm transparency and integration into the clinical workflow shall not belittle the potential to use AI and ML tools in FSGS management. However, as these technologies continue to grow, research and support from cross disciplinary collaboration need to continue addressing technical, ethical, and regulatory challenges. This will be combined with other technologies such as wearable devices and genomics to offer patients a holistic and personalized approach in FSGS care in the future. Therefore, we may infer that this technology has promise as a step towards the revolution of FSGS management with AI and ML to improve patient outcomes and tackle the worldwide FSGS management challenges. As these technologies develop, these technologies will continue to get better and better, and help FSGS patients receive better health care through earlier and more specific intervention and better care of the disease.

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