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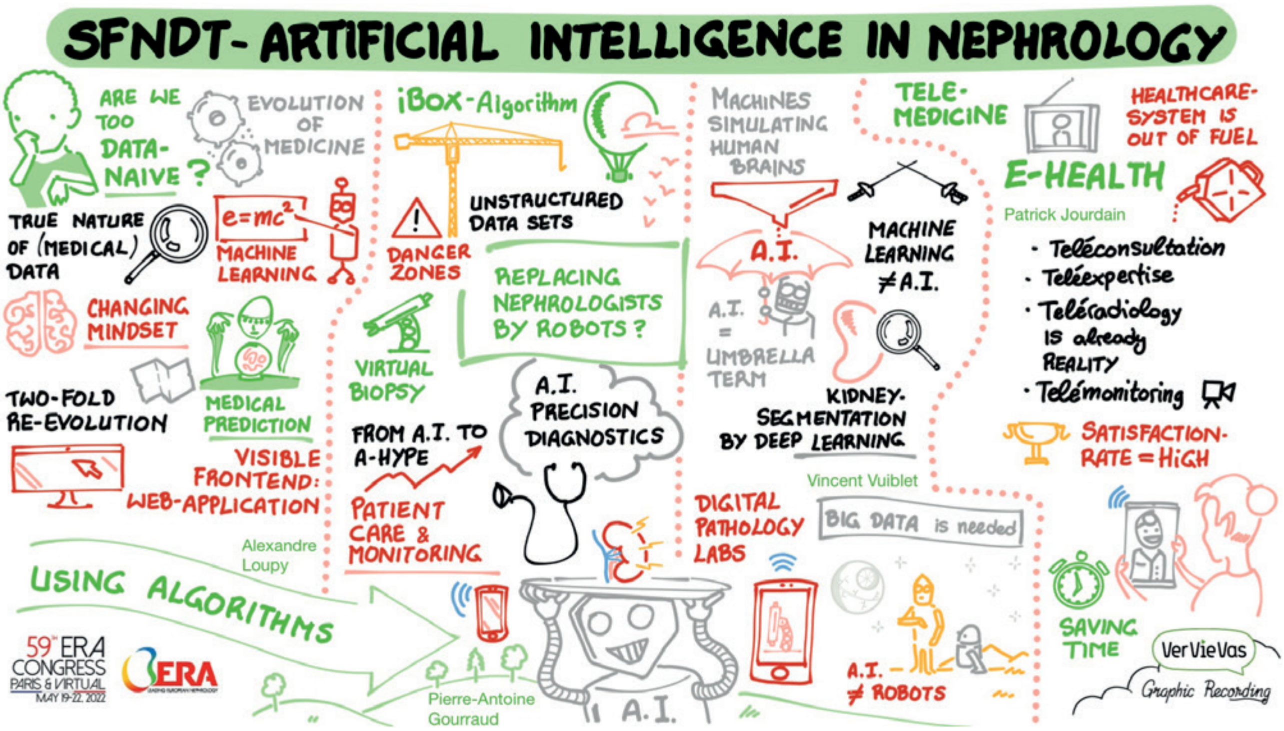
Symposium 0.7
Joint symposia ERA-SFNDT
Artificial Intelligence in nephrology



Computer-assisted decision making in kidney care

Alexandre Loupy, France

Physicians nowadays need to process large amounts of data to master the complexity of 21st-century patients, promptly establish the correct diagnosis, provide risk stratification and disease staging, and ensure an optimal response to therapy. In the niche specialty of kidney transplantation, integrative multi-modality strategies prove useful to this end.

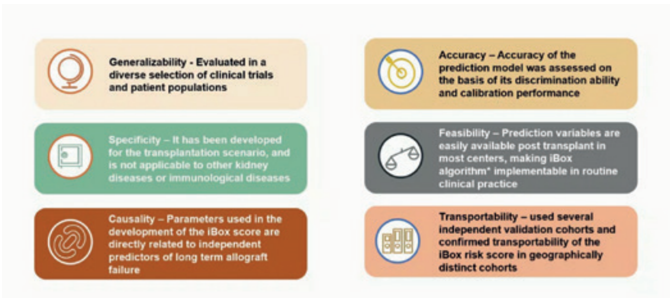


Figure 1.
Features of the iBox algorithm (from ref. 1)

An international consortium, led by Professor Alexandre Loupy, head of the Paris Transplant Group, aimed to devise a universal digital biomarker tool to predict post-transplantation hard outcomes. The team developed the first universal algorithm for predicting the risk of kidney transplant loss - the Integrative Box (iBox) Scoring System and used it to study allocation and prognosis of allografts, as well as diagnosis and treatment efficacy. The group focused on proving that the iBox was generalizable to different transplant systems, database systems, and countries and that the parameters carried causality in the long-term allograft deterioration process, as well as on transportability. Another possible application of the iBox algorithm is patient monitoring and medical decision-making. It appears that iBox provides a reliable prediction of long-term graft survival and can be used as a contextualization tool in designing clinical trials and facilitating faster drug development.

Furthermore, iBox can be viewed as an emerging surrogate endpoint for future clinical trials.

The native kidney is one of the points of interest in kidney transplantation. It is therefore important to identify mechanistically informed biomarkers to frame the decision to perform a biopsy. This again calls for multi-modality. As opposed to testing cell-free DNA to obtain a positive or negative test, probabilistic assessment is used by embedding the test into different standard-of-care parameters, and measuring whether it brings an additional and in-depth value for predicting whether a kidney allograft is rejecting. Concerning precision diagnosis, an artificial intelligence (AI) tool needs to integrate diagnostic parameters. Thus, the group introduced the D6 approach, where D1 is standard pathology, D2 is immunohistochemistry, D3 is clinical context, D4 is mechanistically informed biomarkers, and D5 is the molecular dimension of diagnosis, and D6 is an integration of those. Three ongoing clinical trials are using the D6 approach in their standard diagnostic care, and clinicians are provided with molecular reports which are included in their assessment of how the patient should be treated. Another digital tool, the validated Virtual Biopsy system, predicts what a zero-time kidney biopsy would look like using parameters that are available at the time of transplant. It is currently in the pipeline for implementation in one of the Organ Procurement Organizations in the USA. Finally, AI-based simulation tools used for allograft allocation were monitored in the worldwide transplant activity during the COVID-19 crisis and different practice patterns were compared. By using such data the simulation algorithm can not only be descriptive but also generate policy changes.

From the database to the clinic

Pierre-Antoine Gourraud, France

The practice of medicine is ever-evolving and in the coming years it will not solely be based on the practitioner's experience and memory, but find leverage in the combined powers of on-demand data and real-time computation. Medical records are contributed by multiple sources – acquired from the patient, often written down by a caregiver, produced by medical devices, paid by insurance companies, stored by healthcare institutions, transformed by data scientists, etc., and must be observed as non-material goods, i.e. data.

The use of AI-processed data to make clinically valuable predictions is only one among the many possible AI applications, such as classification, transformation, image recognition, etc. Machine learning prediction has three stages: defining the problem, i.e. the hypothesis, the input of all available data, as the recording of data is no longer cost-limited to significant data, and finally the data prediction. The methodology for evaluating prediction is more important than the models/algorithms themselves. By using computation power, it is possible to employ multiple prediction methods, stress one or challenge another, operate with multiple classifiers, etc. Therefore, the focus is no longer on the model, but on the evaluation of the robustness of the prediction performance.

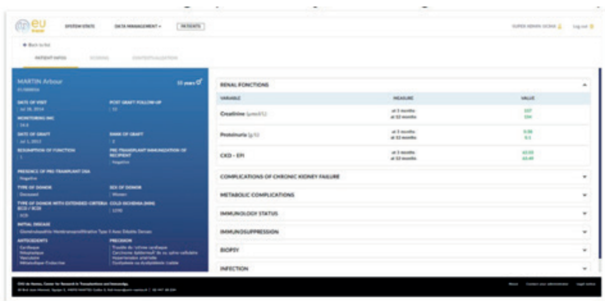


Figure 2.
Development of interfaces to manage and secure on-demand computation and aggregated statistics

In the context of the European project led by Professor Alexandre Loupy, a clinical decision support system is being built that combines integrative data and algorithm analytics principles into a platform, enabling the crunching of data from the database onto the bench, i.e. the clinic. The first key success factor of this platform is that the existing, validated and certified reference set databases come first. The application is therefore a window into the reference data, and the algorithm build comes on top of this data. The application uses distributed reference data, meaning that only the results of the computation travel, whereas the individual pieces of data used to make a decision remain in the database, which is the emerging principle of data governance. Also, the focus on the individual patient is the starting point of all computations supporting decision-making at the bedside. The user interface of the application provides graphical access to all data, lays out data of a single patient in an actionable way, and presents interactive results of analytics and prediction. The functionalities can trigger iterative enhancement of how to use the combined power of on-demand data access and computation.

Therefore, the road from database to clinic leads from creating value by combining data sources and data transformations via building clinical support with reference data, while looking at IA not as a revolution, but as a computational experiment.

Artificial intelligence in nephropathology

Vincent Vuiblet, France

Artificial Intelligence is an umbrella term for phrases such as data science, artificial intelligence, machine learning, and deep learning. There are certain misconceptions between deep learning and machine learning. The most common one is that deep learning is superior to machine learning, which is incorrect because the method's effectiveness is dependent on the issue at hand, as well as the quantity and type of data employed. Another misconception is that AI resembles C3PO, a human-like robot from Star Wars. The truth is that general AI or Super AI remains in the field of science fiction. However, narrow AI, which is suited for a specific task or an association of specific tasks, has been the focus of research ever since the middle of the 20th century.

From their first use in medicine in 1970, computers have made their way into the clinic, and nowadays AI is mentioned in 20,519 publications on PubMed, 82% of which have been published in the last 4 years. Three main fields of research of specific application of AI in nephropathology are segmentation, which involves identification inside the histologic component, classification, which is the foundation of the tool helping the pathologist to make a diagnosis, and quantification, which plays a vital role in prognosis. AI can aid nephropathologists by improving inter-pathologist reproducibility, time-saving, optimization of classification, accessing data otherwise invisible to pathologists, and finally, by integrating and compiling heterogeneous data from multiple sources (histology, electronic health records, biology).

To develop the use of AI in nephropathology, the following three elements are essential: data from Whole Slide Imaging (WSI), data-expert nephropathologist, and data scientist expert. Concretely, the prerequisites are digital pathology laboratories, 'dating sites' or locations where nephropathologists and data scientists would cooperate, and a network of nephropathologists who would collaboratively conduct research in multicentric studies. AI is an essential and strategic issue in nephropathology because it would facilitate the comprehension of pathology algorithms, enable nephropathology to be the lead field of AI-based tools development, maintain its digital sovereignty and ensure economic sustainability.

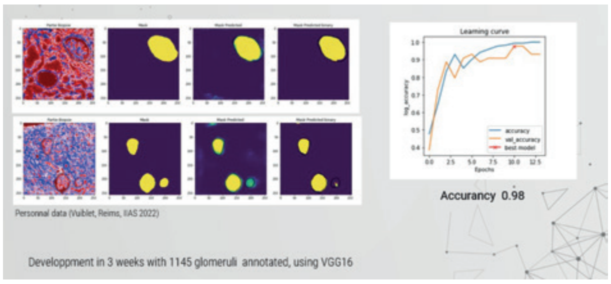


Figure 3.
Glomeruli detection by deep learning

Like the entire medical realm, nephropathology will be profoundly and positively transformed by AI, and medical professionals will inevitably be involved in the development and validation of their future AI-based tools. To keep up with imminent developments, pathology laboratories must quickly adapt to the needs of digital pathology, nephropathologists and data scientists have to work together, and big data needed to train AI models needs to rely heavily on multicenter collaboration.

Connected tools in nephrology

Patrick Jourdain, France

Telemedicine is very likely to become a significant part of chronic renal disease management as informatics and communication capabilities increase, such as the widespread availability of smartphones and the internet, as well as older patients' growing adoption of new communication technology. Another reason for promoting telemedicine development is the healthcare system's resource exhaustion, which is on the decline. Some of the drivers of a shift in viewpoint in favor of telemedicine include an increase in the number of elderly patients, a movement in the culture of senior health, an increase in the prevalence of hypertension, and an increase in the life expectancy of cardiovascular patients.

The umbrella term of e-health includes predictive medicine with a foundation in big data, health wellness with coaching, e-learning and connected medical tools, and telemedicine. Telemedicine covers different fields as well, such as teleconsultation, which used to involve the doctor, the patient, and the video link in between, but is now evolving to include connected devices. Tele-expertise, another aspect of telemedicine, is a discussion between different healthcare professionals and this kind of immediate cooperation saves valuable time for the patient, thereby amending therapy or providing treatment in the earlier disease stages. Tele-radiologic examination, especially echocardiography, is on expansion in France, where more than one hundred hospitals perform magnetic resonance imaging and tomodensitometry remotely, permitting highly specialized or training centers to interactively discuss the case. Tele-monitoring, with connected tools, focuses on structured telephone support to adapt care plans, and it can be complex or light, depending on factors such as the presence or absence of access to doctors, connected tools, assessment of results, nurse coordination, support of care, laboratory measurements and mono/polypathology.

Although benefits in terms of telemedicine include substantial time-saving and improved quality of care, telemedicine is not for all patients and under all circumstances. For instance, patients who find it difficult to use the application or patients with acute abdominal pain or with severe hypertension. Also, there are certain barriers for use of telemedicine in different countries, such as cost, legal grounding, culture, and infrastructure, and most importantly, in terms of chronic kidney disease has the strongest impact on the quality of life, and prioritization. Another challenge is how to combine single pathologies registered in the clinical information management system into polypathologies in an integrated data management system, to follow up with patients and monitor different contributing factors from different pathologies suffered by the individual patient. Nevertheless, telemedicine is a near-term reality that should be viewed as a continuous and integrated process in the life of the patient.

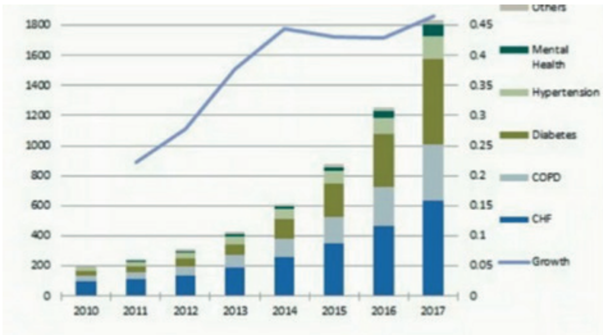


Figure 1. World Telehealth Patients (thousands) By Disease

Figure 4.
The use of telemedicine in different specialties

Further readings

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3. Hermsen M, de Bel T, den Boer M, et al. Deep Learning-Based Histopathologic Assessment of Kidney Tissue. J Am Soc Nephrol. 2019;30(10):1968-1979. doi: 10.1681/ASN.2019020144.
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All the speakers reviewed and approved the content.