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SpectralHealth

Application of Hyperspectral Imaging in Healthcare

Deliverable D1.1

Use cases State-of-the-art description and Innovation

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Project acronyms

Abbreviation	Meaning
2D, 3D	Two-dimensional, Three-dimensional
AI	Artificial Intelligence
AR	Augmented Reality
ATMP	Advanced Therapy Medicinal Product
AUC	Area Under the Curve
CNN	Convolutional Neural Network
FMUP	Faculty of Medicine of the University of Porto
FTIR	Fourier Transform Infrared Spectroscopy
HELICoiD	HypErspectraL Imaging Cancer Detection
HSI	Hyperspectral Imaging
IM	Innovative Medicine
ITEA	Information Technology for European Advancement
LUMC	Leiden University Medical Center
MALDI-TOF MS	Matrix-Assisted Laser Desorption/Ionization Time-of-Flight Mass Spectrometry
ML	Machine Learning
mμSORS	Micro Spatially Offset Raman Spectroscopy
QC	Quality Control
RGB	Red, Green and Blue (Color Channels)
ROC	Receiver Operating Characteristic
SoA	State of the Art
SWIR	Short-Wave Infrared
UC	Use Case
UMC	University Medical Center
UV	Ultraviolet
VIS/NIR	Visible / Near-Infrared
WP	Work Package
H3D-VISIONAIR	Hyperspectral 3D Vision and Augmented Reality Platform
PCC	Project Coordination Committee

1. Introduction

1.1. Aim of the activity

The goal of this document is to provide a state-of the art analysis of the use of hyperspectral imaging in the different use cases in the field of Surgery (UC1), Diabetes (UC2), Dermatology (UC3) and Microbiology (UC4).

The documents form the direct basis for the requirements to be defined in Task 1.2 and will be used as reference in prototype development, piloting and evaluation. It will also form the basis for work packages 2-6.

The descriptions are based on open literature and the knowledge provided by the clinical partners in the project. Each of the targeted clinical areas is described in a standardized way. In the first section, a short introduction is given that provides the background & context of the clinical area. The second section describes the clinical and technical state-of-the-art and the third section describes the challenges and innovations.

1.2. Contributors

Use case	Description	Authors
1	Surgery	Leiden University Medical Center
2	Diabetes	FMUP
3	Dermatology	Philips Consumer Lifestyle
4	Microbiology	Johnson & Johnson IM
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2. Use case 1 Surgery

2.1. Introduction

Surgical decision making relies heavily on visual inspection and pre-operative imaging. However, many clinically relevant tissue properties such as perfusion, oxygenation, tumour infiltration, and nerve location are not directly visible to the human eye. Hyperspectral imaging (HSI) captures a complete spectral signature for each image pixel and enables non-contact, label-free tissue characterization[1]. During the past decade, HSI has emerged as one of the most promising optical imaging technologies for image-guided surgery[1,2].

In oncological surgery, complete tumour resection while preserving healthy tissue is essential for patient outcome. Similarly, in nerve-sparing and vascular procedures, accurate identification of critical anatomical structures is needed to reduce complications. HSI offers the possibility to provide objective biochemical information during surgery, complementing conventional white-light imaging, fluorescence imaging and surgeon experience[2,5].

Unlike conventional RGB imaging, which captures only three broad colour channels, HSI acquires tens to hundreds of narrow spectral bands. This enables estimation of physiological parameters including tissue oxygenation, haemoglobin concentration, water content and metabolic state. Such biomarkers can support tumour delineation and tissue viability assessment during surgery[1,2].

2.2. State-of-the-art analysis

Medical HSI systems have evolved from laboratory instruments into compact devices suitable for intraoperative use[1]. Major application areas include tumour margin assessment, tissue viability assessment, perfusion monitoring, identification of anatomical structures and fluorescence-guided surgery augmentation[2].

Several flagship projects have demonstrated the feasibility of HSI in surgery. The HELICoiD project demonstrated hyperspectral imaging for brain tumour detection during neurosurgery through machine-learning based tissue classification[3]. Subsequent studies further demonstrated intraoperative visualization and tumour delineation capabilities using HSI-based decision support systems[4]. Deep-learning approaches including convolutional neural networks, transformers and spectral-spatial learning architectures have significantly improved classification performance[1,2].

Current research demonstrates successful use of HSI in neurosurgery, colorectal surgery, liver surgery, head-and-neck surgery and reconstructive surgery[1,2]. Studies have shown that hyperspectral signatures can differentiate healthy and malignant tissue, estimate oxygen saturation, identify ischemic regions and support intraoperative decision making[2,3,4].

A rapidly emerging trend is the integration of HSI with artificial intelligence. AI models can exploit subtle spectral patterns that are difficult for humans to perceive. This has enabled automated tumour recognition, real-time tissue classification and quantitative surgical guidance. Nevertheless, widespread clinical adoption remains limited due to workflow integration challenges, limited standardisation, sensor-specific variability and computational complexity[1,2].

2.3. Innovation and challenges

The SpectralHealth project addresses multiple recognised barriers to adoption. First, the project advances real-time AI-driven tissue analysis through hardware-independent hyperspectral processing pipelines and efficient machine-learning models. This contributes directly to the project agnostic HSI data concept and hyperspectral data-cube analysis innovations. Such capabilities may facilitate interoperability across vendors and hospital environments.

Second, SpectralHealth develops the H3D-VISIONAIR platform, integrating hyperspectral sensing with augmented reality visualisation. Rather than requiring surgeons to switch between displays, analysed information can be visualised directly within the operating field through AR overlays. This addresses a key human-factors limitation reported in current image-guided surgery systems[5].

Third, SpectralHealth investigates complementary tissue assessment through analysis of aspirated surgical fluids. This extends existing HSI approaches beyond surface imaging and may provide additional biochemical information for tissue classification. To our knowledge, this represents a novel extension of current intraoperative HSI workflows.

Finally, miniaturised sensors, optimised illumination systems and model-compression techniques are expected to reduce system size, power consumption and cost. These developments will facilitate broader deployment of HSI technology in routine surgical practice.

By combining HSI, explainable AI and AR visualisation, SpectralHealth aims to move from retrospective image analysis towards actionable real-time surgical decision support. The expected outcome is improved tumour resection accuracy, preservation of healthy tissue and reduced complication rates.

2.4. Literature

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3. Use case 2 Diabetes

3.1. Introduction

Diabetes mellitus represents a major global health challenge, requiring regular monitoring to prevent acute and chronic complications, including hypoglycaemia, peripheral vascular dysfunction, neuropathy and diabetic foot ulcers. Despite significant advances in diabetes management, current continuous glucose monitoring systems generally rely on minimally invasive sensors, while the assessment of vascular complications often requires separate diagnostic procedures.

Hyperspectral imaging (HSI) is an emerging non-invasive optical technology capable of capturing spatially resolved spectral information associated with tissue composition, oxygenation and physiological alterations. Combined with artificial intelligence (AI) and machine learning (ML), HSI offers opportunities for metabolic assessment, peripheral microcirculation monitoring and the early identification of diabetes-related complications [1–4].

The SpectralHealth diabetes use case aims to investigate these capabilities through the development of wearable and multimodal monitoring solutions, integrating HSI, physiological sensors, AI-based analysis and interoperable data-processing pipelines.

3.2. State-of-the-art analysis

Recent studies have demonstrated the potential of HSI for assessing physiological and vascular alterations associated with diabetes. Dremin et al. [1] demonstrated the feasibility of combining polarized HSI and ML to identify diabetes-related skin alterations. In diabetic foot care, González-Villacorta et al. [2] reported pooled sensitivity of approximately 84% and specificity of 79% for predicting ulcer healing in a systematic review and meta-analysis. Previous research has also highlighted the potential of HSI for tissue oxygenation assessment and wound monitoring [3]. Nevertheless, broader clinical validation remains necessary.

More recently, Sheen et al. [4] investigated short-wave infrared (SWIR) spectral imaging for diabetic peripheral neuropathy detection in 188 patients. Their approach achieved an area under the ROC curve of 0.885 and a classification accuracy of 82.4%, while demonstrating the feasibility of miniaturised multispectral imaging systems.

Regarding non-invasive glucose monitoring, Wawerski et al. [5] demonstrated the feasibility of using HSI and ML for estimating glucose concentrations in controlled solutions. Although these findings support the potential of spectral analysis, they do not establish its clinical performance in human tissues. Complementary optical technologies have also shown promising results. Zhang et al. [6] investigated depth-selective Raman spectroscopy in a study involving 230 participants, reporting a mean absolute relative difference of 14.6% for glucose estimation. Similarly, Song et al. [7] explored enhanced FTIR spectroscopy combined with ML for glucose-related classification. However, these technologies rely on different optical principles and their results cannot be directly extrapolated to wearable HSI systems.

Recent work by Liu et al. [8] further explored HSI combined with ML for non-invasive screening of type 2 diabetes using tongue spectral information, reinforcing the potential of spectral imaging for metabolic assessment.

Despite these advances, significant challenges remain, including physiological variability, interference from tissue constituents, motion artefacts, device miniaturisation, limited clinically annotated datasets and insufficient standardisation. Public resources such as the HyperVein dataset [9] support the development of spectral processing methods, while research on diabetes data harmonisation [10] highlights the broader importance of interoperability and reusable datasets.

3.3. Innovation and challenges

The SpectralHealth diabetes use case aims to advance current approaches by combining HSI, multimodal physiological monitoring and AI within an integrated, non-invasive framework.
The main planned innovations include:

- Wearable HSI-based glucose monitoring: Development of a miniaturised optical sensing solution to investigate the non-invasive estimation of blood glucose variability, assessing its feasibility for repeated or continuous monitoring.
- Multimodal haemodynamic assessment: Integration of HSI-derived information with complementary physiological measurements to investigate blood flow, tissue oxygenation and vascular alterations associated with diabetes-related complications.
- AI-driven spectral analysis: Development of ML models for spectral feature extraction, multimodal data fusion and identification of clinically relevant

physiological patterns, prioritising robustness, explainability and computational efficiency.

- Data harmonisation and interoperability: Development of standardised HSI data structures, interfaces and processing pipelines to support integration across different acquisition systems and promote reusable AI-based solutions.
- Clinical and technical validation: Evaluation of the developed solutions in experimental and clinical settings, including comparison with established reference methods, assessment of usability and investigation of their potential clinical applicability.

The major challenges include the detection of weak and overlapping glucose-related optical signals, interindividual variability in tissue characteristics and skin pigmentation, sensor calibration, environmental conditions, computational requirements and the availability of sufficiently diverse clinical datasets. Robust validation will therefore be essential to distinguish experimental feasibility from clinically reliable performance.

3.4. Literature

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4. Use case 3 Dermatology

4.1. Introduction

Skin diseases represent one of the most prevalent categories of medical conditions worldwide and have a substantial impact on quality of life, healthcare utilisation and healthcare costs. Common conditions including melanoma, non-melanoma skin cancer, psoriasis, eczema, acne and chronic wounds require frequent monitoring and assessment by dermatologists. However, access to specialised dermatological care remains limited in many regions, resulting in delayed diagnosis and treatment.

Current dermatological assessment relies heavily on visual inspection, dermoscopy and subjective clinical evaluation. While experienced clinicians can often identify disease patterns accurately, assessment variability between observers remains a significant challenge. Furthermore, many relevant biological characteristics, including tissue oxygenation, inflammation, vascularisation, hydration and pigment distribution, are only partially visible under conventional imaging conditions.

Hyperspectral imaging (HSI) offers the capability to non-invasively capture detailed spectral information from skin tissue. Unlike conventional RGB imaging, which records only three colour channels, HSI acquires dozens to hundreds of spectral bands across visible and near-infrared wavelengths. This allows objective quantification of chromophores such as melanin, haemoglobin and water, providing insight into physiological skin status beyond visual appearance [1,2].

Recent advances in sensor miniaturisation, mobile computing and artificial intelligence have accelerated interest in deploying HSI not only in clinical settings but also in consumer health products. The combination of compact imaging hardware, cloud-based analytics and personalised AI creates opportunities for continuous skin monitoring, personalised treatment recommendations and preventive healthcare.

4.2. State-of-the-art analysis

Hyperspectral imaging has been investigated extensively for skin lesion analysis and skin cancer detection. Multiple studies have demonstrated that hyperspectral signatures can differentiate benign lesions from malignant melanoma with high sensitivity and specificity [1,3]. By analysing spectral variations associated with melanin concentration, vascular changes and tissue morphology, HSI systems can reveal diagnostic information not visible in standard photographs.

Research has shown promising results for the classification of melanoma, basal cell carcinoma and squamous cell carcinoma. Several machine learning studies have reported classification performance comparable to expert dermatologists when spectral information is combined with spatial image features [3,4].

Beyond oncology, HSI has demonstrated value for quantitative skin characterization and monitoring of dermatological conditions. Spectral biomarkers can assess erythema, pigmentation, vascularisation, tissue oxygenation, hydration status and epidermal composition, providing objective measurements of skin health and disease progression. HSI has been investigated for inflammatory skin diseases such as psoriasis, atopic dermatitis and rosacea, where it enables non-invasive assessment of disease severity and treatment response. Additional applications include wound healing and burn assessment, microcirculation analysis, scar characterization, skin aging studies and evaluation of cosmetic or therapeutic interventions, highlighting the broader potential of HSI as a tool for personalized dermatology and longitudinal skin monitoring [2].The integration of AI with dermatological imaging has become a major research direction. Deep learning approaches, including convolutional neural networks and vision transformers, have achieved substantial improvements in automated skin lesion classification [4].

Most current systems rely primarily on conventional RGB images. Although effective for many applications, these approaches remain susceptible to variations in lighting conditions, skin pigmentation and image quality. HSI provides significantly richer information and may therefore improve robustness and explainability of AI-based diagnostic systems.

Recent research has focused on spectral-spatial neural networks capable of simultaneously analysing image structure and spectral signatures. Such models have demonstrated improved performance for disease detection and tissue characterisation compared with RGB-based approaches [1,2].

The consumer health market has seen rapid growth in devices capable of measuring skin characteristics. Commercial products increasingly incorporate optical sensors to estimate skin pigmentation, hydration, UV exposure and treatment response. Examples include smart mirrors, smartphone-based skin analysis applications and beauty devices equipped with integrated sensing technologies. While these systems provide users with personalised recommendations, most rely on RGB imaging and simplified models of skin appearance.

Current consumer solutions generally lack the spectral resolution and range required for quantitative biochemical skin assessment. Consequently, there remains a gap between clinical-grade dermatological imaging and consumer health (imaging) technologies. Recent advances in sensor miniaturization of multi-channel sensors are creating opportunities for the integration of hyperspectral imaging (HSI) into consumer healthcare and personal care devices. While current consumer products predominantly employ RGB or multispectral sensing in the (near) visible wabvelength range of 400-1100nm, HSI can provide substantially richer spectral information for the assessment of skin composition, including pigmentation, vascularization, and inflammatory status and when extended to also include the infrared wavelength range allow for further interrogation of skin hydration and sebum. Combined with advances in artificial intelligence, miniaturized HSI has the potential to enable more comprehensive skin characterization and support the development of personalized digital skin models ("digital skin twins"), adaptive device settings and longitudinal skin-health monitoring. However, significant challenges remain regarding sensor miniaturization, cost, power consumption, data processing and validation in consumer environments.

Innovation and challenges

The target innovation is a trustworthy AI-driven hyperspectral skin intelligence framework that demonstrates the capability to quantitatively characterize key skin properties and/or response to treatment and supports the future development of adaptive and personalized consumer health applications. Despite significant progress, several challenges continue to limit widespread adoption of HSI in dermatology which need to be addressed to achieve scalable and personalised dermatological care. These challenges are related to Data and Validation, Hardware & System Integration, AI & Computational Methods, Personalization & Monitoring and Trust, Privacy & Adoption as summarized in Table 1

Table 1. Key Challenges for AI-Enabled Hyperspectral Skin Characterization

Challenge Domain	**Key Challenges**
Data and Validation	Limited availability of large annotated hyperspectral skin datasets; limited validation in uncontrolled consumer environments; limited integration between clinical and consumer health settings.
Hardware and Sensing	Challenges in miniaturizing hyperspectral sensors while maintaining spectral accuracy,

	signal-to-noise ratio and affordability; sensitivity to ambient lighting, device positioning and user motion; sensor-specific differences that reduce algorithm transferability.
AI and Analytics	High computational complexity of hyperspectral image analysis; insufficient explainability of AI-driven skin assessment systems; challenges in generalizing AI models across diverse skin types, ethnicities, age groups and device generations.
Deployment and Personalization	Difficulty translating spectral biomarkers into actionable and personalized recommendations; limited capability to model longitudinal changes in skin physiology for continuous monitoring and digital skin twin applications.
Trust, Privacy and Adoption	Privacy, governance and secure handling of longitudinal personal skin-health data; establishing user trust and acceptance of AI-generated skin-health insights.

The SpectralHealth project directly addresses several limitations of the current state of the art. Current dermatological AI systems are typically developed for specific sensors and imaging devices. The SpectralHealth project introduces hardware-independent hyperspectral data representations and processing pipelines, enabling models to operate across multiple sensor platforms. This reduces vendor lock-in and improves scalability across healthcare and consumer applications.

A central innovation of SpectralHealth is the development of personalised skin assessment models. By combining hyperspectral imaging with longitudinal user data, the system can account for individual variability in pigmentation, vascularisation, hydration and treatment response. Such personalised approaches are expected to improve robustness across diverse populations and skin types while reducing algorithmic bias.

Unlike many existing medical imaging solutions, SpectralHealth explicitly bridges clinical dermatology and consumer wellness applications. The project investigates integration with personal care devices, including advanced skin sensing technologies used in aesthetic and

skincare applications. This enables measurement-driven personalisation of treatments and supports continuous monitoring outside traditional healthcare environments.

A recurring concern in AI-assisted healthcare is the limited transparency of deep learning models. SpectralHealth therefore incorporates explainable AI techniques that allow both clinicians and consumers to understand which spectral biomarkers contribute to specific recommendations or classifications. This approach increases user trust, improves regulatory acceptance and facilitates adoption in both medical and consumer settings.

4.3. Literature

[1] Tran MH et al. *Medical Hyperspectral Imaging: An Updated Review of Technology Advancements and Biomedical Applications*. Journal of Biomedical Optics.

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5. Use case 4 Microbiology

5.1. Introduction

Faster turnaround in medicinal product manufacturing is desirable but is currently constrained by the limited availability of efficient, rapid microbial testing methods, particularly for unfilterable samples. The bulk of all samples to be tested for bioburden and/or sterility in the pharmaceutical industry is still tested using traditional (growth-based) methods. There are a few 'rapid' methods available and implemented, particularly for Advanced Therapeutic Medicinal Products (ATMPs) - but these still require considerable incubation times and have no on/in or even at-line potential. This use-case will explore alternative detection / enumeration / identification and fluid-handling approaches for microbial contamination.

5.2. State-of-the-art analysis

The market for rapid microbial methods is gradually expanding. Solutions that automate microbial QC workflows are slowly being implemented in the pharmaceutical industry. Many focus on automation of the environmental monitoring process – others are applicable for product testing (bioburden/sterility/…). Despite this, general adoption is low, implementation is slow and most importantly, there is no 'one-size-fits-all' solution. The available technologies / methods are highly dependent on the sample/product characteristics. Moreover, sometimes these technologies are destructive, which is undesirable due to the fact of the requirement for identification post-enumeration/detection. The use of dyes or other chemically bound detection molecules hamper identification (e.g. through MALDI-TOF MS). The wide range of product types (synthetic, biologicals, ATMPs, device-combination products), their galenic form (tablets, solutions, suspensions, creams, device, …) and physico-chemical characteristics (viscosity, solubility, …) complicates broad implementation efforts. For example, often the technology requires the sample to be filterable.

The industry acknowledges these limitations – and therefore is evaluating / implementation specific (available) solutions for specific pharmaceutical matrices.

Some alternative methods haven been successfully implemented, which paves the way for next-generation rapid microbial methods with even shorter throughput times and/or potential for on/in/at-line solutions.

State-of-the-art rapid quantitative methods (for filterable samples only) still take 24-48 hours to generate a result – and are still in evaluation phase. Only a few are in actual

validation phase at the time of writing. Available and adopted rapid qualitative methods for sterility testing have a time to result of minimum 5 days (often more) compared to the conventional 14-day sterility test. All these technologies are offline QC-lab testing approaches.
In both cases (rapid bioburden / enumeration and rapid sterility / presence absence), there is still a lot of room for improvement.

5.3. Innovation and challenges

This project proposes a miniaturization approach, combined with optimized fluid handling and molecular sensing to revolutionize microbial detection for unfilterable samples with the aim for a same-day enumeration method and a 24h sterility testing method.

Challenges include obtaining the required special and spectral resolution and adequate sample presentation while maintaining a reasonable throughput (sample volume).