Microprocessors and Microsystems 116 (2025) 105157

Contents lists available at ScienceDirect

Microprocessors and Microsystems

journal homepage: www.elsevier.com/locate/micpro

STRATUM project: AI-based point of care computing for neurosurgical 3D decision support tools

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A R T I C L E I N F O

Keywords:
Multimodal imaging
European project
Point-of-care computing
Artificial intelligence
High-performance computing
Neurosurgery
Brain tumour

A B S T R A C T

Integrated digital diagnostics are transforming complex surgical procedures, with brain tumour surgery being among the most challenging. STRATUM, a five-year Horizon Europe-funded project, aims to develop an advanced 3D decision support system leveraging real-time multimodal data processing powered by artificial intelligence. A key innovation of STRATUM is its design as an energy-efficient Point-of-Care computing system, seamlessly integrated into neurosurgical workflows. This system will provide surgeons with real-time, AI-driven insights, enhancing decision-making accuracy and efficiency. By optimizing surgical precision and reducing procedure duration, STRATUM is expected to improve patient outcomes while streamlining resource utilization within European healthcare systems.

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[1] Members of the STRATUM Consortium are detailed in https://www.stratum-project.eu/stratum-consortium-members/ and 10.5281/zenodo.15102360.

https://doi.org/10.1016/j.micpro.2025.105157
Received 31 March 2025; Accepted 13 May 2025
Available online 14 May 2025

1. Introduction

Brain and Central Nervous System (CNS) cancer ranked as the 12th leading cause of cancer-related mortality in 2022, with approximately 321,731 new cases and 248,500 deaths reported globally across all ages and genders [1]. By 2050, these figures are expected to rise by 56.6 % in incidence and 64.8 % in mortality [2]. Among young individuals under 34, CNS cancer was the second most common cause of cancer-related deaths (30,427 deaths), following leukaemia [1]. In children under 14, it also ranked second in both incidence and mortality, with 24,677 reported cases and 12,249 deaths worldwide [1]. Notably, brain tumours account for over 90 % of CNS cancers, posing significant challenges due to their high mortality and morbidity, particularly in paediatric patients [3].

Brain tumours are generally categorized into two main types: primary and secondary. Primary tumours originate in the brain and hardly ever metastasize to other organs, whereas secondary tumours begin in other parts of the body, such as the lungs or breasts, and later spread to the brain. Based on the World Health Organization (WHO) classification of CNS tumours, primary brain tumours are classified into four grades [4], mainly determined by the appearance of the cells under a microscope. *Grade 1* tumours grow slowly and do not invade surrounding tissues, making them highly treatable with surgery. *Grade 2* tumours also grow at a slow pace but have the potential to infiltrate nearby brain tissue. *Grade 3* tumours appear more abnormal under a microscope, can spread into surrounding brain tissue, and often require additional treatments alongside surgery. *Grade 4* tumours are the most aggressive, characterized by rapid growth and the need for intensive treatment. Additionally, the risk of recurrence after surgery increases the higher the grade.

Neurosurgery is the primary treatment for brain tumours. During the procedure, the neurosurgeon performs a craniotomy, an opening in the patient's skull, to access the tumour. Using a neurosurgical navigation system guided by preoperative Magnetic Resonance (MR) images, the surgeon aims to remove the entire tumour whenever possible. Complete tumour removal, known as *gross total resection*, significantly improves patient survival. However, if full resection risks damaging critical brain structures, the surgeon removes as much of the tumour as safely possible. This helps alleviate brain pressure and reduces the remaining tumour burden for post-surgical treatments such as radiation therapy or chemotherapy. Additionally, a small tumour sample is typically extracted during surgery and sent for intraoperative pathological analysis, where a pathologist examines it under a microscope to determine the tumour type, grade, or origin. The intraoperative pathological diagnosis, which can take up to 45 min, assists surgeons in making informed decisions during tumour resection by determining the most appropriate surgical approach based on the tumour's type and grade. Additionally, other tools, such as Intraoperative Neurophysiological Monitoring (IONM), are used to help surgeons minimize the risk of damaging critical brain tissue, thereby preserving the patient's Quality of Life (QoL).

Neurosurgeons face several challenges when performing brain tumour surgeries, particularly in accurately identifying tumour tissue and distinguishing it from normal brain structures. One major limitation is the lack of specialized tools that enhance visualization and provide real-time, personalized tissue diagnostics to guide surgical decisions. This is especially critical for gliomas, which diffusely infiltrate surrounding brain tissue, making it difficult to differentiate tumour margins with the naked eye. Residual tumour tissue left behind is a leading cause of recurrence, morbidity, and mortality [5]. Additionally, the absence of real-time interpretation and analysis tools for the vast amount of data collected from independent systems before and during surgery further complicates decision-making. Another significant challenge is the long waiting time for intraoperative pathology consultation, which can take up to 45 min and disrupt surgery, increasing the risk of complications. In some cases, multiple consultations are required, extending surgical time, and in certain instances, the procedure may be aborted if the tumour type lacks a surgical solution. Furthermore, there are no commercial tools available to analyse and visualize brain shift, a phenomenon where brain tissue moves after craniotomy and resection, reducing the accuracy of patient-to-image mapping and the effectiveness of preoperative imaging for intraoperative guidance [6]. The use of photosensitive drugs or contrast agents in fluorescent-guided surgery also presents risks, as they can cause side effects and have limited effectiveness for certain tumour types. These agents are not recommended for paediatric cases or pregnant women, even though complete resection of low-grade tumours has been shown to significantly improve patient outcomes [7], particularly in children [8].

Therefore, an advanced neurosurgical decision-support tool capable of delivering fast, accurate, and highly personalized diagnostics, such as the one proposed in STRATUM, could help optimize surgical decision-making, minimize errors and delays during procedures, and reduce associated medical costs.

This paper presents the STRATUM Horizon Europe funded project (ID: 101137416) [9] and its preliminary results, being an extension of a previous conference publication [10]. In addition to extending several sections, the main new contributions are related to the preliminary results achieved in the development of the intraoperative STRATUM acquisition system for multimodal data collection and the data characterization. It also introduces early developments related to the implementation onto different Hardware (HW) accelerators of the proposed data processing algorithms.

2. Project objectives

The primary goal of STRATUM is to create a clinically validated 3D Decision Support Tool for brain surgery guidance and diagnostics. This tool will leverage multimodal data processing powered by Artificial Intelligence (AI) algorithms and will be designed as an energy-efficient Point-of-Care computing solution (Fig. 1). By enhancing surgical precision and patient outcomes, STRATUM aims to shorten surgery duration, optimize resource utilization, and improve procedural efficiency, ultimately contributing to the sustainability of healthcare systems. STRATUM is expected to reach the Technology Readiness Level 7 (TRL7): "*Demonstration of system or prototype in a real environment*" during its five years of execution. To accomplish this, STRATUM is focused on achieving the following six specific objectives:

1) Advance personalized medicine by leveraging multimodal data, including emerging imaging techniques like Hyperspectral (HS) Imaging (HSI) and AI, through the creation of a large public multimodal database containing data from over 500 brain tumour patients.
2) Enhance intraoperative diagnostic accuracy for brain tumours, leading to improved surgical outcomes and better patient QoL by increasing the rate of gross total resection while minimizing the removal of healthy brain tissue within the safety margin compared to current procedures.
3) Reduce neurosurgery duration by reducing the need for intraoperative pathological assessment and utilizing High-Performance Computing (HPC) platforms for real-time data processing, enabling the surgeon to access rapid and up-to-date diagnostic information during surgery.
4) Improve the cost- and energy-efficiency of neurosurgical workflows by integrating various data sources into an interactive 3D Graphical User Interface (GUI), reducing surgical time, and minimizing the expenses related to the use of contrast agents and intraoperative pathological analysis.
5) Conduct a two-year clinical study to validate the prototype across three clinical sites in Spain and Sweden, including an early Health Technology Assessment (HTA).

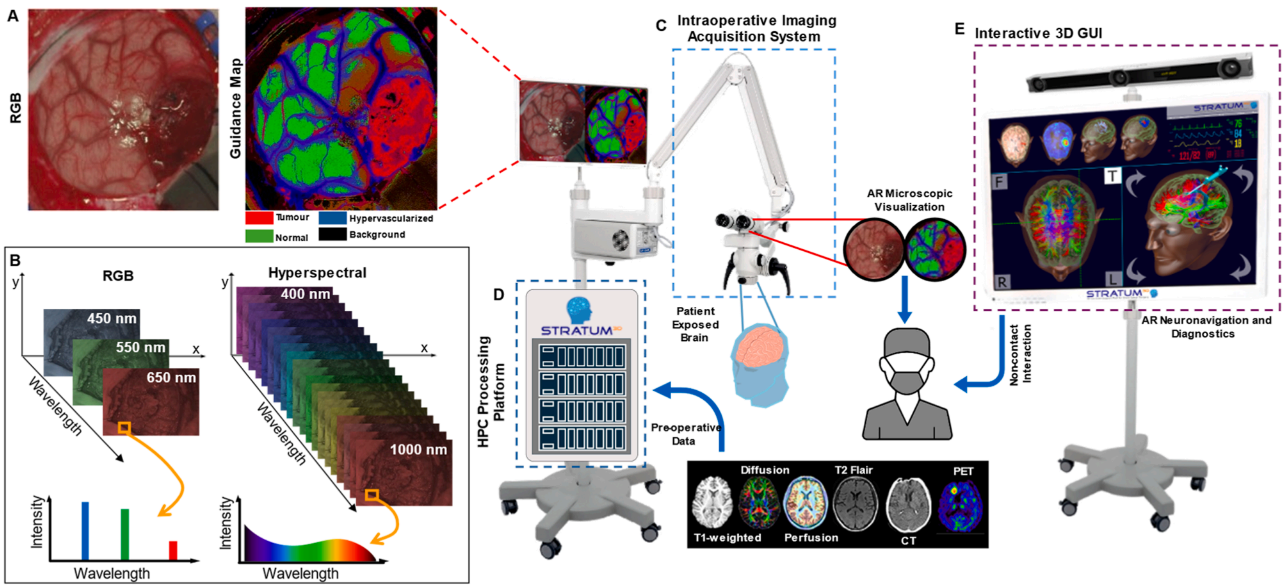

Fig. 1. STRATUM project overall concept. RGB: Red-Green-Blue; HPC: High Performance Computing; PET: Positron Emission Tomography; CT: Computed Tomography; AR: Augmented Reality; GUI: Graphical User Interface.

6) Develop an initial business plan and a strategic roadmap to achieve TRL9 following the project's completion.

3. Project consortium and previous works

The STRATUM consortium (Table 1), coordinated by the University of Las Palmas de Gran Canaria (ULPGC), is an interdisciplinary and international collaboration comprising 12 partners from six European countries (Spain, The Netherlands, Sweden, France, Italy and Germany) . This diverse consortium brings together experts from various fields, including *IT scientists* (telecommunication, electronic, biomedical, and computer science engineers), *clinicians* (neurosurgeons, oncologists, neuroradiologists, neuropathologists, etc.), *health researchers* (molecular biologists, biostatisticians, mathematicians, physicists, health economists, etc.), and *social sciences and humanities (SSH) professionals* (psychologists, linguists, etc.) [11]. By working collaboratively, the consortium aims to develop optimal solutions for individual challenges as well as for the system as a whole, integrating their diverse expertise into the STRATUM tool. Next, the most relevant previous works of the consortium partners in the related fields of STRATUM are described.

3.1. *Hyperspectral medical imaging*

HSI is an emerging imaging modality in the medical field, valued for its non-invasive, non-contact, non-ionizing, and label-free sensing capabilities, enabling rapid acquisition and analysis of diagnostic information [12]. By combining conventional imaging with spectroscopy, HS cameras capture both spatial and spectral data, providing insights beyond human visual perception (Fig. 1A, B). While HSI has been widely used across various fields for years, its application in medicine has recently shown promising results, particularly in cancer detection, driven by advancements in machine learning algorithms and modern computational power [12].

Several members of the STRATUM consortium (ULPGC, UPM, UNIPV, TU/e, SERMAS, RS, and FIISC) have conducted pioneering research in the field of HSI for cancer detection, with a particular focus on brain cancer analysis. These works were initiated within the European FP7 project HELICoiD [13], which demonstrated as proof of concept to enhance intraoperative brain tumour delineation (Fig. 2) and improve real-time visualization of critical tissues through AI-driven analysis [14–16]. These initial studies were later expanded through other research projects (ITHaCA [17], NEMESIS-3D-CM [18] and

Table 1
STRATUM consortium members.

Partner Name	Acronym	Country	Type	Main Expertise
Universidad de Las Palmas de Gran Canaria	ULPGC	Spain	University	Medical data processing using AI and participatory research
Technische Universiteit Eindhoven	TU/e	Netherlands	University	Medical data processing using AI
Region Stockholm (Karolinska University Hospital)	RS	Sweden	Hospital	Clinical and health research
Barcelona Supercomputing Center	BSC	Spain	Research and Technology Organisation	HW and Software (SW) development through HPC
SAS UPMEM	UPMEM	France	Small and Medium Enterprise	Industry research and development in HW for Processing in Memory (PIM)
Universita Degli Studi Di Pavia	UNIPV	Italy	University	HW/SW development through HPC
Universidad Politecnica de Madrid	UPM	Spain	University	HW/SW development through HPC
Servicio Madrileno de Salud (Hospital Universitario 12 de Octubre)	SERMAS	Spain	Hospital	Clinical and health research
Rheinland-Pfalzische Technische Universitat	RPTU	Germany	University	HW/SW development through HPC
Fundación Canaria Instituto de Investigación Sanitaria de Canarias (Hospital Universitario de Gran Canaria Dr. Negrin)	FIISC	Spain	Hospital/Health Technology Assessment Body	Clinical and health research, including health technology assessment
OPTOMIC ESPAÑA S.A.	OPTOMIC	Spain	Small and Medium Enterprise	Industry research and development in medical devices
European Citizen Science Association	ECSA	Germany	Non-Governmental Organization	Citizen science and participatory research

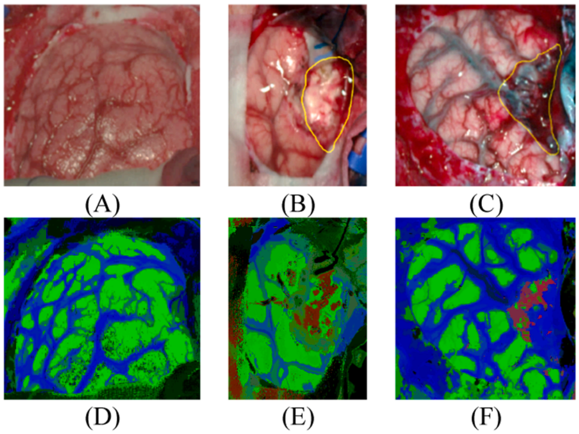

Fig. 2. HELICoiD classification results obtained from the validation database employed in [14]. (A,B,C) Synthetic RGB images; (D,E,F) Thematic maps of the HS image, where the tumour tissue is in red colour, the normal tissue in green, the hypervascularized tissue in blue and the background in black. (A,D) Normal brain tissue; (B,E) Primary grade 4 glioblastoma; (C,F) Primary grade 1 meningioma.

ASTONISH [19]) and collaborations, increasing databases and evaluating different types of AI-based algorithms and approaches [20–23]. The company OPTOMIC presents an extensive expertise in designing, manufacturing, and commercializing medical devices. Furthermore, a strong collaboration between ULPGC and OPTOMIC is utilizing HSI technology to develop an innovative HS-based colposcope aimed at the early detection of cervical dysplasia [24]. Finally, TU/e has extensive expertise in processing HS medical data, with a focus on selecting informative spectral bands and classifying tissues using both traditional and advanced machine learning algorithms. TU/e has also developed algorithms specifically for identifying glioblastoma tumors [20] and skin feature detection [25] in collaboration with RS.

3.1.1. High performance computing for medical applications

Future advancements in complex, high-quality imaging and monitoring devices used in medicine will require processing vast amounts of data to support real-time decision-making for surgeons. Currently, the extremely large sizes of medical imaging datasets need robust HW capabilities (memory, storage, transmission, etc.) to handle data processing, particularly for achieving real-time computation. For instance, prestored medical imaging data such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) scans can exceed 100, 150, and 10 MB, respectively, depending on resolution and acquisition system configurations. Meanwhile, intraoperative imaging data, including HSI and High-Definition (HD) imaging, can reach sizes up to 1 GB and 100 MB per image, respectively. In the case of HD video systems capturing 24 frames per second, the data throughput can reach 2.4 GB/s. Given the vast range of tasks and data types in medical imaging applications, manually analysing and interpreting such large volumes of data through visual inspection is both time-intensive and costly. To address this challenge, STRATUM leverages HPC platforms to integrate, process, and interpret multimodal data using advanced and robust AI algorithms. This approach enables the rapid delivery of detailed, precise, and highly personalized diagnostics to guide brain surgeries in real time, drawing on the expertise of BSC, UNIPV, UPMEM, and RPTU.

UNIPV's expertise in HPC for medical applications stems from its collaboration with ULPGC on the HELICoiD and ITHaCA projects, where the team developed a parallelized version of the entire processing chain. Specifically, the UNIPV team designed a multi-GPU (Graphics Processing Unit) implementation of the processing pipeline, successfully meeting real-time processing requirements [16]. Additionally, UNIPV specializes in developing AI and deep learning parallel algorithms optimized for GPUs and FPGA (Field-Programmable Gate Array) devices [26,27].

BSC has extensive expertise in HPC infrastructures, AI application acceleration through SW-HW optimization, and the advancement of European processors for HPC systems [28,29]. Additionally, BSC specializes in AI and deep learning techniques tailored for biomedical applications, enabling the analysis of large and complex datasets using GPU, FPGA, ASIC (Application-Specific Integrated Circuit), and PIM accelerators [30–32]. Notably, BSC has played a key role in developing and optimizing the European Distributed Deep Learning Library and the European Computer Vision Library [33] for precision medicine. STRATUM will capitalize on BSC's expertise to deploy and enhance AI-driven applications on state-of-the-art HPC systems.

UPMEM's PIM technology is particularly well-suited for applications demanding high throughput and low latency, such as the multimodal data processing in STRATUM. Each UPMEM PIM chip integrates multiple Data Processing Units (DPUs) that function independently and asynchronously, enabling parallel execution of complex algorithms directly where the data is stored. This capability is crucial for real-time analysis and visualization during neurosurgical procedures, providing surgeons with immediate access to critical information without the delays associated with conventional systems. Additionally, UPMEM is developing an AI-specific chip designed to significantly enhance processing power and efficiency for AI-driven applications like those in STRATUM. This next-generation chip is optimized for high-performance tasks, supporting STRATUM's AI algorithms in conducting extensive data analysis and delivering decision support in critical medical environments.

3.1.2. Co-creation in health research

Co-creation in health research projects engages end-users and other stakeholders throughout the design, development, and testing phases of a system or tool. This collaborative approach ensures that their expectations, preferences, and needs are taken into account. The primary objective of co-creation is to enable the seamless integration of newly developed systems or tools into existing digital infrastructures and clinical workflows.

Several STRATUM partners (ULPGC, ECSA and FIISC) incorporate in their teams' experts in SSH, having extensive experience in this field through their involvement in various national and international projects, such as IC-Health [34], WARIFA [35,36] and SEEDS [37,38]. Furthermore, within STRATUM, the co-created prototype will be validated through a two-year clinical study, leveraging the extensive expertise of Karolinska University Hospital (RS), Hospital Universitario de Gran Canaria Dr. Negrín (FIISC), and Hospital Universitario 12 Octubre (SERMAS) in this field.

4. Concept and methodology

4.1. Overall concept

The STRATUM project is creating an advanced and interactive 3D Decision Support Tool to enhance diagnosis and clinical decision-making in neurosurgical workflows by incorporating (i) an innovative intraoperative imaging acquisition system for capturing RGB, HS and depth data of the exposed patient brain during surgeries (Fig. 1C), (ii) an HPC processing platform where the multimodal pre-stored and in-situ data is processed in real-time through innovative AI-based algorithms (Fig. 1D), and (iii) an interactive 3D GUI for Augmented Reality (AR) neuronavigation and diagnostics, managing also the system in a non-contact way (Fig. 1E).

4.1.1. Intraoperative imaging acquisition system

The intraoperative imaging acquisition system captures in-situ data during neurosurgery. HSI will serve as both an image guidance and diagnostic tool, generating thematic maps to distinguish tumour types and delineate their margins from healthy brain tissue (Fig. 1A and C). Additionally, the tool will integrate HD video imaging and depth data, providing high spatial resolution and depth information to reconstruct 3D brain surfaces for surgical guidance. These data, combined with pre-stored information, will contribute to the development of a diagnostic and integration algorithm. This algorithm will follow a top-down approach, breaking down the overall process into smaller, independently developed and tested modules. This modular approach reduces complexity by allowing each module to be addressed separately. The algorithm will be functional from the outset, with its capabilities expanding as additional modules are developed. Parallel development of different modules by separate teams will improve efficiency, while individual testing of each module will simplify the validation process.

A combination of well-established and emerging AI-based algorithms, such as Support Vector Machines (SVMs), Random Forest (RF), k-Nearest Neighbours (KNN), Artificial Neural Networks (ANNs), hierarchical k-means, Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), will be explored for data classification and segmentation. Additionally, the robustness of these AI algorithms will be assessed to align with European Commission initiatives for trustworthy and secure AI, ensuring compliance with principles such as robustness, explainability, transparency, and data protection [39].

4.1.2. High performance computing platform

The STRATUM project is focused on developing a highly heterogeneous HPC platform capable of addressing the diverse demands of various workloads and real-time system requirements (Fig. 1D). This initiative seeks to integrate high-end processors with multiple accelerators to overcome performance bottlenecks and meet the specific needs of different medical applications. The resulting HPC platform will incorporate GPUs, FPGAs, and PIM accelerators, optimizing each data-processing application based on its unique performance characteristics.

In particular, GPUs (Nvidia) are leveraged for their powerful parallel processing capabilities, which are essential for accelerating AI-driven medical computations. Meanwhile, FPGAs (Xilinx) are employed for their reprogrammable nature, allowing them to be tailored to specific algorithmic requirements. This adaptability enables high-throughput acceleration for critical medical imaging and data processing tasks, ensuring efficient resource allocation and bandwidth management. The STRATUM project places a strong emphasis on optimizing memory access latency, memory usage, and bandwidth utilization.

Additionally, the integration of PIM technology (UPMEM) brings data processing closer to memory storage, significantly reducing latency and energy consumption associated with data transfers. This advancement enhances overall system performance, particularly for real-time medical applications. By overcoming the *memory wall* constraints of traditional compute-centric architectures, PIM technology enables superior performance, making it highly effective for managing large-scale, data-intensive medical workloads.

The integration of various in-situ data sources and the real-time processing of both in-situ and pre-stored multimodal data will be executed within the HPC processing platform. This project aims to develop innovative AI-driven processing algorithms, which will be accelerated using a heterogeneous computing platform consisting of diverse HW and SW accelerators, selected based on the specific performance demands of each algorithm.

The development of the HPC platform will primarily follow a bottom-up approach, beginning with the creation of small modules that will later be combined to form top-level components. Initially, different use-case applications will be analysed to identify computationally intensive kernels. Next, performance-critical kernels will be profiled and evaluated to pinpoint underlying bottlenecks and determine the real-time system requirements for the STRATUM tool. The next step involves selecting the most suitable HW platform to optimize and accelerate each performance-critical kernel. For custom HW design, High-Level Synthesis tools such as OpenCL, Vivado, and Bluespec, along with traditional HW description languages, will be utilized to achieve optimal performance. The HPC platform will serve as the core of the STRATUM tool, facilitating the integration of the acquisition system with other data sources and ensuring seamless communication of results to the user interface.

The proposed HPC platform is structured into three key tiers:

1) The first tier is dedicated to data processing, carefully managing each data source independently to build modular components. Real-time processing plays a pivotal role in this stage, ensuring swift data analysis and preparation for subsequent phases. The emphasis on real-time processing is driven by the need to keep up with rapidly evolving data streams, enabling timely insights and informed decision-making.
2) The second and third tiers of the HPC platform focus on integrating processed data and presenting it in a meaningful way. Once data from various sources has undergone intricate processing, the next step is seamless integration. This phase demands both accuracy and speed, as the rapid fusion of results is crucial for generating comprehensive insights. Real-time integration enables dynamic adjustments and correlations, providing users with up-to-the-minute information and a holistic view of the data.
3) The final tier is dedicated to rendering the synthesized results in a clear and actionable format. Real-time rendering plays a critical role in transforming processed data into meaningful visualizations, ensuring that neurosurgeons and other users can quickly interpret complex analyses. Fast rendering allows for the immediate presentation of insights, supporting timely and well-informed decision-making. By combining real-time processing with rapid visualization, the platform enhances responsiveness to evolving data landscapes, ultimately empowering users with actionable intelligence.

4.1.3. Interactive 3D GUI

The STRATUM tool will feature an interactive, user-friendly, and non-contact 3D graphical interface, allowing neurosurgeons to visualize a 3D model of the patient's brain alongside diagnostic results from advanced algorithms (Fig. 1E). This system will leverage intraoperative AR neuronavigation, integrating pre-operative imaging data such as MRI and CT scans with HS data. To ensure precise intraoperative guidance, the platform will account for brain shifts and deformations in real time. Additionally, the integration of IONM and life support data will provide continuous feedback on both the surgical procedure and the patient's condition, enhancing decision-making during surgery. The non-contact interaction with the display system will uphold aseptic conditions in the operating room, allowing surgeons to directly interact with critical information without compromising sterility.

The following approaches will be explored for touchless interaction: gesture recognition, voice commands, and proximity sensors. Gesture recognition technology utilizes sensors, such as cameras or depth sensors, to detect and interpret hand movements. By performing predefined gestures in the air, users can control medical devices without the need for physical contact with buttons or touchscreens. This method is intuitive, hands-free, and particularly beneficial for users with limited mobility or dexterity. Proximity sensors, on the other hand, detect the presence or movement of nearby objects without direct contact. In medical applications, these sensors can be used to activate interface elements or trigger specific functions based on the user's hand proximity. This enables seamless, touch-free interaction, reducing the risk of contamination while enhancing usability and convenience.

The information will be presented in a precise, structured, and systematic manner, incorporating feedback from neurosurgeons and other stakeholders to ensure it meets their specific needs. This co-creation process, characterized by continuous exchanges of advice and suggestions, will be maintained throughout the project's duration to refine and optimize the system.

To achieve the project's goal of reaching TRL7, the GUI will be developed in compliance with the IEC 62,304:2006 international standard [40]. This standard plays a crucial role in medical device software development, emphasizing structured processes, requirements specification, risk management, usability engineering, verification and validation, and configuration management. Adhering to these guidelines ensures the GUI is designed, implemented, and maintained in alignment with regulatory requirements, ultimately enhancing usability and safety. Additionally, the entire development of the fully functional prototype will follow the ISO 13485:2016 international standard for medical devices [41], ensuring the highest levels of quality and safety throughout the process.

4.2. Co-creation process

The user perspective will be integrated throughout all phases of the STRATUM design to ensure that expectations, preferences, and needs are addressed through a co-creation methodology. To facilitate this process, focus groups comprising participants from different countries will be established, fostering collaboration through virtual or in-person meetings.

The co-creation process will begin with the identification of a shared, open, and inspiring vision that serves as the foundation for creativity. This will be followed by an in-depth exploration of various scenarios, weighing their pros and cons to determine the most effective solutions. Participants will then generate ideas and propose innovative alternatives for different aspects of the STRATUM tool, including requirements definition, GUI design, system usability, and safety. Finally, the developed tool will undergo technical validation and evaluation, refining concepts and integrating feedback to enhance the overall design.

The co-creation protocol that will be followed in STRATUM is based on the proposal of McGlade et al. [42] and consists of three main stages (Fig. 3): *co-design, co-production* and *co-delivery*. Each stage has different steps, and each step includes different focus group sessions. Focus groups will be the main technic to be used, however, individual interviews and questionnaires will be considered during the entire execution of the project with the end-users and stakeholders that directly participate in the project [43].

4.3. Overall methodology

The STRATUM project is a 5-year project (60 months) which follows an interactive, iterative, and incremental methodology divided into four main phases as presented in Fig. 4. The first three phases align with the project's Work Packages (WPs), Milestones (MS), and six Specific Objectives (SOs). Project management and coordination and communication, dissemination, and commercialization activities will be active during these 3 phases, closely following and supervising the activities performed within the project and disseminating the main results achieved to the scientific community and the general public as well as to prepare a preliminary business plan and a roadmap to reach TRL 9 for the future commercialization of the STRATUM tool. Phase 4 is intended to be executed after the project finalization.

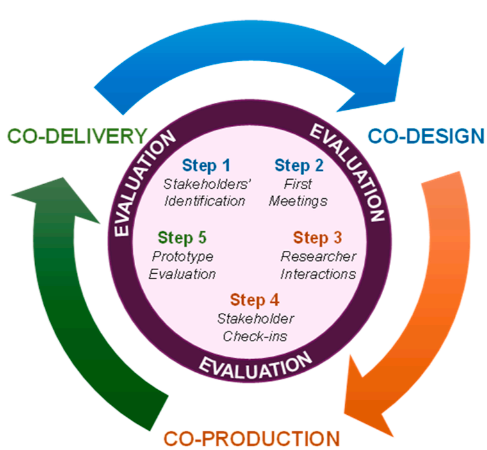

Fig. 3. Co-creation methodology used in the STRATUM project, based on the proposal from [42].

4.3.1. Phase-1: Specifications, requirements & ethics

Phase 1 starts at the beginning of the project, where IT scientists, industrial experts, neurosurgeons and clinicians, and the HTA body of STRATUM consortium share their expertise to establish the specifications and definitions for the development and evaluation of the 3D Decision Support Tool for the neurosurgery use case. In this phase, the protocol of the clinical study for subjects' enrolment is prepared and submitted to the ethical committees of each clinical site, including the registration number of the clinical study. Moreover, the open Data Management Plan (DMP) is prepared in this phase, as well the co-creation protocol and the plan for the exploitation, dissemination and communication of STRATUM results.

4.3.2. Phase-2: Prototype development, integration and technical validation

Phase 2 follows an iterative agile methodology to develop the STRATUM tool in two parallel work lines, where the HW and SW developments progresses together providing feedback between them, including also a co-creation methodology to ensure achieving meaningful results for end-users.

In this phase, the intraoperative imaging acquisition systems based on HSI are defined, designed and developed to perform the in-situ data collection during surgeries, as well as to collect all the multimodal pre-stored and in-situ data. The STRATUM clinical data acquisition and management is carried out in this phase, generating at the end of the project a publicly available multimodal database. These data are used for the algorithms and HPC platform design and development that are developed also in this phase. Additionally, in this phase the development of the interactive easy-to-use non-contact 3D GUI combined with AR intracranial navigation is performed. Finally, the integration of the HW and SW developments, as well as the interconnection of the different data acquisition systems is completed at this stage, delivering a fully working prototype on month 36. This prototype is then technically validated using the data collected in the observational clinical study that is conducted from month 15 to 36 of the project. Finally, the fully working prototype is clinically evaluated in phase 3 by conducting a historically controlled non-randomized clinical study using the data collected during the observational study as the historical control group.

4.3.3. Phase 3: Prototype demonstration and evaluation in a real environment

In this phase, the demonstration and evaluation of the fully working prototype during neurosurgical procedures is carried out by conducting a historically controlled non-randomized clinical study the last two years of the project. This study will deliver a complete report of the clinical study on month 60. Since not all the European hospitals has the same imaging/data modalities available for neurosurgical procedures, three prototypes will be installed in the operating rooms of the three clinical sites from Spain and Sweden. This clinical study will report the strengths and weakness of the project, ensuring its usability and usefulness independently of the equipment and capabilities of the operating room. It will cover all the necessary steps for later regulatory approvals. Additionally, the prototype will be subject to an early process of HTA, including cost-effectiveness and economic impact assessment for the Swedish and Spanish contexts, together with an examination of the potential organizational impact. Moreover, in this phase, a preliminary business plan will be prepared and delivered at the end of the project, including the roadmap to reach TRL9 for the future commercialization of the STRATUM tool two years after the project ending.

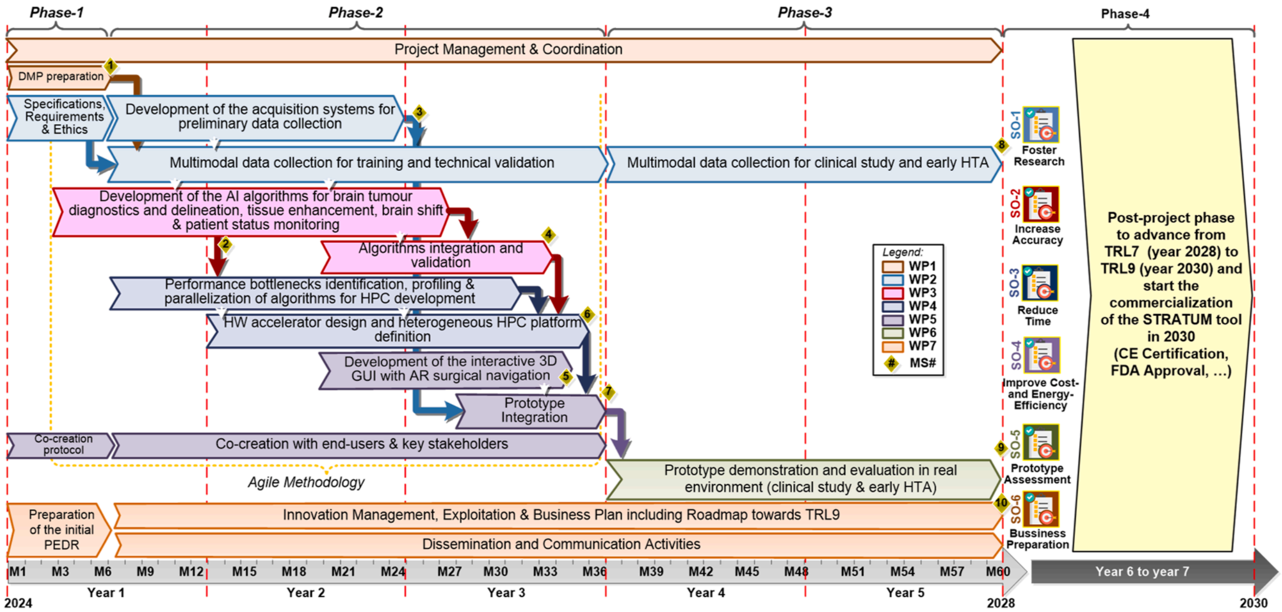

Fig. 4. STRATUM methodology approach. SO: Specific Objective; WP: Work Package; MS: Milestone; DMP: Data Management Plan; PDER: Plan for Exploitation, Dissemination and communication of Results. TRL: Technology Readiness Levels; HTA: Health Technology Assessment; CE: Conformité Européenne; FDA: Food and Drug Administration.

5. Implementation work plan

STRATUM is organized into seven WPs interrelated as shown in Fig. 5. WP1 and WP7 are transversal, while the other 5 are scientific WPs (WP2 to WP6).

- WP1 (Management and Coordination) adopts a collaborative management approach, incorporating the PRINCE2™ methodology to ensure active participation in planning and control processes through effective information and communication tools. Its objectives include scientific coordination and administrative management, led by the project manager, scientific coordinator, and the ULPGC European Affairs Office project management group.
- WP2 (Intraoperative Acquisition System and Data Collection) focuses on defining the medical and technological specifications for the STRATUM tool while developing data acquisition systems for clinical sites. It will also establish protocols and secure ethical approvals for data collection. WP2 is essential to the project's success, as it lays the groundwork for effective data management and ethical compliance.
- WP3 (Diagnostic and Integration Algorithm Development) is dedicated to designing and developing processing algorithms for surgical guidance and diagnostics, incorporating both pre-stored and real-time data. It creates advanced algorithms to analyse, manage, and integrate data from multiple sources during neurosurgical procedures. Close collaboration with WP2 on data acquisition and WP4 on HPC platform development ensures seamless integration, with the final outputs contributing to the fully functional prototype in WP5.
- WP4 (HPC Processing Platform Development) focuses on developing an HPC platform to accelerate algorithms, enabling real-time performance in brain surgery. It will design a heterogeneous system that integrates high-end processors with specialized accelerators optimized for medical workloads, ensuring efficient handling of diverse computational demands.
- WP5 (Interactive 3D GUI and Prototype Co-creation and Integration) is devoted to designing and developing an intuitive, non-contact 3D GUI while integrating outputs from WP2, WP3, and WP4 to build a fully functional prototype for demonstration in real neurosurgical scenarios in WP6, with system performance evaluation. It highlights

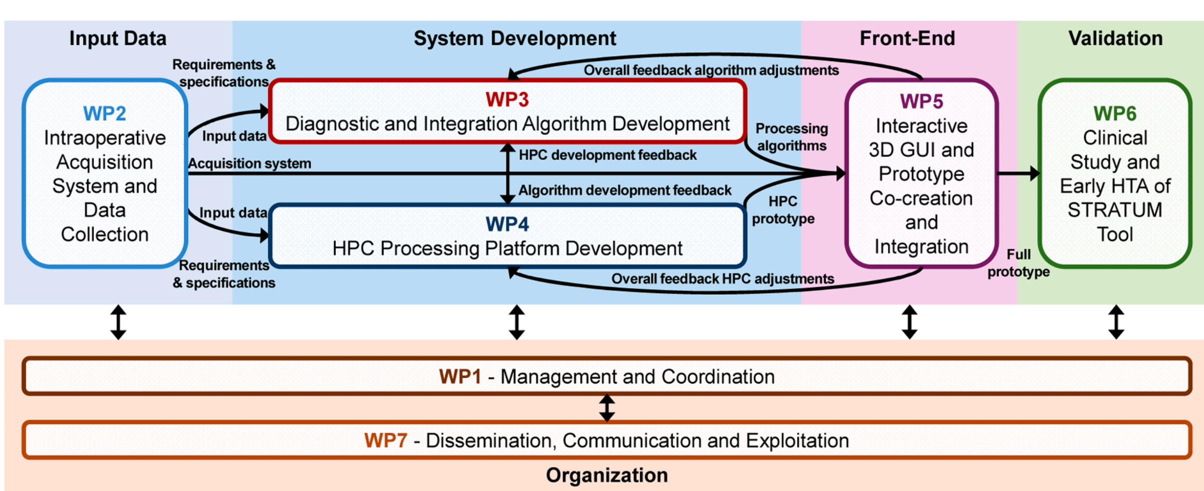

Fig. 5. STRATUM project implementation work plan.

the essential involvement and feedback of surgical partners and other stakeholders, fostering a continuous, iterative co-creation process to ensure the STRATUM tool aligns with end-users' needs and requirements.

- WP6 (Clinical Study and Early HTA of STRATUM Tool) aims to validate and assess the fully-working STRATUM prototype from WP5 while conducting an early HTA. Prototype installations at each clinical partner site will enable a two-year clinical study to evaluate diagnostic accuracy, safety, and economic impact. Active involvement and feedback from medical partners are essential in confirming the project's feasibility.
- WP7 (Dissemination, Communication and Exploitation) is dedicated to developing and executing a strategic plan for effectively disseminating project results through collaborative activities among participants. It will also establish a roadmap for result exploitation, guiding the STRATUM tool's progression from TRL7 to TRL9. This includes formulating joint impact strategies and creating a business plan for its commercialization.

6. Preliminary project results

6.1. Preliminary HSI processing framework

In earlier studies [23], we employed a robust k-fold cross-validation approach to show that combining HSI with a processing framework holds great potential as an intraoperative tool for the in-vivo identification and delineation of brain tumours, including both primary (high-grade and low-grade) and secondary tumours. This framework (Fig. 6) was based on spatial and spectral information (after perform a preprocessing of the raw HS data), using a combination of dimensionality reduction, supervised classification, spatial filtering, and unsupervised segmentation. Finally, employing a majority voting algorithm, the results from both supervised and unsupervised approaches are merged [23].

In STRATUM we consider this framework as a preliminary algorithm for the development of the real-time diagnostic and guidance algorithm based on HS data. However, this framework was developed based on the in-vivo brain cancer dataset [23,44] captured in two previous projects where a custom intraoperative acquisition system was employed [14,45].

The system included a VNIR (Visual and Near Infrared) HS pushbroom camera (Hyperspec® VNIR A-Series, Headwall Photonics Inc., Fitchburg, MA, USA) capable of capturing 826 spectral bands within the 400–1000 nm range. It featured a Full Width at Half Maximum (FWHM) of ~2.5 nm and a maximum spatial resolution of 741 × 1004 pixels, utilizing a pushbroom mechanism for data acquisition [14]. Nonetheless, due to the high spectral resolution could include redundant information, it was studied that the reduction from 826 to 128 bands through a sampling interval increasing from 0.73 to 3.61 nm, did not decrease the classification performance to discriminate between tumour and normal tissue [46]. The illumination system was based on a 150 W Quartz Tungsten Halogen (QTH) lamp, coupled with a fibre optic cold light illuminator. This was used to prevent direct heat exposure from the QTH lamp on the brain tissue. The HS camera lens was positioned 40 cm from the brain surface, resulting in a pixel size of 128.7 µm and a maximum acquisition time of 60 s.

Data captured using this system [23,44] is employed in STRATUM as a preliminary dataset for carrying out preliminary experiments both in WP3 and WP4 developments.

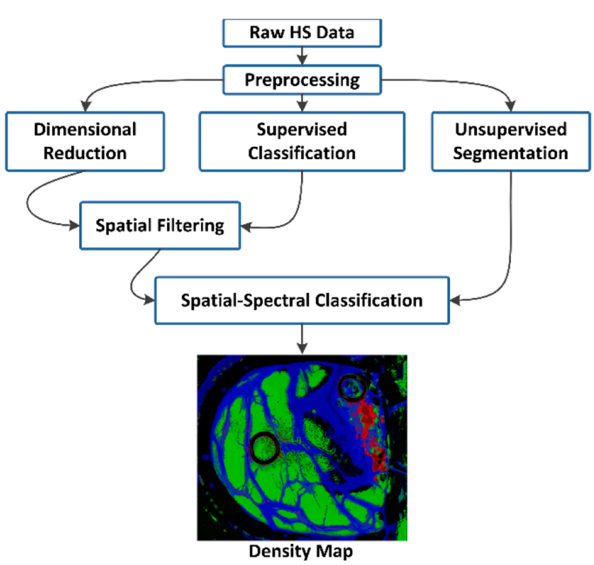

Fig. 6. HSI processing framework based on preprocessing, dimensionality reduction, supervised classifier, spatial filtering, and unsupervised segmentation [23].

6.2. Proposed intraoperative HS acquisition system

The proposed HS acquisition system developed in WP2 within STRATUM is based on the use of Liquid Crystal Tuneable Filters (LCTFs) for filtering the light emitted by the acquisition system, performing a spectral scanning through the different wavelengths covered by the LCTFs. Hence, the system can use a standard monochromatic camera with high spatial resolution, instead of using specific HS cameras that require spatial movement (*pushbroom*) or has reduced spectral and spatial resolution (*snapshot*) [47].

This LCTF-based illumination system consists of the Kurios VB1 and the Kurios XE2 (Thorlabs Inc., NJ, USA) for the visible (420–730 nm) and NIR (650–1100 nm) spectral ranges, respectively. The integrated system aims at producing HS images in a wavelength range from 420 to 1100 nm, with a maximum configurable number of 680 spectral bands, using a sampling interval of 1 nm. Nevertheless, the system is configured with a sampling interval of 5 nm, capturing 136 bands between 420 and 1100 nm to achieve an acquisition time of ~30 s. The FWHM is wavelength dependent and ranges from 6 to 13 nm and from 13 to 24 nm for the visible and NIR LCTFs, respectively. In terms of spatial resolution, a 12.3 MP monochromatic camera Kiralux LP126MU (Thorlabs Inc., NJ, USA) is able to provide an image of 4096 × 3000 pixels per wavelength.

Since there are not available yet intraoperative in-vivo brain images captured with the STRATUM acquisition system, a method to generate a simulated database of in-vivo brain tissue with the spectral characteristics of the data captured by the STRATUM LCTF-based system from the previous pushbroom-based dataset was proposed. This simulated dataset helps to (i) initially evaluate the classification performance of the preliminary framework using data captured with the STRATUM acquisition system (WP3) and (ii) to initially evaluate the preliminary implementations of this framework in different acceleration platforms (WP4).

6.3. Proposed LCTF-based data simulation approach

The proposed LCTF-based data simulation approach considers the different parameters of the acquisition systems at hand (Table 2), as well as other properties of the devices, such as the quantum efficiency of the pushbroom HS camera sensor and the LCTF-based system, and the power density of the light sources. The pushbroom HS camera sensor was an Adimec-1000 m (Teledyne Adimec, Eindhoven, Netherlands) and its quantum efficiency was digitalized from its Operating and Technical Manual (rev. 1.2.doc). The quantum efficiency of the LCTF-based system was obtained using an spectrometer (CCS200/M, Thorlabs Inc., NJ, USA) capable of capturing data from 200 to 1000 nm. The power density data of the halogen illuminator OSL2IR (Thorlabs Inc., NJ, USA), which was used as a reference light source for these

Table 2
Acquisition systems parameters for the LCTF-based data simulation approach.

Parameter	Pushbroom-based System	LCTF-based System
Spectral range (nm)	400–1000 (max) / 450–900 (effective)	420–730 (VIS) / 650–1100 (NIR) / 420–1100 (Total)
Sampling interval (nm)	0.73 (min) / 3.61 (selected)	1 (min) / 5 (selected)
FWHM (nm)	~2.5	6–13 (VIS) / 13–24 (NIR)
Spatial resolution (pixel)	741 × 1004	4096 × 3000
#Spectral bands	826 (max) / 128 (selected)	680 (max) / 136 (selected)

experiments, was extracted from the manufacturer's website.

It is worth noting that the proposed experiments are performed using the effective bandwidth of the pushbroom HS camera, i.e., the spectral range between 440 and 900 nm [44]. Hence, although the developed LCTF-based acquisition system developed in STRATUM can reach larger wavelengths, the simulated LCTF-based data will cover only such spectral range (440–900 nm) with 93 equispaced bands at a sampling interval of 5 nm. Additionally, it is important to highlight that this simulation is only performed spectrally, as it is carried out on a pixel-by-pixel basis and no spatial properties are modified from the original pushbroom HS data.

The proposed approach (Fig. 7) for generating the simulated LCTF-based HS images from the pushbroom HS data essentially consists of the following steps:

1) Acquire or retrieve the raw data from the pushbroom HS camera;
2) Estimate the illuminance in the camera by compensation based on the quantum efficiency of the pushbroom HS sensor;
3) Compensate for the light tint introduced by the original QTH lamp in the previously measured illuminance;
4) Estimate the transmittance of the LCTF-based system (lamp-filter ensemble) by applying the result from step 3 and the spectral characterisation of the output of the LCTF filters.
5) Simulate the image obtained with an LCTF-based system using the estimated illuminance (Step 2) and the transmittance of the LCTF-based system (Step 4).

This simulation approach provides the corresponding LCTF-based HS image of an original pushbroom HS image. This does not exclude the need to apply the flat field correction to standardize HS images, thus, this procedure is applied to the raw HS image, as well as the dark and white references, and then the flat field correction is applied to the simulated data.

6.3.1. *Spectral analysis of the simulated LCTF-based data*

To evaluate the proposed LCTF-based data simulation approach, a calibration target, SG 3333 Zenith Polymer Wavelength Standard (SphereOptics GmbH, Gewerbestr, Germany), was used. Fig. 8 shows the mean spectral signature captured with the pushbroom HS camera compared to the simulated LCTF-based data. A strong similarity can be noticed between both spectral signatures, although the simulated data presents less details mainly due to the increased sampling interval (3.76 to 5 nm) and FWHM (~2.5 to 6–24 nm). A larger discrepancy is observed in the short wavelength region, from 440 to 450 nm, that is produced mainly due to the low power density of the light source and the low transmittance of the LCTF system in that region, increasing the signal to noise ratio.

6.3.2. *Classification performance using the simulated LCTF-based HS data*

In order to evaluate the feasibility of using the proposed intraoperative LCTF-based acquisition system for capturing relevant HS data in STRATUM to develop the processing algorithms for intraoperative brain tumour diagnosis and delineation, a comparison between the classification performance of using the simulated LCTF-based HS data versus the original pushbroom data has been carried out. The classification results were obtained following the data partition based on a 5-fold cross-validation employed in [23], and using the two different input data: (i) the pushbroom HS dataset and (ii) the simulated LCTF-based HS dataset. Additionally, experiments were performed using five supervised machine learning classifiers with different configurations: a SVM classifier with the linear kernel (*SVML*) and the Radial Basis Function kernel (*SVMrbf*); a KNN classifier using the Euclidean and Cosine distances (*KNN-E* and *KNN—C*, respectively); and a *RF* classifier. Fig. 9 shows the F1-Score performance results where is possible to observe that the results using the simulated LCTF-based data provides similar results respect to the use of the original pushbroom data. Hence, the use of the LCTF-based acquisition system ensures that the HS database to be acquired in STRATUM will satisfy the minimum requirements to obtain comparable results to the ones obtained in previous projects.

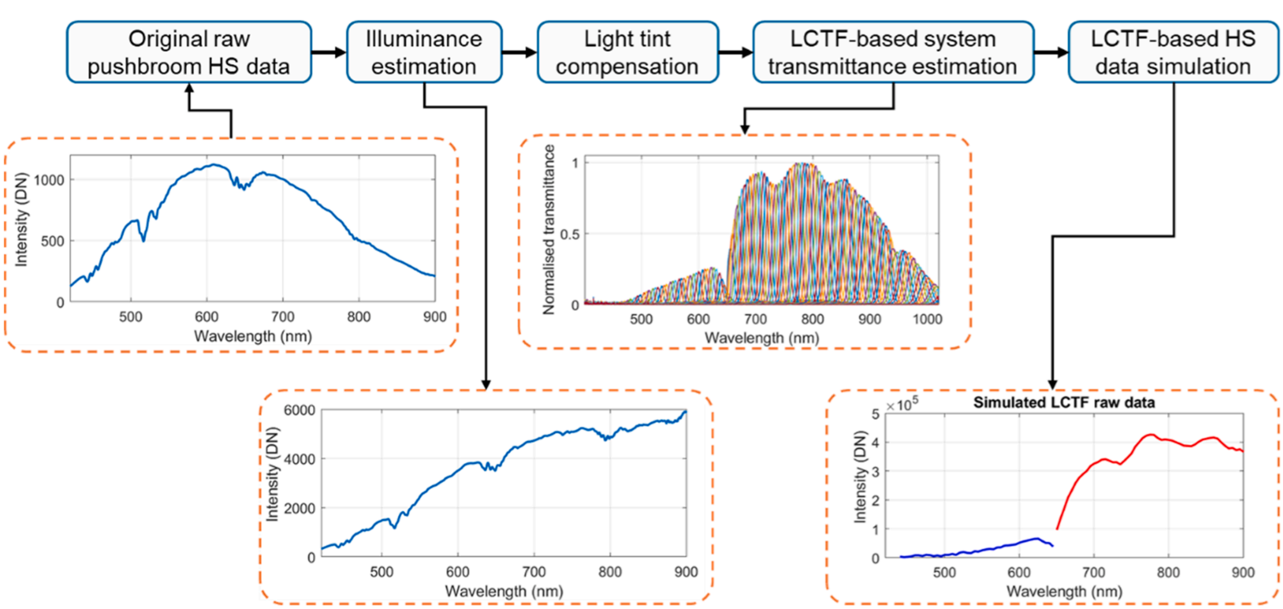

Fig. 7. Proposed approach for generating the simulated LCTF-based HS images from the pushbroom HS data.

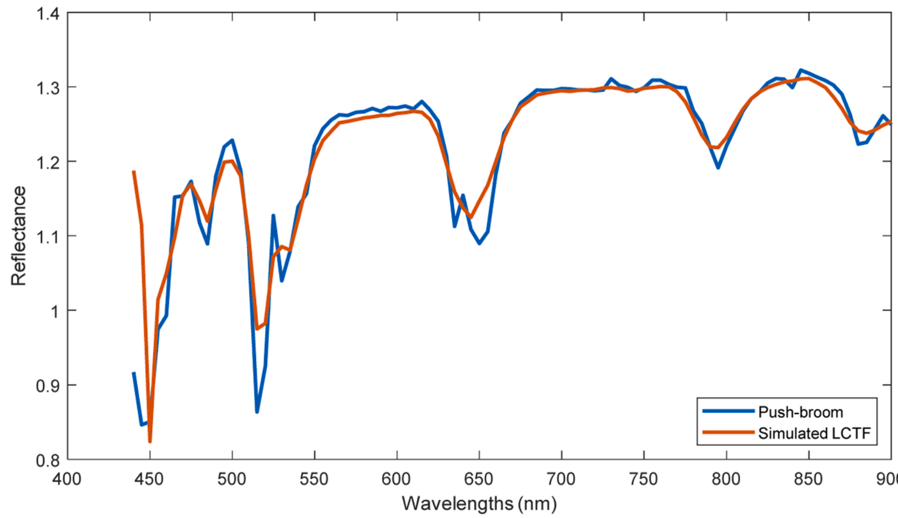

Fig. 8. Comparison between the spectral signatures of the SG 3333 Zenith polymer captured with the pushbroom HS camera (blue) and the simulated LCTF-based HS data (orange).

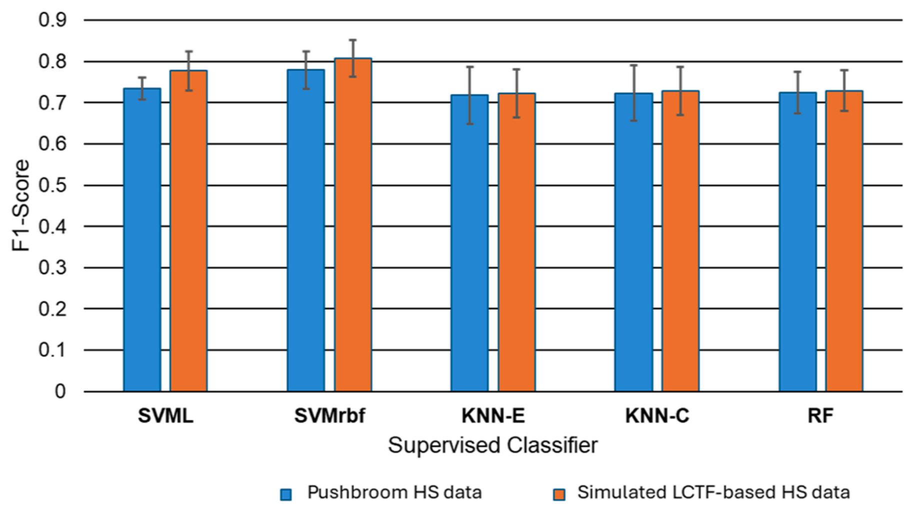

Fig. 9. Classification performance results using different supervised machine learning classifiers comparing the use of the original pushbroom HS data (blue) versus the simulated LCTF-based HS data (orange).

6.4. Preliminary HSI processing framework characterization and profiling

Accurate and efficient processing of HS data is key for STRATUM's real-time intraoperative use. To support STRATUM's goal of improving brain tumour delineation and surgical outcomes, we seek to perform careful benchmarking and performance profiling of the HSI processing framework (Fig. 6). For that, a profiling-driven performance study using LCTF-based HS data was performed.

For the proposed experiments, two sets of HS image samples from the available simulated datasets were selected (Table 3): *cropped* and *full-size*. The *cropped* HS image dataset is composed of HS images which have been cropped to the region of interest where the parenchymal area is presented, making them smaller than the original full sensor captures [23]. These simulated data is conformed by 93 spectral bands and varying spatial dimensions (i.e., columns ranging from 330 to 752 pixels, rows from 300 to 721 pixels, and file sizes from 55 MB to 290 MB). Similarly, the *full-size* HS images simulate the spatial properties of the camera sensor employed in the proposed intraoperative HS acquisition system, spanning the entire sensor area at 3000 × 4096 pixels, with 93 spectral bands, totalling 6.4 GB per file.

The HSI processing workflow was benchmarked to analyse the performance of the different algorithms and determine the most computationally intensive kernels. As previously shown in Fig. 6, the workflow starts with the data preprocessing step, which includes: i) an specific task (*BSQ-to-BIP*) to make a transformation of the simulated HS data from BSQ (Band Sequential) format to BIP (Band Interleaved by

Table 3
Characteristics of the simulated HS image samples employed in the proposed experiments. HS image numbers correspond to the HS brain dataset published in [23].

HS Image ID	*Cropped Size*		*Full-Size Dimensions*	
	(height × width × bands)	*(MB)*	(height × width × bands)	*(MB)*
008–01	460 × 549 × 93	135	3000 × 4096 × 93	6400
012–01	443 × 497 × 93	118	3000 × 4096 × 93	6400
015–01	376 × 494 × 93	100	3000 × 4096 × 93	6400
020–01	378 × 330 × 93	67	3000 × 4096 × 93	6400
022–03	592 × 471 × 93	150	3000 × 4096 × 93	6400
034–02	300 × 342 × 93	55	3000 × 4096 × 93	6400
058–02	721 × 752 × 93	290	3000 × 4096 × 93	6400

Pixel) format; and ii) a calibration and normalization task (*Calibration & Normalization*) related to the flat field correction of the HS data using both white and dark references and a spectral signature normalization between [0, 1]. Then, the preprocessed HS data is processed in three different steps: i) a dimensional reduction to obtain the first component of the *PCA* (Principal Component Analysis) algorithm; ii) a pixel-wise supervised classification based on the *SVM* algorithm; and iii) an unsupervised segmentation based on the K-Means (*KMeans*) clustering algorithm. After this, the results from the *PCA* and *SVM* algorithms are used as input to a spatial filtering approach based on the k-nearest neighbours (*KNN*) algorithm. Finally, the outputs from the KNN and KMeans steps are combined in the spatial-spectral classification approach using a majority voting (*MajorityVoting*) algorithm.

For the performance study, the HSI processing framework was executed on high-end computing nodes from the MareNostrum 5 (MN5) supercomputer. For the general-purpose CPU performance evaluation, a computing node equipped with two Intel Xeon Platinum 8480+ 56C 2 GHz and 256 GB of main memory was used. For the GPU performance evaluation, a node equipped with two Intel Xeon Platinum 8460Y+ 40C at 2.3 GHz, 512 GB of main memory, and four NVIDIA Hopper H100 64 GB HBM2 was used.

6.4.1. CPU performance evaluation

For the general-purpose CPU performance evaluation, Fig. 10 shows the overall execution time for the end-to-end HSI processing analysis pipeline running in a single core for seven different HS image samples (*cropped* and *full-size*). Overall, we observe that, from all the execution kernels, *KNN* and *KMeans* are responsible for 98 % of the time spent in the pipeline, where *KNN* is significantly more time-consuming, taking 65–82 % of the time, while *KMeans* takes 13–31 % of the time. Also, we observe that execution times grow linearly with the HS image size (i.e., number of pixels) on the *cropped* set, which is the one that has different HS image sizes among samples. An average execution time of 88.2 s was obtained for the *cropped* images, while for the *full-size* HS images an average of 463 min was obtained (5.2× longer execution times). It is important to note that these results were obtained from single-core executions. Multi-core implementations and support for AVX2/AVX-512 on Intel Xeon are expected to provide substantial speedups in further experiments.

6.4.2. GPU performance evaluation

For the GPU performance evaluation, Fig. 11 shows the overall execution times for the GPU-enabled HSI processing analysis pipeline running on a single NVIDIA Hopper H100. Compared to the CPU experiments, GPU executions show a significant speedup, ranging from 34× to 352× . Nevertheless, we still observe that *KNN* and *KMeans* are the most time-consuming kernels of the GPU processing pipeline. Notwithstanding the GPU acceleration, the CPU preprocessing stage *BSQ-to-BIP* becomes the main performance bottleneck. In the case of *full-size* HS images, the execution time remains relatively constant (i.e., average of 75 s) across all samples, dominated by *KMeans (GPU)* and *KNN (GPU)*. In the case of *cropped* HS images, the execution time is reduced to 1.2 s per image on average.

7. Conclusions

The integration of digital diagnostics has the potential to enhance the execution of complex surgical procedures across various anatomical sites, with brain tumour surgery being one of the most challenging. The STRATUM project addresses this critical use case as a reference for a broad range of surgeries, aiming to improve patient safety, enhance diagnostic accuracy, and optimize healthcare pathways.

At its core, STRATUM focuses on developing a 3D decision support tool designed to reach TRL7. This system leverages real-time multimodal data processing powered by AI algorithms and will be integrated as a Point-of-Care computing tool within the neurosurgical workflow. By doing so, it represents a major step forward in merging advanced technology with medicine, fostering the next generation of neuronavigation systems.

A key innovation of STRATUM lies in its ability to incorporate both existing and emerging data sources, such as HSI technology, and process them in real time. This will empower neurosurgeons to make informed, efficient, and precise decisions during procedures, potentially maximizing tumour resection rates while minimizing the risk of neurological deficits, ultimately benefiting patients.

The project's development follows a co-creation approach, engaging key stakeholders and end users throughout the process. This collaborative framework ensures that the STRATUM system is tailored to the real needs of medical professionals, significantly contributing to advancements in brain surgery care.

Beyond the clinical setting, the long-term impact of STRATUM extends to optimizing healthcare resources. By enabling more time-efficient surgical procedures, it is expected to reduce patient risks—such as prolonged anaesthesia exposure and postoperative complications—while enhancing the overall efficiency of European healthcare systems.

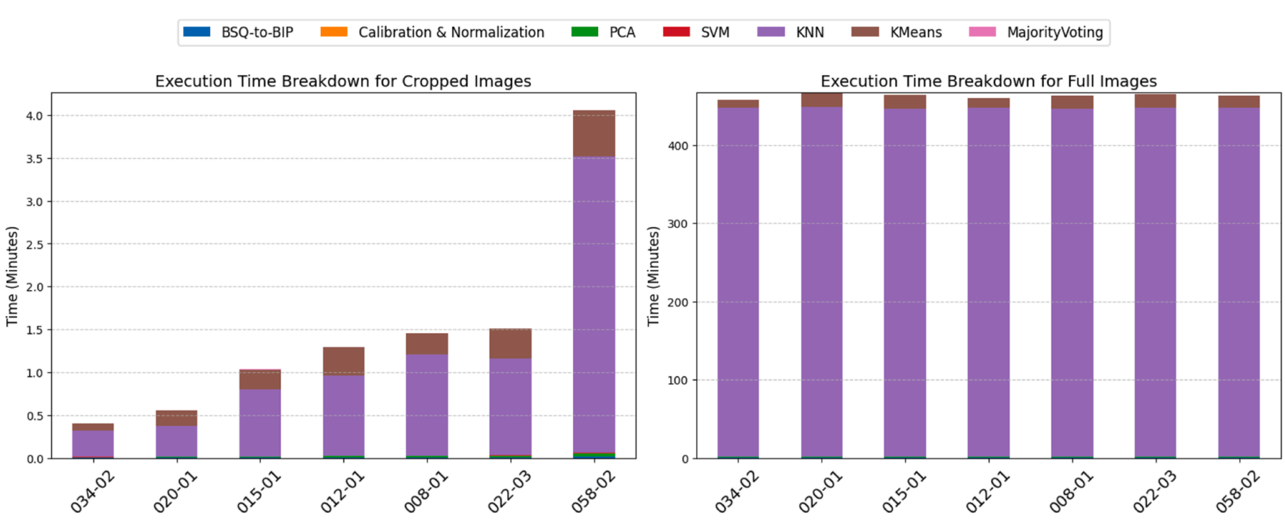

Fig. 10. Execution time of the STRATUM HSI processing pipeline on a single-core Intel Xeon Platinum 8480+ using the simulated *cropped* (left) and *full-size* (right) HS images.

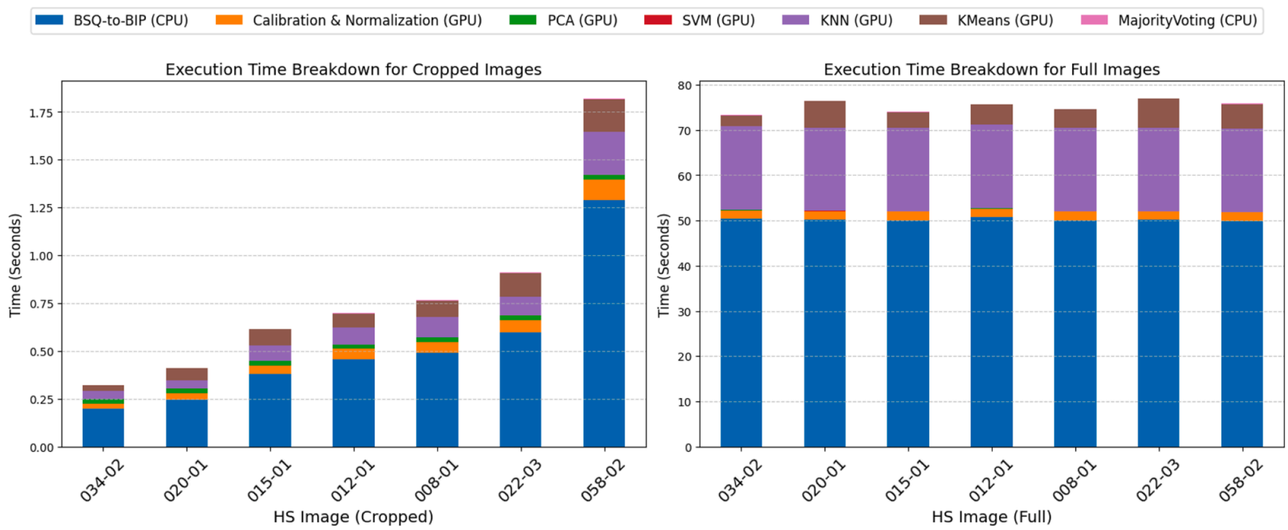

Fig. 11. Execution time of the STRATUM HSI processing pipeline on a single NVIDIA Hopper H100 using the simulated *cropped* (left) and *full-size* (right) HS images.

Current works within this project are focused on the development of the intraoperative acquisition system for data acquisition during neurosurgical procedures using a HIS system based on a LCTF illumination system. In this sense, an approach for simulating the resultant LCTF-based data from previously captured in-vivo human brain HS images using pushbroom HS cameras with high spectral resolution. This simulation was assessed through a spectral analysis using a reference polymer and also comparing the classification performance using the proposed HSI processing framework respect to the original pushbroom HS data. Additionally, a characterization and a profiling of the proposed framework was carried out using two simulated HS dataset with different spatial characteristics (*cropped* and *full-size*). In this analysis, the different steps involved in this processed pipeline were studied using a general-purpose CPU and a single NVIDIA Hopper H100. Results showed that the KNN step is the most time-consuming task in the CPU implementation, while the use of a GPU implementation achieved an improved speed-up ranging from 34× to 352×, being the preprocessing stage to convert the HS data format from BSQ to BIP executed onto the CPU the main bottleneck of the pipeline.

Future work will focus on optimizing the preprocessing stages of the HSI processing pipeline. Moreover, a key goal is to isolate and analyse each kernel individually and conduct a detailed performance analysis using microarchitectural counters (e.g., instructions, cycles, IPC, LLC misses), roofline modelling to assess memory- and compute-bound behaviour, and memory profiling. Finally, we seek to explore HW acceleration strategies, including the deployment of the pipeline on FPGA accelerators and PIM-enabled DIMM RAM modules, to further reduce latency and energy consumption.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work has been developed under the STRATUM project which received funding from the European Union's Horizon Europe Programme HORIZON-IA action under grant agreement No 101137416. Finally, the members of the STRATUM Consortium are detailed in https://www.stratum-project.eu/stratum-consortium-members/ and https://zenodo.org/records/15105148.

Data availability

The data that has been used is confidential.

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