Can we use machine learning to improve the interpretation and application of urodynamic data?

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REVIEW

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Can we use machine learning to improve the interpretation and application of urodynamic data?: ICI-RS 2023

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Abstract

Introduction: A "Think Tank" at the International Consultation on Incontinence-Research Society meeting held in Bristol, United Kingdom in June 2023 considered the progress and promise of machine learning (ML) applied to urodynamic data.

Methods: Examples of the use of ML applied to data from uroflowmetry, pressure flow studies and imaging were presented. The advantages and limitations of ML were considered. Recommendations made during the subsequent debate for research studies were recorded.

Results: ML analysis holds great promise for the kind of data generated in urodynamic studies. To date, ML techniques have not yet achieved sufficient accuracy for routine diagnostic application. Potential approaches that can improve the use of ML were agreed and research questions were proposed.

Conclusions: ML is well suited to the analysis of urodynamic data, but results to date have not achieved clinical utility. It is considered likely that further research can improve the analysis of the large, multifactorial data sets generated by urodynamic clinics, and improve to some extent data pattern recognition that is currently subject to observer error and artefactual noise.

KEYWORDS

artifical intelligence, machine learning, pattern recognition, urodynamics, urodynamic data

1 | INTRODUCTION

There is no doubt that machine learning (ML, programs that can improve their performance automatically), and more popularly the wider but poorly defined "artificial intelligence", is a mainstream topic in the media and medical field at present. The significant increase in published scientific articles on this topic in different medical fields shows the interest and need for innovation. Articles and features abound that paint doomsday scenarios of machine takeover or predict labor crises due to job losses. The World Ethical Data Foundation has released an "Open Suggestion" forum,[1] to encourage contributions to the training, building, and testing of artificial intelligence models in an ethical manner.

Issues of regulation, transparency, and responsible use are high on the public agenda.

One Think Tank at the International Consultation on Incontinence-Research Society meeting held in Bristol, United Kingdom, in June 2023 focused on the application of ML specifically to urodynamic data, rather than attempting to respond to the wider issues listed above. The aim was to concentrate on topics that impact urodynamics patients in their diagnostic pathway, and to identify the research questions that might be answered by using ML.

Urodynamic studies (UDS) have been performed and interpreted in a similar manner for several years. However, their value can be controversial due to the lack of standardization on the quality of the UDS tracing, interpretation of specific UDS parameters, and reporting of findings.[2–4] Recently, there has been an increased interest in the utilization of different levels of artificial intelligence, including ML algorithms, to standardize the interpretation of specific UDS parameters to raise the value of UDS as a clinical decision-making tool.

It is important to understand that neural networks, on which ML is based, require like any other tool appropriate and targeted applications. As Professor Lionel Tarassenko of Oxford wrote back in 1998, "Neural networks are not, nor will they ever be, a 'black-box' solution into which data can be poured in the expectation that an answer will emerge."[5] Specifically in urology, consideration of the use of ML has led to recent guidelines from the editors of one journal[6] and guidance for reporting new applications under the STREAM-URO Framework.[7] The need for such guidance emphasizes that good practice and specialist guidance are needed to ensure the appropriate use of this clearly powerful tool. A good understanding of the limitations of the ML approach is required.

There are, though, good reasons to expect ML to have a range of useful applications in urodynamics. Here, there are large historical test databases, diagnostics, and assessments made to some extent on pattern recognition, and noisy data signals are a feature of the discipline. ML is very relevant and is particularly useful in all of these situations. Also, urodynamics is known to have some variation according to the skill of the operator and interpreter.[8] Thus, any data processing that can be more objective and consistent than a human operator may result in more accurate diagnoses. ML thus is likely to be able to result in patient benefit.

2 | THE ADVANTAGES, LIMITATIONS, AND RISKS OF ML APPLIED TO CLINICAL DATA

ML algorithms might potentially enhance diagnostic accuracy, generate more accurate differential diagnoses, and improve patient outcomes when applied to diagnostic tools like urodynamics. The effect of noisy signals and interoperator variation can likely be minimized. As noted above, ML is well suited to an environment where such noisy data, variation in interpretation, and large volumes of data coexist. The need for better objectivity in the use of UDS and for a better quality of measurement has been highlighted in the literature, for example (references). In the past, the application of ML has been somewhat limited by its need for substantial processing power, but now that required power is commonly feasible and affordable. However, it is also essential to be aware of its limitations and risks. Ongoing research, validation processes, and robust regulatory frameworks are crucial to overcoming these challenges and maximizing the benefits of ML.

A central challenge in building ML models is that algorithms are highly "data-hungry" to reach acceptable performance levels.[9] Algorithms should be trained using data that closely resemble the format and quality of the expected data during usage.[10] Even if the available data is known to be unreliable or subject to variability, reconciling the use of noisy data sets with the maxim "garbage in, garbage out" poses a dilemma. While large and noisy data sets are generally better for learning complex patterns, for fine-tuning or evaluating a model, a smaller set of examples with curated labels becomes necessary to develop meaningful systems.[7]

Another critical issue is that biases in data collection significantly affect performance and generalizability. Nonmedical algorithms have shown how they can mirror human biases in decision-making.[11] Racial biases could inadvertently be in algorithms due to existing disparities in healthcare delivery and pre-existing data. For instance, limited studies in specific populations can bias algorithms predicting outcomes from findings, such as the Framingham Heart Study, to predict the risk of cardiovascular events in non-White populations, leading to both overestimations and underestimations of risk.[12] If only one or a few centers' data are used for training in ML, the results will be biased towards the practices in those centers. The application of ML in UDS raises the question of what defines the norm and reveals a weakness in its current use. Unlike binary judgments, urodynamics involves learning complex rules from data, making algorithm training challenging. Additionally, high-value data often exist in unstructured formats, requiring preprocessing for algorithm access. Furthermore, individual models need to be built and validated for each diagnosis. Independent validation data sets from different populations or periods that played no role in model development are crucial as they will identify any performance issues especially significant in complex healthcare practices, such as urodynamics.[10] With such precautions, ML techniques can possibly overcome some current deficiencies in interpretation.

Ethical issues are another essential point to consider. Confidentiality must be reimagined as ML makes withholding information increasingly difficult, since the incorporation of personal data is done by the software automatically and possibly not traceably, thus compromising patient privacy.[8,11] Moreover, any software algorithms have the potential to be designed and used unethically. In the clinical context, ML designers may face similar temptations, and the results more difficult to detect. Clinical decision-support systems could now more easily be programmed to prioritize financial gains without healthcare providers' awareness, creating ethical tension between the intentions behind system design and the goals of care teams and patients.

The healthcare education system requires transformation accordingly.[13] Clinicians using machine-learning systems should familiarize themselves with the system's construction, underlying data sets, and limitations. Overreliance on machine-learning models can lead to automation bias and reduced vigilance for errors, making it challenging to identify incorrect advice.[10] It remains to be seen whether clinicians will be held responsible for judgments made by ML software. Prospective clinical evaluations of the models in real-world settings are essential to assess their performance beyond retrospective analysis based on historical data sets. In the process, it will be necessary to reduce, using evidence from such evaluations, any resistance from practitioners or patients (or their lawyers) to the automation of diagnostic machines.

Other limitations arise from the architecture of ML systems. Even though computing power is sufficiently advanced to bring ML techniques within the reach of everyday hardware, the processing power required is still vastly greater than that needed to carry out classical data processing. It may in many instances, therefore, be more economical in terms of time and energy to pursue those historic methods, rather than substitute all of them with ML. An example of this is the feature incorporated in some urodynamic machines that prompts the operator for zeroing or cough at appropriate points of the test. This can be successfully achieved with simpler algorithms rather than by ML. Another limitation of the method is that ML systems provide the end user with a "black box," delivering an output with little or no detail on the factors that led to the output. If the underlying features identified and used are unknown, it will likely hinder the development of new therapies and theories, since the result is presented without known causes.

The potential advantages of ML when applied to urodynamics are listed in Table 1, and the possible disadvantages, with potential mitigations, are listed in Table 2.

3 | APPLYING ML TO UROFLOWMETRY AND CYSTOMETRY DATA

Two areas are used as examples of the promise, as well as the limitations, of ML in urodynamic pressure and flow data. One is where ML has been applied to uroflowmetry, trying to answer two research questions: "can we use sonoflowmetry to substitute for conventional uroflowmetry?" and, "can we reduce the need for pressure-flow studies in male lower urinary tract symptoms (LUTS)?".

A sound-based deep learning algorithm (Audioflow®) was developed to estimate uroflowmetry parameters and identify abnormal urinary flow patterns,[15] showing an agreement with conventional uroflowmetry for maximum flow, average flow, and voided volume of 77%, 85%, and 84%, respectively. For detection of abnormal uroflow (according to experts' criteria) the area under the curve (AUC) was 0.89.

A convolutional neural network (VGG16 model) was applied to conventional uroflowmetries of a cohort of male patients with LUTS to predict bladder outlet obstruction (BOO) and detrusor underactivity (DU),

TABLE 1 Summary of advantages to the use of ML in urodynamics.

Advantages of ML when applied to urodynamics	
Perform well in noisy environments	Real-time test guidance that responds to user practice and experience
Designed for pattern recognition in unstructured environments	Operates objectively in contrast to human interpretation
Extract the influence of multiple variables from large data sets	Cost savings may be gained by automation and time saving[14]
May promote standardization in reporting, event and artifact labeling, and maintenance of quality at all levels of expertise	Potential for reduction of variability in diagnosis between clinicians

Abbreviation: ML, machine learning.

TABLE 2 Summary of limitations and risk mitigations of the use of ML in urodynamics.

Limitations/risks[11] of ML in urodynamics	Mitigations
Unknowingly magnify bias	Use carefully selected data and consider potential biases: Gender/age division, the minimum number of studies for each diagnosis, a minimum of races and minorities inclusion to reduce bias Utilize extensive even if noisy data for initial ML training, mindful of "garbage in, garbage out" principle. Later, refine with more accurate data for optimization
Privacy, security, and confidentiality	Observe regulations regarding data privacy and security, particularly if constructing a centralized database
Ethical principles of data use	Address ethical considerations and ensure transparency of training sets and methods
Algorithms could be designed to mislead	Independent validation studies on diverse and representative data sets
Influence on insurance companies, reimbursements, recommending drugs, tests to increase profit	Ensure clinicians' education about the construction, data sets, and limitations Include likelihood and confidence intervals in all results
Overreliance, automation bias	Ascertain if validation is needed for each UDS diagnosis Develop an equally robust protocol for the validation of uncommon diagnoses Educate users regarding automation bias and the need for vigilance for errors Consider periodic revalidation Establish clinician training in ML advantages and limitations to ensure safe implementation
Inappropriate or incomplete application of technique	Include ML specialist in the project team

Note: The think tank noted that many recommended points are common to every type of diagnostic technology.

Abbreviations: ML, machine learning; UDS, urodynamic studies.

showing an AUC of 0.73 and 0.72, respectively.[16] A different approach used raw data from male LUTS patients' uroflowmetries to predict DU, applying the partial least squares regression algorithm, with an AUC of 0.80 and an optimum sensitivity of 73% and specificity of 85%.[17] Such studies have used both flow curve shape and standard uroflowmetry parameters, but these algorithms still have not reached adequate robustness and reliability to substitute for conventional uroflowmetry and pressure-flow studies.

Another example with similar results is the use of ML in filling cystometry, which has been explored to detect artifacts, detrusor overactivity (DO), and assessing average detrusor pressure garnered from the area under the urodynamic curve. Manifold learning and dynamic time-warping algorithms were used in a study that included 799 UDS traces.[18] The AUC of the training sets was 0.84, leading to an overall accuracy of 81%, and the optimum sensitivity and specificity of detecting DO events were 77% and 81%, respectively, in the testing set. A single center study[2] analyzed 805 urodynamic traces of patients with spina bifida, identifying and clustering DO waves; models were designed to detect clinician-identified DO. The time-based model with all 3 pressure channels had the highest AUC of 0.92, with 84% sensitivity and 86% specificity. In another study, ML algorithms were applied to data in an attempt to predict response to overactive bladder (OAB) treatments.[19] The algorithms were found to be accurate and even superior to expert urologists in some areas, though the study noted that ML may complement but not supplant a physician's judgment, especially in the subtleties of physician–patient interaction.

Another interesting application of ML in cystometry is to identify the AUC detrusor pressure to predict upper urinary tract deterioration risk in neurogenic patients.[20] Using the Trapezium and Simpson index and neural network Multilayer Perceptron analysis better results were found in the AUC to predict urinary complications in pediatric patients, compared to conventional predictive factors (detrusor leak point pressure $>40\ cmH_2O$, maximum detrusor pressure $\geq 40\ cmH_2O$).

These examples show that while there is potential for innovative ML analysis of urodynamic data, there is still some way to go before it can be sufficiently accurate for clinical use. The present levels of performance may however be a useful guide and adjunct for human operators, while research using larger, labeled data sets may yet prove acceptable stand-alone efficacy for specific diagnostic questions. Benchmarks for such acceptability could be >95% accuracy for BOO diagnosis from uroflowmetry alone compared to UDS and for the diagnosis of DO, DU, or BOO from UDS. As for current urodynamic methodologies, likelihood scores and confidence intervals will be necessary so that diagnoses can be properly assessed in clinical practice.

4 | APPLYING ML TO URODYNAMIC IMAGING DATA

Further examples of the use of ML in urodynamic data are found when imaging is considered. X-ray fluoroscopic video urodynamic data and ultrasound bladder scans are common diagnostic tools to assess lower urinary tract (LUT) function during storage and voiding of urine and offer detailed assessment methods to investigate alterations in LUT behavior in various patient groups. The interpretation of urodynamic imaging data requires adequate training and expertise, and research indicates that interobserver agreement levels of urodynamic and video urodynamic data vary.[8,21] The quantity of potentially useful information available in these diagnostic data is enormous and methods to extract relevant parameters that may be of clinical importance from these large data sets are essential to improve the diagnostic value of urodynamic imaging data.

In contrast to conventional pressure-based urodynamics, the use of ultrasound to detect bladder shape and behavior during storage and voiding is noninvasive and may omit some of the sensory artifacts associated with catheter insertions and the use of nonphysiological filling rates. A recent study utilized novel data analytical methods to assess the shape of the bladder in the transversal plane during water loading-induced natural bladder filling in healthy women and women diagnosed with OAB who had undergone previous urodynamics.[22] It was shown that the sphericity index of the bladder in transverse view significantly increases during involuntary bladder contractions (DO) in OAB patients, and as such this development may serve as a noninvasive diagnostic tool to assess bladder shape and behavior. The identification of parameters associated with nonvoiding involuntary contractions that can be investigated using ultrasound imaging of the LUT indicates that this noninvasive tool gives us access to measurements of LUT behavior that can be analyzed in a data-driven approach. Another recent study presents methods that may enable semiautomated detection of bladder neck funnelling and the measurement of posterior urethra-vesical angles in women on ultrasound imaging.[23] It was shown that the semiautomated approaches developed in this study have high repeatability and agreement with manual raters. The further refinement of these methods using ML may improve the diagnostic value of ultrasound imaging of the LUT and may help to identify novel parameters associated with LUT dysfunction for clinical interpreters to focus on. ML may also help in this modality also to reduce interobserver variability and variability in diagnostic interpretation between different clinicians.[21]

Video UDS using fluoroscopic imaging of the bladder and surrounding structures, offers another accessible diagnostic tool that provides a detailed data set with information regarding LUT behavior. The information contained in these data sets is difficult to extract for trained clinicians, and automated approaches may help to analyze video urodynamic data in an efficient and objective manner. A recent study designed ML tools that analyzed video urodynamic data obtained from spina bifida patients to classify the severity of bladder dysfunction in this patient group.[24] It was shown that models built from urodynamic pressure recordings and fluoroscopic video urodynamic data were able to classify LUT dysfunction in an automated approach with a moderately high accuracy (70%). Another study used fluoroscopic imaging to identify parameters associated with changes in bladder shape and bladder neck movement before and after therapeutic interventions for stress urinary incontinence.[25] It was suggested, however, that parameters regarding bladder shape and bladder neck movement were altered by the intervention and may be related to the observed clinical effect.

By enabling more detailed investigation of the LUT using ultrasound and fluoroscopic urodynamic imaging data combined with data-driven pattern recognition approaches of LUT behavior in different patient groups, the development of ML tools to analyze and interpret urodynamic imaging data may enable the identification of novel diagnostic parameters regarding LUT behavior and assess the relationship between these parameters and LUT dysfunction. These advances have great potential to improve our understanding of the different aetiologies associated with LUT dysfunction and enable a more accurate, efficient, and objective diagnosis of different pathologies. Furthermore, these developments, if properly validated, may help to improve our understanding of the exact working mechanisms of currently used therapeutic approaches and potentially lead to the identification of pathophysiological mechanisms that can be targeted in novel therapeutic developments.

5 | PROPOSALS AND GUIDELINES FOR FUTURE WORK WITH ML IN URODYNAMICS

Given, then, that applications are possible but have not yet reached full potential for clinical use, the Think Tank developed the following suggestions for the use of ML in urodynamics:

- Continue using classical processing methods where sufficiently useful, for instance, filtering noise from pressure data, or existing software aids for good urodynamic practice.
- Ensure training methods and data sets are described transparently.
- Continue current user training initiatives, treating ML as a tool but not a substitute for operators.
- Involve ML specialists in study design and practice.
- Maintain principles of good clinical practice, as for all research.
- Focus on areas that have well-defined endpoints/outputs, to enable labeling for training and testing to be carried out with sufficient clarity, for example, BOO is well-defined, intrinsic sphincter deficiency is not.
- For those endpoints defined in accord with the suggestion above, giving a likelihood of the result, rather than a binary yes/no result, is likely to be more realistic and useful clinically.
- Consider clinical areas that focus on patient benefit, rather than, for example, methods of measurement.

The following areas are proposed as useful directions for research studies. In each case, it is suggested that the requisite large volume of clinical data is assembled, labeled where necessary for the ML technique employed, and the outcomes independently validated using diverse, supervised data sets.

- Can areas of diagnostics or classification be identified where practitioners consider patterns to exist, but which cannot be defined reliably, for example, flow curve shape, or artifact recognition?
- Can we assemble large, labeled data sets that include both good and variable ("noisy") quality data for training and testing for real-world clinical application?
- Can analysis of symptom measures, bladder diaries and patient phraseology give more diagnostic accuracy in tandem with current methods?
- Can automatic prompts be developed to guide patients when completing bladder diaries and symptom scores?
- Can we improve the use of multifactorial inputs, combining lifestyle, behaviors, symptoms and signs, to better inform clinical diagnosis and management?
- Can we identify any barriers that exist for user and patient acceptance of automated diagnostics?

CONFLICT OF INTEREST STATEMENT

Andrew Gammie has consultancy and project grants from Laborie. Bruna M. Couri is an employee of Laborie. The remaining authors declare no conflict of interest.

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