**Demonstration Projects**

Call for Ideas to Boost the Competitiveness of the Estonian Manufacturing Industry

**Final Report**

*Please fill in the Final Report in Estonian or English*

*The content of the Final Report is published also in AIRE GitHub*

*To be filled by the Lead of the Development Team*

**Demonstration Project Title**

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| CO-VISION: a co-registration AI model validation on renal tumour CT scans |

**Company**

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| **Company Representative Name**  *(First name, Surname)* | Dmytro Fishman |
| **Company name** | Better Medicine OÜ |

**Development Team**

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| **Development Team Lead Name**  *(First name, Surname)* | Joonas Ariva |

**Objectives of the Demonstration Project**

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| The project aimed to demonstrate the feasibility and validate the performance of an AI-based co-registration model for longitudinal CT scans, initially focused on renal tumours. The objective was to build a system capable of accurately aligning multiple CT scans from the same patient acquired at different time points, enabling consistent comparison and tumour tracking. The demonstration focused on developing and benchmarking co-registration methods and building a synthetic validation pipeline. |

**Activities and results of the Demonstration Project**

Challenge addressed (i.e. whether and how the initial challenge was changed during the project, for which investment the demonstration project was provided)

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| The challenge addressed in the CO-VISION project was the difficulty and time consumption involved in comparing longitudinal CT scans, especially in the context of renal tumours. Due to limited availability of longitudinal kidney CT scan pairs at the start of the project, the development began with lung CT data, which was more accessible and enabled faster prototyping. This allowed the team to make significant progress in building and testing the core components of the system, including AI-based co-registration models and a custom synthetic data generation pipeline.  Later in the project, kidney data from the Tartu University Hospital (TUH) was incorporated. Using the synthetic pipeline, we created simulated longitudinal kidney scans for validation. This shift aligned well with the original objective and demonstrated the generalizability of our approach. |

Activities implemented and results achieved

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| 1. Implemented and validated the CorrField algorithm for CT scan co-registration using lung and kidney data from local hospitals. Initial focus was on kidney tumors, but we first focused on lung data because of abundance of longitudional scans. Later, when the pipeline for synthetic longitudional data was developed, scans with kidney tumors were used for evaluation as well. 2. Developed two AI-based registration models: one U-Net-based and one GAN-based. 3. Created a synthetic validation pipeline that can generate paired CT scans with known transformations, allowing for objective benchmarking. 4. Applied this pipeline to lung and kidney data, supporting organ-agnostic testing. 5. Validated that the synthetic pipeline and AI models provide a reliable framework for future co-registration development. |

Data sources (which data was used for technological solution)

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| 1. CT scans from Tartu University Hospital (under TUH ethical approvals) 2. Public datasets including NLST, KiRC, and TotalSegmentor 3. Synthetic paired CT scans generated using custom data generation pipeline |

Description and justification of used AI technology

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| We used a multi-model AI approach in the CO-VISION project to explore and validate different strategies for co-registration of CT scans. The first algorithm used was CorrField, one of the most well-known classical deformable image registration algorithms in the field. CorrField is widely regarded for its robustness and has been proven effective in various medical imaging tasks. We showed that it works reliably on CT scans and used its output — the dense deformation fields (DDFs) — as supervision for training our first AI model.  The first AI model developed was based on the U-Net architecture. U-Net is one of the most established and widely adopted deep learning models in medical image analysis. It is known for its simplicity, efficiency, and high accuracy in various segmentation and prediction tasks. Our lab has extensive experience with U-Net, and in this project, we adapted it to learn to predict the DDF directly from paired CT scans. Results showed that U-Net was capable of reproducing CorrField outputs with high precision, validating it as a strong baseline model for learned co-registration. It has also performed well when compared to CorrField on synthetic data that we have generated separately.  Building on this, we also developed a second AI model based on the Vox2Vox architecture — a 3D generative adversarial network (GAN). Unlike the U-Net model, Vox2Vox does not rely on precomputed DDFs from CorrField or any other algorithm. Instead, it uses a generator-discriminator setup to produce realistic DDFs directly, learning to align CT scan pairs in an unsupervised or weakly supervised manner. In our experiments, Vox2Vox performed better than U-Net, producing more accurate and anatomically plausible deformations.  This combination of classical, supervised, and adversarial approaches allowed us to comprehensively assess the performance of each method and justify their use within the pipeline. |

Results of testing and validating of the technological solution

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| The developed co-registration models — CorrField, U-Net, and Vox2Vox — were tested on both real and synthetic data to assess their performance in aligning longitudinal CT scans.  Figure 1 (below). Comparison of Dense Displacement Fields (DDF) produced by CorrField, Vox2Vox, and U-Net. The color of DDF shows the strength of the displacement - the brighter the stronger. The red keypoints serve as anchor points to visualise the proper slices along axial plane. We have used 2 stage CorrField with default hyperparameters. Both, Vox2Vox and U-Net models were trained on the NLST training set. The images are taken from validation set  A collage of images of a lung  AI-generated content may be incorrect.  Figure 2 (below). The MSE boxplot of CorrField, U-Net, and Vox2Vox. The synthetic dataset has been used in order to assess all of the models.  A chart with lines and numbers  AI-generated content may be incorrect.  A close-up of a diagram  AI-generated content may be incorrect.A close-up of a colorful brain  AI-generated content may be incorrect.  Figure 3 (above). 3D visualisation of generated DDFs for kidney with tumor (left) and Lung from NLST (right). These displacements show how voxels of both organs have moved from one CT scan to another. |

Technical architecture of the technological solution (presented graphically, where can also be seen how the technical solution integrates with the existing system)

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| The diagram illustrates the technical workflow of the CO-VISION solution and its integration with the Better Medicine Viewer platform. The process begins with the initial and follow-up CT scan, which are processed using AI-based registration models (CorrField, U-Net, or Vox2Vox) to compute a deformation matrix that aligns the scans.  This deformation matrix enables co-registration, allowing for precise comparison of anatomical structures between scans. The system then extracts quantitative metrics such as volume, area, and diameter of lesions or organs, which are displayed within the Better Medicine Viewer, supporting radiologists in tracking disease progression over time.  The solution is modular, scalable, and tightly integrated into the existing Better Medicine platform, enabling advanced longitudinal analysis of CT scans in a clinical setting. |

Potential areas of use of technical solution

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| * Longitudinal tumour tracking in oncology * Automated radiology assistant platforms (e.g. Better Medicine’s BMVision) * Follow-up scan comparison in treatment monitoring * Pre-operative planning in complex tumour cases |

Description of User Interface (i.e. How does the client 'see' the technical result, whether a separate user interface was developed, command line script was developed, was it validated as an experiment, can the results be seen in ERP or are they integrated into work process)

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| No dedicated UI developed during this project. Results are currently available as part of the internal experimentation pipeline.  Better Medicine team integrate the solution into the BMVision platform UI, where radiologists can view registered scans and derived insights |

Follow-up activities and plans for future (e.g. developments, potential for scalability, creation of spin-offs aso)

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| Expand to other organs (e.g. liver, pancreas)  Scale up training with additional annotated data  Prepare for regulatory validation and clinical integration  Publish a paper related to the results of this project |

**Lessons learned**

*i.e. assessment whether the technological solution actually solved the initial challenge*

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| The project confirmed the viability of AI-based co-registration for CT scans. While the switch to lung data at first was pragmatic due to better access to longitudional studies, the architecture has proven flexible and applicable to kidney tumors. The synthetic pipeline that we have developed prooved itself as a valuable asset for future testing and development. Initial goals were achieved, and the technical solution is already influencing the company’s product strategy. |

**Projekti lühikirjeldus (AIRE kodulehele, eesti keeles)**

*Projekti pealkiri, millist väljakutset lahendati, projekti eesmärk, millist tehisintellekti tehnoloogiat valideeriti, projekti tegevused ja tulemused, kuni 10 lauset*

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| CO-VISION projekt käsitles väljakutset, mis seisneb ühe ja sama patsiendi erinevatel aegadel teostatud kompuutertomograafia (KT) uuringute võrdlemises – ülesanne, mis on radioloogide jaoks aeganõudev. Projekti eesmärk oli valideerida tehisintellekti kasutamist pildipaaride automaatseks koregistreerimiseks, võimaldades täpsemat ja tõhusamat kasvajate arengute jälgimist. Rakendasime ja testisime kolme erinevat koregistreerimise lähenemist: CorrField – klassikaline algoritm; U-Net-mudel, mis treeniti CorrFieldi väljundite põhjal; ning GAN-põhine mudel (Vox2Vox), mis õpib deformeeruvusvälju otse andmetest. Tulemuste hindamiseks töötasime välja sünteetiliste andmete genereerimise töövoo, mis simuleerib aja jooksul tehtud KT-uuringute paare erinevate organite lõikes. Kuigi esmane testimine toimus kopsude andmetel, laiendasime lahendust edukalt neeru-uuringutele, näidates selle skaleeritavust ja üldistatavust erinevatele organitele. Lahendus on integreeritud Better Medicine Viewer’isse, võimaldades radioloogidel visualiseerida koregistreeritud uuringuid ja kvantifitseerida kasvajate mahu, pindala ja diameetri muutusi. Projekt kinnitas, et AI-põhine koregistreerimine on nii tehniliselt teostatav kui ka kliiniliselt väärtuslik, rajades teed selle laiemale kasutuselevõtule radioloogia töövoogudes. |

**Project description (to be published on AIRE webpage, in English)**

*Project title, what challenge was addressed, aim of the project, what AI technology was validated, project activities and results achieved, max 10 sentences*

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| Project title: CO-VISION: a co-registration AI model validation on renal tumour CT scans  The CO-VISION project addressed the challenge of comparing multiple CT scans taken from the same patient over time which is a time-consuming task for radiologists. The project aimed to validate the use of AI for automating image co-registration, enabling more accurate and efficient tracking of tumour progression. We implemented and tested three co-registration approaches: CorrField, a classical algorithm; a U-Net-based model trained on CorrField outputs; and a GAN-based model (Vox2Vox) that learns deformation fields directly. To benchmark performance, we developed a synthetic data generation pipeline that simulates longitudinal scan pairs across different organs. While initial testing was conducted on lung data, we extended the solution to kidney scans, demonstrating its scalability and cross-organ applicability. The solution is being integrated into the Better Medicine Viewer, to allow radiologists to visualize registered scans and quantify changes in tumour volume, area, and diameter. The project confirmed that AI-based co-registration is both technically feasible and clinically valuable, laying the groundwork for broader adoption in radiological workflows. |