

# Team Results Document

## BioSense EPFL



**BIOSENSE EPFL**

**University: EPFL**

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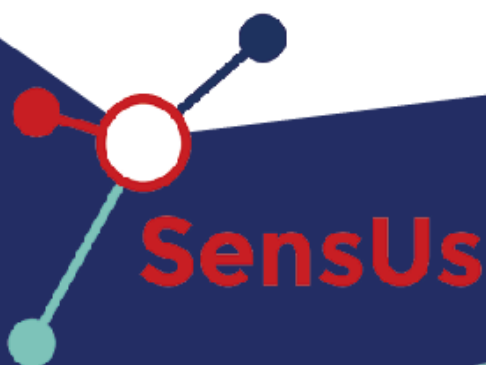
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**08.08.2025**



**SensUs 2024**  
**Acute Kidney Injury**

## 1. Abstract: Summary for the SensUs website

Monitoring kidney function today relies on infrequent lab tests, often missing the early signs of disease or making repeated hospital visits a frequent event. To address this, BioSense EPFL has developed a biosensor for semi-continuous, non-invasive creatinine monitoring. Our platform combines the power of Surface-Enhanced Raman Spectroscopy (SERS) with advanced deep learning. This label-free approach, incorporated with the unique deep learning algorithm, directly captures and quantifies creatinine's unique molecular fingerprint, avoiding the use of fragile biological reagents and enhancing long-term stability. In this work, we present and build upon our developed prototype, demonstrating the feasibility of the approach to molecular sensing. We hope this document serves as a stepping stone towards realizing future healthcare devices.

## 2. AP award: Biosensor developed for the Eindhoven Testing Event

### 2.1. Molecular recognition

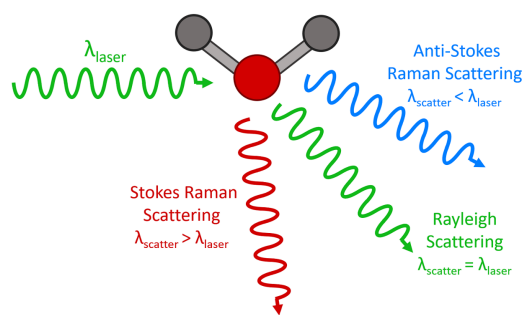


Fig.1 : Raman spectroscopy

The biosensor detects creatinine using Raman spectroscopy, a label-free molecular recognition strategy. Instead of relying on biological elements like antibodies or enzymes, it exploits the intrinsic vibrational signature of creatinine molecules. In Raman spectroscopy, a laser beam illuminates the sample, and the scattered light is analysed. A small fraction of the light undergoes inelastic scattering (Raman scattering),

where the light's energy changes due to interactions with the sample's molecular vibrations (Fig. 1) (*What Is Raman Spectroscopy?*, n.d.). These vibrational modes are unique to each molecule and act like a molecular fingerprint. Creatinine exhibits distinct Raman-active vibrational modes, particularly around 608, 680, 846, and 910  $\text{cm}^{-1}$ , which can be used to identify and quantify it (Bispo et al., 2013; Delrue & Speckaert, 2022).

When creatinine molecules are deposited onto the sensor surface, they adsorb directly onto gold nanostructures without the need for chemical conjugation or binding agents (Karn-orachai & Ngamaroonchote, 2021). This direct interaction enables selective detection, since the Raman peaks arise only from molecules in close contact with the enhancing surface. The lack of biorecognition elements simplifies the sensor design, reduces long-term degradation risks and supports continuous, reagent-free sensing.

### 2.2. Physical transduction

The sensor uses Surface-Enhanced Raman Spectroscopy (SERS) as its transduction method. A laser (785 nm) illuminates the gold-coated nanostructured surface, where the adsorbed creatinine molecules reside. The nanostructures support localized surface plasmon resonance (LSPR),

generating strong electromagnetic fields at the surface (“hot spots”) (Stiles et al., 2008). Raman is a weak phenomenon that happens approximately one out of  $10^8$  photons. The electromagnetic fields at the surface amplify the Raman signal from nearby molecules by up to  $10^6$  times, converting molecular vibrations into measurable optical signals.

The intensity and position of the Raman peaks in the scattered light correspond to the concentration and identity of the analyte (Ye & Spencer, 2017). The use of a dry, nano/microliter-scale sample in contact with a uniform SERS-active substrate ensures consistent signal generation. No intermediate tags or reagents are required, as the signal depends only on the physical proximity between creatinine and the nanostructured surface.

This approach allows non-invasive, real-time quantification of creatinine with high specificity, stability and sensitivity.

### 2.3. Cartridge technology

The cartridge enables semi-continuous biosensing of ISF using Raman spectroscopy (Fig.2). It combines precise fluid handling with controlled substrate movement to allow sequential analysis of micro-droplets on a nanostructured substrate. A manual positioning stage allows micron-scale translation of the sensing substrate while a microfluidic dispensing module deposits  $\sim 1 \mu\text{L}$  ISF droplets at predefined substrate locations. A measurement cycle, therefore, consists of: (1) Dispensation of a droplet onto a clean region of the substrate. (2) Drying of the sample. (3) Raman measurement and (4) Translation of the stage. This process repeats across 25 discrete sensing spots, enabling multiple measurements per cycle.

By integrating localized droplet delivery, substrate repositioning and in-situ Raman readout, the cartridge supports reliable, repeatable biosensing while minimizing signal drift and substrate fouling, which are common challenges in continuous sensing applications.

### 2.4. Reader instrument and user interaction

Our sensor uses a commercial Raman spectrometer (*miniRaman Spectrometer* | *Lightnovo*, n.d.) with a fully integrated readout circuit. The measured spectrum is sent directly from the spectrometer to a computer for pre-processing consisting of (1) baseline correction of fluorescence through asymmetric least squares method, (2) spike removal through a median filter, (3) area normalization for spectral comparison, (4) smoothing using a Savitsky-Golay filter to reduce high frequency noise, (5) outlier detection and rejection through Mahalanobis distance calculations and (6) cropping to remove regions

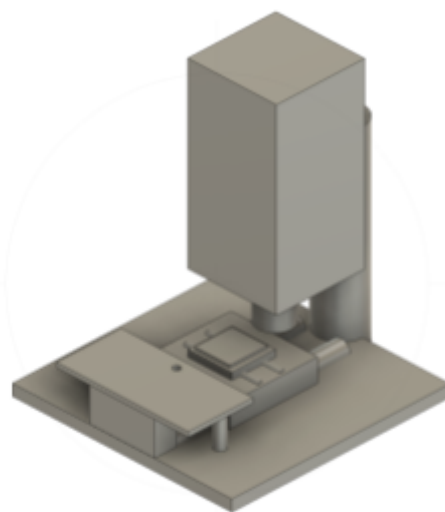


Fig. 2: Scheme of the tabletop SERS testing bench. Showing a sample inlet, a movable stage containing a nanotextured gold substrate and the Raman spectrometer

with high noise and no relevant Raman signal. The filtered data is then fed into a pre-trained neural network for a final concentration estimation of the sample. The sensor is a prototype and thus does not reside over a user-friendly interface and is only operable by trained team members.

### 3. IN award: Biosensor innovation

#### 3.1. Wearable sensor

##### 3.1.1. Technological novelty of wearable sensor



Fig. 3: Handheld Raman spectrometer (*miniRaman Spectrometer* | *Lightnovo*, n.d.)

Our sensor builds upon the robust platform of Raman Spectroscopy, enabling semi-continuous, label-free creatinine monitoring. The Raman Spectroscopy platform used is further enhanced through the incorporation of nanotextured gold substrates to enhance the Raman scattering phenomenon. The recorded spectrum is additionally thoroughly processed and analysed using a deep learning approach. Raman Spectroscopy's inherent ability to record molecular fingerprints allows the platform to go beyond creatinine sensing towards a more universally applicable sensing platform with little more than tuning of the Deep Learning model (Belhaouari et al., 2025; Fan et al., 2023). Not only does this approach allow for a highly versatile platform, but it also allows for simultaneous detection of analytes. We want to highlight the significant advantages this platform offers due to its lack of fragile biological and chemical elements, strongly favouring the stability of this platform for long-term application.

The proposed wearable device integrates three main components: a microfluidic cartridge, a compact Raman spectrometer and an alignment mechanism, all compatible with portable and on-body formats. Miniaturised, portable Raman systems already exist commercially (Fig. 3), enabling on-demand, real-time spectral readouts. The envisioned microfluidic cartridge is designed for time-resolved sampling of biological fluids, such as blood or urine. The microfluidics are envisioned to have a microneedle extraction system and would allow for a sequenced deposition of sample droplets onto predefined sensing areas of the SERS substrate. Due to the restraint posed by the substrate fouling and carryover, the device uses minimal sample volumes. Hereby, the device's lifetime is limited by the

sample volumes and the substrate area. Furthermore, the device would integrate an alignment mechanism to allow the different samples to be independently analysed by the Raman spectrometer. Together, these features form the basis for a reagent-free, semi-continuous, and wearable SERS sensor that combines microfluidics, automated sampling, and ML-driven signal processing for reliable, non-invasive creatinine monitoring.

### 3.1.2. Technical feasibility of wearable sensor

While our sensor is expected to be bulkier than traditional wearable designs, the sensing principle of our sensor is supported by our laboratory prototype. Our initial testing, elaborated further in section 3.2.2, highlights the sensors' ability to measure creatinine in clinically relevant levels accurately. Miniaturization of the spectrometer is therefore the key design challenge. While hand-held Raman spectrometers are commercially available, coin or chip-sized spectrometers are still an active area of research (Park et al., 2023).

Beyond the spectrometer, the transition from the laboratory prototype to a fully functioning wearable sensor is restrained by several more elements.

1. Substrate Area and Lifespan: As mentioned, our device is semi-continuous. This implies usage is limited by the sample size and the substrate area. Smaller devices highly rely on more precise microfluidics or stagnant substrate areas when miniaturizing.
2. Automated Microfluidic Cartridge: The droplet deposition of the prototype lacks user friendliness and is highly adapted to the laboratory setting. A final product would need an automated and reliable sample extraction module with precise sample allocation on the SERS substrate.
3. Optical Alignments and Robustness: In addition to sample allocation on the substrate, the spectrometer needs to be well aligned with each sample. This requires the use of high-resolution motors and can make the device highly fragile and not well suited for one-person use.

These challenges of integration and miniaturization are not inherent to the fundamental sensing principle demonstrated in the laboratory setting. Therefore, the path forward requires a strong engineering effort to translate the proposed sensing scheme into a compact, automated and user-friendly device. While this is non-trivial, the underlying scientific foundation is strong.

## 3.2. Reliability of sensor output

### 3.2.1. Technological novelty of the reliability concept

Our biosensor addresses a major limitation of traditional sensing systems: signal drift and instability due to reagent degradation. By using label-free SERS, our sensor avoids these issues entirely.

A key novelty of our biosensor is the use of a transformer-based deep learning model for spectral quantification. While traditional models like partial least squares (PLS) rely on linear relationships and manually selected spectral features, our model processes the entire pre-processed Raman spectrum as raw input, capturing both subtle and complex patterns. The architecture combines multiple transformer encoder layers for capturing long-range dependencies, and convolutional layers to extract local features. This hybrid design enables the model to handle spectral noise, baseline variability and overlapping peaks, which are common challenges in SERS-based sensing (Luo et al., 2022). Trained on spectra covering creatinine concentrations from 30 to 300  $\mu\text{M}$ , the model achieved a mean absolute percentage error (MAPE) of 5% on the validation set, showing strong generalisation across sample replicates.

One challenge is residual signal drift from creatinine molecules that chemisorb strongly to the gold surface. To address this, we propose two strategies. First, we use nanoliter droplets to localize each sample and reduce cross-contamination. This strategy was effective in our tests, though its integration into portable microfluidic devices remains to be demonstrated. Second, we propose enhancing the deep learning model to account for background signals from previous samples, enabling signal correction even if the substrate is reused. This approach avoids the need for harsh cleaning or substrate replacement. While not yet implemented, this concept can be integrated into the existing model architecture using training data that includes residual background signals.

### 3.2.2. Technical feasibility of the reliability concept

We have demonstrated the core sensing principle through a laboratory prototype using SERS on a commercial gold-coated nanostructured substrate. Creatinine samples (30-300  $\mu\text{M}$ ) were prepared in phosphate-buffered saline (PBS) and deposited into microwells on the SERS surface. Raman spectra were collected using a custom-built confocal Raman spectrometer at 785 nm, followed by data preprocessing and regression modelling.

A total of 952 spectra were acquired and processed. After denoising and baseline correction, a transformer-based deep learning model trained on this dataset achieved a mean absolute percentage error (MAPE) of 5%, confirming accurate quantification across the relevant concentration range. The system produced distinct Raman peaks corresponding to creatinine, and the peak intensities increased consistently with higher creatinine concentrations (Fig. 4).

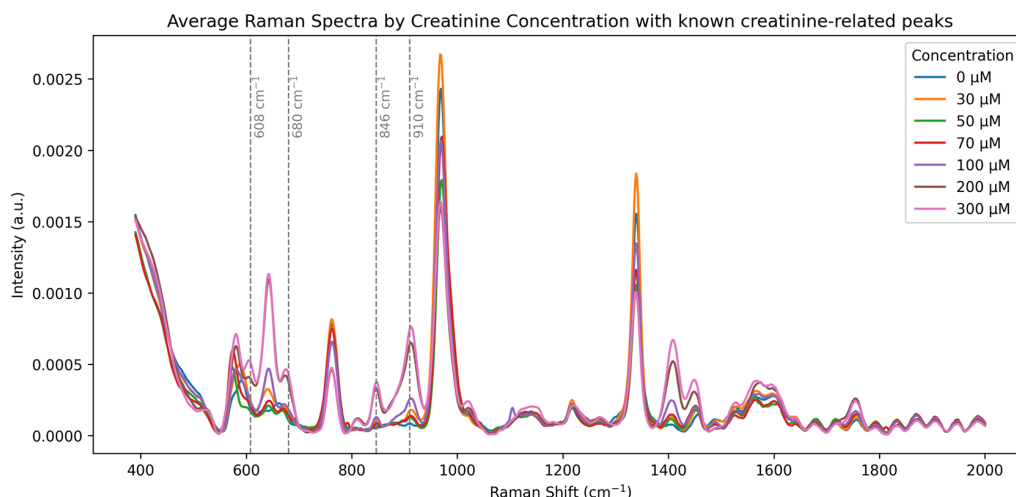


Fig. 4: Average pre-processed spectra by concentration. Peaks around creatinine characteristic Raman peaks (608, 680, 846 and 910  $\text{cm}^{-1}$ ) are highlighted.

Although the current setup used static, dried samples in PBS, it lays a solid foundation for a wearable format. The SERS substrate is reagent-free and reusable, supporting continuous sensing. To transition toward a wearable system, we propose integrating a microfluidic cartridge to deliver droplets of biological fluid (e.g., ISF, blood, urine) to the sensing surface.

The critical elements for feasibility include: (1) the quality and reproducibility of the SERS substrate, (2) the ability to handle and place microfluidic samples reliably, and (3) the stability of the optical readout in portable conditions.

Limitations include the lack of testing in simulated ISF and the use of a single substrate. Future work will address these by testing in biologically relevant matrices, using real-time flow, and exploring regenerable substrates for repeated use.

### 3.3. Original contributions

*From the BioSense EPFL team:*

Daniel and Simone, who developed the SERS method in collaboration with BIOS and LQNO, came up with a new method of evaluating SERS Spectra using machine learning techniques. It consists of intercepting the last layer of the trained neural network in the configuration of a transformer network and performing PCA on it. This method was not yet applied to SERS and shows incredibly promising results. The findings show that the neural networks can generate non-coherent results in the final layer, yet previous layers can still capture meaningful information and relations. By extracting and transforming these layers, a significantly improved model was established by completely bypassing the last layer of the neural network. The best model achieved a MAPE of 5% for creatinine samples between 30 to 300 microliters in PBS. The initial measurement presented here have also been taken by Daniel and Simone. The initial idea of using SERS for creatinine detection was given by Prof. Hatice Altug. This was followed up by a collaborative literature review by the team, the coaches and our Supervisor Prof. Altug. During initial testing the rest of the Team participated mainly through brainstorming and focused on other sensing principles. Further development and testing of the sensor is an ongoing effort by the whole team.

*From Jiayi Tan:*

Following this year's BioSense EPFL team, I have had the pleasure of observing their work on different sensor platforms. In the final week's leading up to the competition, the team has decided to pursue a SERS-based creatinine sensor. Daniel and Simone have taken part in a collaborative effort with Prof. Christophe Galland and Prof. Hatice Altug to implement SERS for creatinine sensing. Hereby, the two students took an original approach to spectral processing, showing promising results. The approach taken represents a novel step towards ensuring reliable and precise sensor output. These results were possible through their active engagement throughout the spring of 2025 in taking measurements and developing their own signal processing strategy. The team as a whole showed high autonomy when working on their different projects, with little supervision from myself or the coaches. The final design and implementation of the SERS platform was done by the team independently.



Jiayi Tan



Cyrill Reding



Fakhriyya Mammadova



## 4. TP award: Translation potential

### 4.1. Customer interviews

Our team has conducted 3 interviews with doctors and professionals from Italy and Switzerland, and we have also conducted a survey of 12 doctors and professionals from Italy.

#### **Interview 1: with Dr Simone Vettoretti**

##### Main challenges in creatinine and potassium level measurement:

*Accessibility & logistics:* Monitoring currently requires either the patient to travel to a facility or a healthcare worker to visit them. Travel is inconvenient for patients (especially elderly), and home visits are expensive.

*High prevalence & cost:* CKD affects 7–10% of the Italian population (2013 data); diabetes ~3%.  $\frac{1}{3}$  of CKD patients are diabetic, and  $\frac{1}{3}$  of diabetics have CKD. Chronic disease patients cost 4× more in healthcare due to hospital stays. By 2035, 30% of CKD patients are expected to also have diabetes and heart failure.

*Medical necessity:* Guidelines recommend both administering certain drugs and closely monitoring creatinine & potassium to avoid severe side effects.

Patient Compliance & Monitoring Gaps: 1.Many patients (especially >70 years old, often living alone) have cognitive impairment, making regular check-ups and medication adherence difficult. 2.Home-based monitoring could prevent adverse events.

Potential Benefits of Self-Monitoring Systems: 1.Reduced hospital visits and improved side-effect management (e.g., preventing hyperkalemia). 2.Doctors could receive real-time or periodic data from an app to detect patterns (diet, medication effects) and intervene earlier. 3.Elderly patients are now generally comfortable with technology, but a good UI is essential.

Measurement Methods: 1.No widely available alternatives to blood testing. 2.Finger-prick testing could be feasible but must account for differences between venous and capillary concentrations. 3.Continuous real-time monitoring is not needed — periodic checks at defined intervals are sufficient.

Role of Lifestyle & New Drugs: 1.Diet and hydration have an impact but are secondary to new drug therapies that significantly improve patient outcomes — albeit with potential side effects requiring careful monitoring. 2.Pharmaceutical companies developing these drugs could have strong interest in such monitoring devices.

#### **Interview 2: with Dr. Davide Diena**

Clinical Use Cases: The biosensor would be particularly valuable in remote settings (rehab centers, retirement homes, rural areas) and post-surgery for early creatinine/potassium detection.

Reliance on Biosensor Data: If the technology becomes widely adopted and proven reliable, biosensor readings alone could be trusted without requiring confirmatory lab tests.

Impact on Monitoring Frequency: Reliable home monitoring would increase the frequency and ease of creatinine/potassium checks, improving early detection and management and decrease hospital visits.

Patient Challenges: The main concern is psychological fixation on numbers. However, modern monitoring devices are user-friendly enough that ease of use and tech literacy are not major barriers, even for elderly patients.

Critical Applications: Real-time tracking could help prevent sudden cardiac death (especially for potassium abnormalities) and enable faster initiation of renal replacement therapy in surgery patients with known risks.

### **Interview 3: with Dr. Menno Pruijm**

Challenges in Potassium Measurement: 1. More complex to measure accurately because intracellular potassium concentration is much higher than extracellular. 2. Invasive monitoring (e.g., needle insertion) may damage cells, artificially affecting readings. 3. Potassium levels in interstitial fluid show a time delay compared to blood levels.

Impact on Hospital Visits: 1. Could help reduce hospital visits, especially since kidney-related issues can be “silent diseases” where patients remain asymptomatic until advanced stages. 2. Earlier detection through home or outpatient measurement could enable earlier treatment.

Need for Continuous Monitoring: 1. Continuous monitoring is less necessary for most patients; occasional at-home testing may be sufficient. 2. Continuous monitoring would be valuable in specific high-risk cases, e.g., post-kidney transplant patients, where frequent hospital visits are costly and burdensome.

### **Survey Results:**

1. How do you typically measure creatinine and potassium levels in CKM patients?

75%-Standard blood draw with lab analysis(24–48h turnaround) 16.7%-I don't measure these directly; I rely on referrals/lab reports 8.3%-Creatinine with STD Blood draw (few hours turnaround), potassium with point-of-care devices

2. What is your biggest challenge in managing potassium levels in CKM patients?

25%-Delayed lab results 50%-Lack of reliable home-monitoring tools 8.3%-Patient non-adherence to follow-ups 16.7%-No major challenges

3. How frequently do your CKM patients get their creatinine and potassium levels checked?

8.3%-Weekly or more 8.3%-Monthly 25%-Every 3–6 months 58.3%-I repeat creatinine and potassium sampling after changing the prescription of RASi, MRA and diuretics in patients with cardiovascular-kidney-metabolic syndrome

4. If a compact, non-invasive or minimally invasive biosensor could provide real-time creatinine/potassium readings, how useful would it be in your practice?

50%-Extremely useful 41.7%-Moderately useful 8.3%-Slightly useful

5. What concerns would you have about adopting a biosensor-based solution for CKM electrolyte monitoring?

58.3%-Accuracy and reliability 8.3%-Cost and insurance coverage 8.3%-Patient usability and training 8.3%-Integration with existing systems 8.3%-Cost and accuracy 8.3%-Data handling

6. Do you think a device for home monitoring of creatinine and potassium:

30%-would make the management of frailer patients safer 40%-would prevent serious hyperkalemia and AKI in patients with cardiovascular-kidney-metabolic syndrome treated with combination therapy 30%-would help monitoring changes of renal function post AKI

## 4.2. Design of validation study

### 1. Execution summary

A compact, minimally invasive home biosensor is proposed to provide near real-time readings of creatinine and potassium for patients with Cardiovascular–Kidney–Metabolic (CKM) syndrome. Interview results show clinicians currently rely on standard blood draw with lab analysis (24–48h turnaround) and find a home sensor extremely useful, provided accuracy and reliability are adequate. The proposed validation study assesses whether the hypothesized added value — safer medication management, earlier detection of hyperkalemia/AKI, reduced hospital visits and cost — is present and quantifiable.

We designed our device with a focus on the Italian market that can then be transferred to other markets with time and appropriate modifications as well.

### 2. Conceptual Prototype and its Use Case:

A small sensor station connected to a smartphone app. The reader measures creatinine and potassium from the blood samples (like in diabetes) and transmits results to the app. The app stores history, flags threshold breaches, and provides a secure share option to the clinician.

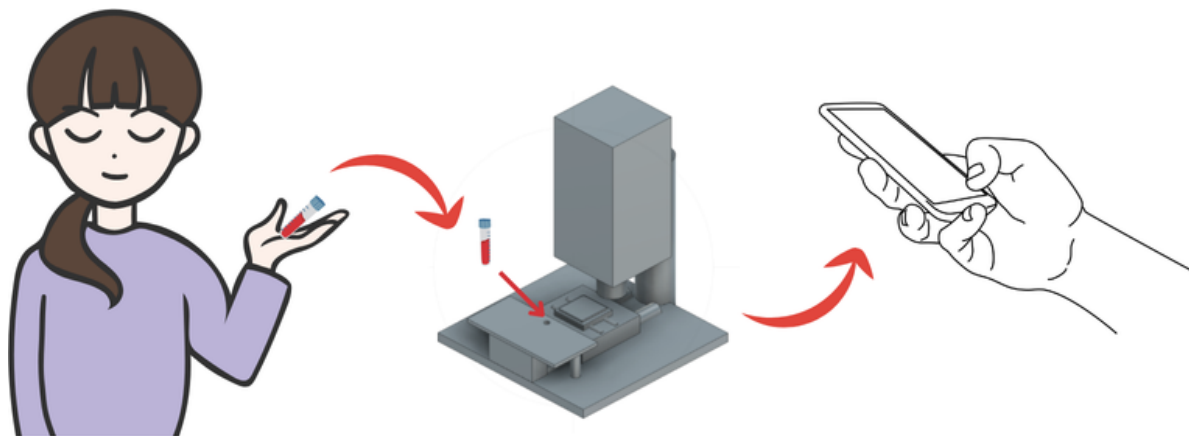


Fig 5: Illustration of a conceptual prototype and its use

The app records and displays numerical values for creatinine ( $\mu\text{mol/L}$ ) and potassium ( $\text{mmol/L}$ ), along with timestamps, trend graphs, and alerts for both the user and their clinician. It also provides suggested action levels based on clinician-defined rules. Connectivity is available via optional Bluetooth or Wi-Fi, with data stored locally and the choice of cloud backup or export. This design ensures integration even in the absence of a centralized health system—an important consideration for the Italian medical market.

**Use case:** Frail CKM patients can check levels at home after medication changes, receive immediate alerts for dangerous readings, and share data with clinicians for early intervention — avoiding the costs, time, and risks of hospital visits, while lowering the risk of catastrophic outcomes.

### 3. Critical Aspects of the Proposed Solution

1. *Analytical accuracy & precision* — measurements must be clinically comparable to lab reference (within pre-specified limits) for creatinine and potassium across the clinically relevant range. Clinicians explicitly named *accuracy and reliability* as their top concern.
2. *Prevention of adverse events* — timely detection of hyperkalemia and AKI risk.
3. *Usability & adherence* — frail patients or their caregivers must be able to perform the measurement reliably at home.
4. *Data storage & sharing* — the app must safely store and present measurements and allow clinicians to access them (important in regions without centralized systems).
5. *Cost & convenience* — the solution should reduce clinic visits and associated costs sufficiently to be attractive to healthcare systems and patients.

### 4. Validation Study

*Hypothesis:* Early detection through home monitoring leads to interventions that prevent escalation to costly emergency care. The solution will reduce average hospital visits per patient.

*Participants:* 80 CKM patients.

*Duration:* 6-week home monitoring + paired lab draws.

*Measurements:*

1. *Clinical outcomes:* Number and severity of hyperkalemia/AKI episodes prevented.
2. *Economic outcomes:* Estimated cost savings from avoided ER visits, reduced hospital stays, and fewer clinic appointments.
3. *Accuracy metrics:* Agreement between the sensor and lab.
4. *Usability:* Completion rates, SUS scores, qualitative feedback.

*Analysis plan*

1. *Clinical prevention effect:* Compare incidence of severe events with and without home readings.
2. *Cost analysis:* Assign monetary values to avoided admissions, ER visits, and extended stays.
3. *Accuracy:* Bland-Altman and sensitivity/specificity for thresholds.

#### 4. *Usability*: SUS and thematic analysis.

*Criteria*: Proceed if  $\geq 50\%$  of severe events are prevented, average cost savings per patient exceed a clinically and economically meaningful threshold, and accuracy and usability meet predefined standards.

**Environmental Impact**: Since our device enables a shift from hospital stays to at-home monitoring, it will greatly reduce environmental impact.

## 5. Team and support

### 5.1. Contributions of the team members

- Joana Pires, Hanqi Lu, Tran Nguyen, Cyrill Reding: Explored and tested different sensing schemes, including functionalized Screen-Printed Electrodes and Graphene Field Effect Transistors (GFET).
- Joseph Spender, Nabil Bellamy, Arno Douady: Developed the microfluidics, the electronics and the cartridge for the different sensing schemes.
- Daniel Elmaleh, Simone Vicentini: Developed and tested the SERS platform.
- Fakhriyya Mammadova: Developed the Translational Potential of the sensor and conducted interviews with Doctors and Professionals.

### 5.2. People who have given support

- Prof. Hatice Altug: Hosted and supervised two student projects in the framework of Surface Enhanced Raman Spectroscopy.
- Prof. Christophe Galland: Hosted and supervised a student project in the framework of Surface Enhanced Raman Spectroscopy.
- Prof. Sandro Carrara: Hosted and supervised student projects in the framework of Screen-Printed Electrodes.
- Prof. Adrian Mihai Ionescu: Hosted and supervised a student project in the framework of GFET.
- Jiayi Tan: Supported and advised semester projects and day-to-day activities of the Team.
- Francesca Rodino: Advised semester projects in the framework of Screen-Printed Electrodes.
- Ali Gilani: Advised semester project in the framework of GFET.
- Sascha Rivera: Coordinated and coached the different semester projects in the different laboratories.
- Emma Genova Coimbra: Supported the team and transitioned the translational potential of last year's team to this year's Team.
- Dr. Simone Vettoretti: Helped with valuable insights and by providing contacts to the doctors in Italy and helped organizing interviews with them.

### 5.3. Sponsors and partners

- MAKE EPFL: Access to student workstations and sponsorship.
- COMSOL: Technical support, in-kind and financial sponsoring
- Lightnovo: Technical support and equipment provider.
- BIOS: Hosted student projects in the framework of Surface Enhanced Raman Spectroscopy.
- LQNO: Hosted student projects in the framework of Surface Enhanced Raman Spectroscopy.
- BCI: Hosted student project in the framework of working with Screen Printed Electrodes.
- NanoLab: Hosted student project in the framework of working with GFET
- BioSense EPFL Student Association: Provided a framework for the SensUs participants of EPFL.

## 6. Final remarks

We would like to thank all the people who supported us throughout this journey. Special thanks to Prof. Hatice Altug, Prof. Christophe Galland, Prof. Sandro Carrara and Prof. Adrian Mihai Ionescu for hosting and supervising our research projects. We are also grateful to Jiayi Tan, Francesca Rodino, Ali Gilani, Sascha Rivera and Emma Genova Coimbra for their continuous guidance and technical support. Their expertise was essential to the development of our biosensor.

Looking ahead, our team plans to further improve the sensor's performance and explore its integration into a fully real-time, wearable device for patients with acute kidney injury. In addition, we aim to expand the application of our SERS-based sensing platform combined with deep learning to detect other clinically relevant biomarkers. We believe this technology has strong potential for broader use in point-of-care diagnostics.

We are proud of what we have accomplished as a team and excited to continue building on this work beyond the SensUs competition.

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