Intelligent Tracing and Process Improvement of Pathology Workflows using Character Recognition

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Abstract

A pathology laboratory processes various types of tissue and cell specimens and plays a vital role in the diagnostic process. However, pathology departments are currently facing a significant challenge due to the steady increase in incoming specimens. Increasing the workforce to match the influx is generally not feasible, so Information and Communication Technology (ICT) is seen as a potential solution. One area where ICT can be applied is in process monitoring and tracing. The increase in incoming specimens has caused queues within the laboratory, resulting in more time spent locating and retrieving individual specimens. Existing methods of tracing specimens, such as barcodes or alphabetic sorting, also require manual labor, adding further overhead. In this paper, we propose a lightweight application of optical character recognition (OCR) for specimen tracing, as part of a larger research project to optimize pathology processes at a large regional hospital in Bergen. We present a specific solution that integrates into a general process monitoring environment, and we compare different implementation techniques, particularly edge detection and neural networks. Our preliminary results indicate that this implementation can achieve an accuracy of up to 93.41%, increase sorting speed up to 54% and save up to 35% of time spent in manual sorting activities. We conclude our findings with a general discussion and outlook onto other areas where this solution could theoretically be applied.

Keywords

Pathology, Image recognition, Optical Character Recognition, workflow, process mining

1. Introduction

Medical treatment begins with a diagnosis, and Pathology (the study of diseases) plays a paramount role in the latter. By assessing morphological changes of cells and tissue at a microscopic level, pathologists provide critical insights for diagnostics and guide subsequent treatments. However, the preparation of tissue samples for microscopic analysis is a laborious process involving numerous manual activities.

At the same time, healthcare systems are facing a shortage of trained professionals in relation to the growing demand for medical services, which is exacerbated by factors such as an ageing population, widespread cancer screening programs and the prospect of *personalized medicine*

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[1]. This scarcity of resources manifests itself in growing waiting lists, increasingly exhausted personnel and overfull weekly schedules for healthcare professionals. Thus, it is crucial to develop innovative solutions that optimize existing processes and reduce unnecessary manual workloads, allowing healthcare professionals to focus on higher-value tasks that require their expertise. This also applies to the diagnostic process provided by the Pathology lab.

Efficient prioritization and optimal resource allocation are crucial for delivering timely and high-quality patient care. Business Process Management (BPM) has emerged as a discipline that is concerned with these issues and provides techniques for process discovery, monitoring and analysis. By tracking the progress of tasks and monitoring key indicators, it enables healthcare providers to identify bottlenecks, streamline workflows, and allocate resources effectively [2].

Traditionally, tracing techniques for Pathology labs rely on barcode scanning. While this facilitates the capture of important data points and enables traceability, it also introduces additional manual overhead. As a result, capturing points throughout the process have to be chosen carefully in order to not unnecessarily introduce extra work.

In light of these considerations, we propose a novel method for enhancing the tracing capabilities of existing process monitoring solutions via optical character recognition (OCR) technology, which allows for more capture points throughout the process while imposing little additional manual overhead. Our work builds on a previously reported process mining project at a large regional hospital in Bergen (Norway) [3]. Concretely, we are addressing two operative challenges of that Pathology department: Locating workflow items within the process at any given time, as well as reducing time spent on manual activities related to tracing. Moreover, we illustrate how this approach can contribute to the analytical challenge of creating a comprehensive process model from the available data. Finally, we provide preliminary quantitative results about how the solution can help to reduce manual labour and how it may be improved in the future.

2. Background on Pathology Workflow

To introduce the problem, that we are going to address in this paper, some background information about the workflow in the Pathology lab is needed. We focus specifically on *Histology*, i.e. the sub-field of Pathology that studies tissues, which stands for a majority of workload by incoming specimen. Fig. 1 depicts an abstract overview of respective processes:

After the initial registration (*Accessioning*) and a macroscopic examination (*Grossing*), relevant regions of the tissue specimen are placed in *cassettes*, which are then subjected to a chemical *processing* step and are eventually placed inside a paraffin *block* (*Embedding*), with the original cassettes serving as a frame for the block. We will therefor use the terms cassette and block interchangeably. The paraffin block is used to cut a section through the tissue on a microtome (*Sectioning*). This thin slice is then placed on a glass slide, which is stained with chemicals that highlight certain cell structures (*Staining*) before a protective coverslip is applied. With the advent of *Digital Pathology*, the slide is *scanned* so that it can be accessed by the responsible pathologist within a *Picture Archive and Communication System (PACS)* [4]. The latter provides an image viewer with advanced zoom functionality, replacing the traditional microscope.

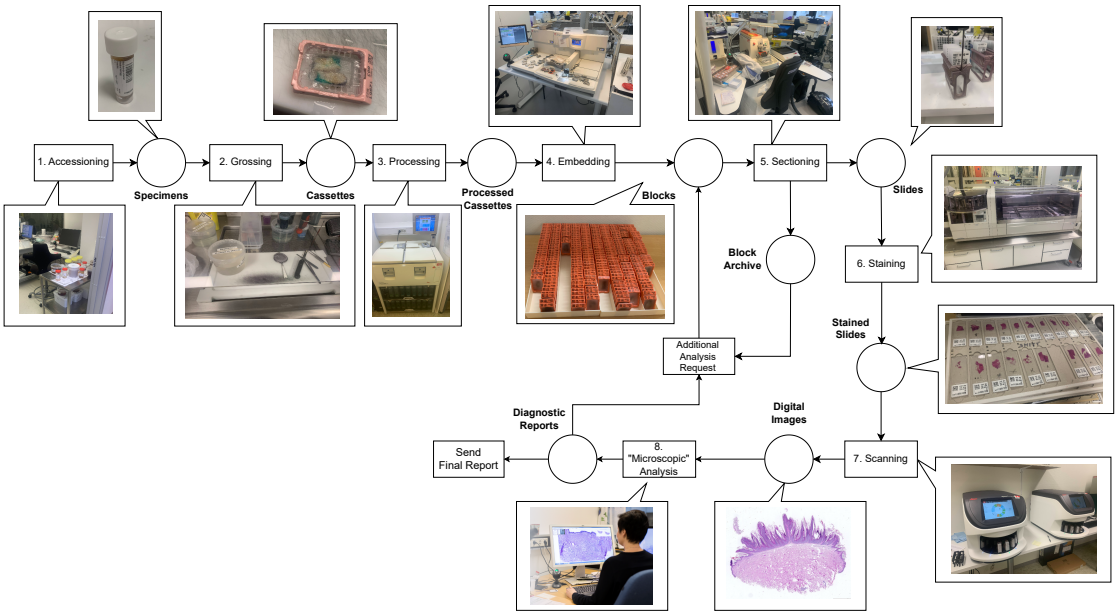


Figure 1: An overview of "Histopathology workflow" [3]

An important aspect of the Pathology workflow is the fact that the "final" "*Microscopy*" stage may generate additional work for the laboratory in the form of orders for further "analysis". With analysis, we mean a type of stain that highlights specific morphological structures (often based on *Immunohistochemistry (IHC)* where antibodies and not chemicals induce the staining) but one may also perform molecular analysis of the existing tissue. Note the possibility for *loops* in the net structure in Fig. 1: If the available image material is not sufficient to provide a conclusive diagnostic report yet, the pathologist may order additional analyses. This means that blocks, which were archived after sectioning, are to be retrieved and put again through the laboratory workflow pipeline.

Fig. 2 contains an abstract domain model, which illustrates this situation: A single *case* may comprise several *specimen* containers, which may result in several cassettes/blocks, which again turn into several *slides*. This also exacerbates the application of traditional process mining algorithms, which are based on the case-centric view. However, due to the aforementioned composite nature of cases in Pathology, the same activity will occur multiple times (depending on the

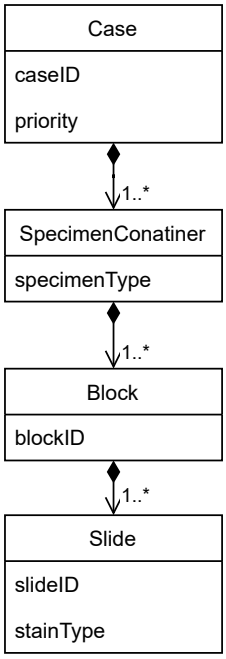


Figure 2: Pathology Domain Model

number of blocks and slides) within one case execution.

This situation is comparable to the one described in [5], where lab visits are comprised of several lab tests, which motivates the need for a *PROCLETs* framework [6]. A peculiarity of the Pathology domain, however, is that all these case artefacts (specimen containers, cassettes, slides) are being worked on in the lab simultaneously while the case is not concluded yet. Thus, the duration of cases varies greatly due to the high degree of heterogeneity: For instance, a small skin biopsy specimen generally results in a single block and single slide while a full prostate resection can produce up to 150 blocks with even more slides, depending on how many additional analyses are requested by the responsible pathologist.

3. Problem Statement: Tracing

In [3], the third and fourth author presented an ongoing project at Haukeland University Hospital in Bergen, which combines process mining, simulation, and optimization methods with the final goal to improve the overall turnaround times of the Pathology lab. While, that work was focusing on how to extract the raw data from a *laboratory information system (LIS)* to produce a process model and the organizational, technical, methodological, practical, and social issues associated with this activity, this paper focuses on the issues related to *tracing*.

The foundation for every process mining (and thus also most process analysis) activity is *event logs*. Bose et al. [7] mentioned three main issues w.r.t. data quality of such event logs: (i) the event log does not contain events that really happened, (ii) the event log contains more events than reality, and (iii) real events are concealed in the log. In this work, we focus on that first issue. This generally applies to all purely *physical* workflows. For such workflows, without any form of automatic tracing, all events have to be entered manually. This causes a serious overhead in terms of manual labour.

In manufacturing processes, two approaches for automatic tracing have emerged: *Barcodes* (1-D, 2-D, QR) and *Radio-Frequency Identification (RFID)*. RFID comes with the advantage of being very efficient and capable of recognizing multiple items simultaneously. Its main disadvantages being, that it is harder to locate single items and the costs of RFID tags and scanners are significantly higher compared to barcodes [8]. The Pathology lab at Haukeland has adopted a tracing solution based on barcodes: Specimen containers, blocks, and slides are tagged.

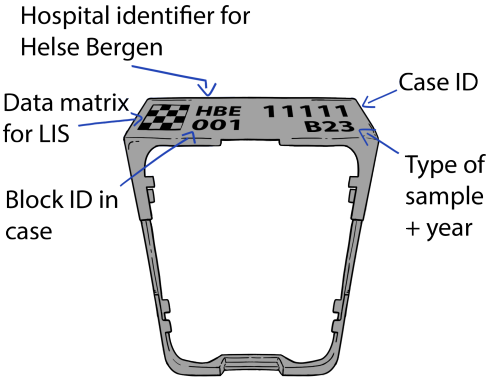


Figure 3: Cassette Tag Layout

Fig. 3 illustrates the layout of a cassette/block. The most central piece of tracking information is a 2-dimensional barcode (data matrix), which contains a unique item identifier, that is assigned by the LIS. The lab technicians working at the workflow stations scan this data matrix when they start working on an item, such that the respective event is logged by the LIS. The remaining information in the form of

regular text provides human-readable semantic context information, i.e. year of the case's first registration, the unique case number, the number of the block within the case and a hospital identifier. This information helps to quickly discover blocks belonging together in a case and in what order they appear, rather than scanning multiple barcodes for this purpose.

While the LIS, partly functioning as a workflow-aware information system, logs the majority of capture points in the "Histopathology workflow" execution, some activities are *completely untracked*. This applies specifically to the "*block archive*", see centre of Fig. 1. When a block has been sectioned, the produced slide is sent on to staining and the block is added to the archive queue. Here, it has to remain accessible in the case that additional analyses are ordered. Currently, the lab at Haukeland has no mechanism in place for registering blocks coming in and out of the archive. In order to make the retrieval possible, all blocks have to be sorted manually in alphabetical order ($year \rightarrow caseID \rightarrow blockId$). This generally binds one lab technician resource to the block archive every day. At the same time, introducing barcode scanning into this station would not create any significant benefit because the LIS has no tray management functionality for archive locations and because barcode scanning of large batches creates significant manual overhead. The latter is also the reason why there are several workflow stations where the respective event does not exist in the event log.

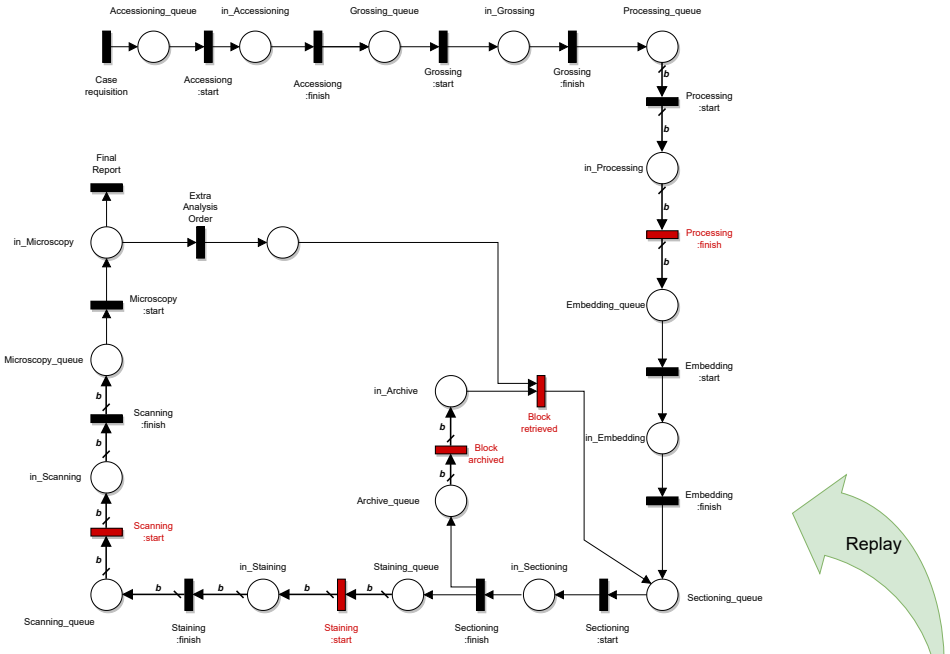
Fig. 4 depicts a Petri net (a refined variant of Fig. 1) serving as the process model (top) and an example log (bottom) that was replayed on that net. The example shows the execution of a single case with two blocks, where during microscopy an additional analysis is requested (see `Token` columns). Events that are highlighted in red mean that the respective events are not present in the log, which we aim to uncover with this work. "Missing out" on certain capture points also causes problems when process artefacts get lost. This situation, rightly so, occurs very seldom. However, when it happens, it can tie up multiple human resources who must invest their time in trying to locate the missing item because the information given by the LIS is not sufficient. In the worst case, this can impair patient safety, if the item cannot be found.

Our main objective with this work is to introduce additional capture points into the process without causing much additional overhead, providing the following benefits:

- Reducing the amount of necessary manual labor in the archive would partially free up at least one lab technician, allowing them to provide support at other workflow stations.
- Additional capture points will make it easier to locate individual blocks in the process.
- The extra capturing points in the event log allow producing a more comprehensive process model, which allows for more accurate simulation results.

4. Related work

In [9] the concept of a specialized laboratory information system is introduced. These systems are characterized by the need to perform a limited number of functions extremely well, as opposed to attempting to fulfill the needs of an entire laboratory [9]. The article outlines four pillars to consider when developing an in-house solution. These four pillars are scalability, building a design team, support costs and total cost of ownership versus long-term benefit. It is crucial for the proposed solution to fulfill the requirements of a specialized laboratory information system and, therefore, should take these four pillars into account.



Case	Timestamp	Event	Token
...	...	...	
B23 12345	2023-05-15 09:15:18	Grossing:finished	B23 12345
B23 12345	2023-05-15 12:01:23	Processing:start	B23 12345 01
B23 12345	2023-05-15 12:01:28	Processing:start	B23 12345 02
B23 12345	2023-05-16 08:00:51	Embedding:start	B23 12345 01
B23 12345	2023-05-16 08:03:10	Embedding:finish	B23 12345 01
B23 12345	2023-05-16 08:03:10	Embedding:start	B23 12345 02
B23 12345	2023-05-16 08:05:42	Embedding:finish	B23 12345 02
B23 12345	2023-05-16 14:11:11	Sectioning:start	B23 12345 01
B23 12345	2023-05-16 14:18:01	Sectioning:finish	B23 12345 01
B23 12345	2023-05-16 14:18:03	Sectioning:start	B23 12345 02
B23 12345	2023-05-16 14:23:42	Sectioning:finish	B23 12345 02
B23 12345	2023-05-16 18:07:01	Staining:finish	B23 12345 01 01
B23 12345	2023-05-16 18:07:03	Staining:finish	B23 12345 02 01
B23 12345	2023-05-17 10:52:00	Scanning:finish	B23 12345 01 01
B23 12345	2023-05-17 10:55:00	Scanning:finish	B23 12345 02 01
B23 12345	2023-05-18 13:01:33	Microscopy:start	B23 12345
B23 12345	2023-05-18 16:08:02	ExtraAnalysisOrder	B23 12345
B23 12345	2023-05-19 07:55:10	Sectioning:start	B23 12345 01
B23 12345	2023-05-19 07:58:55	Sectioning:finish	B23 12345 01
B23 12345	2023-05-19 12:45:44	Staining:finish	B23 12345 01 02
...	...	...	...

2023-05-16 01:00:00; Processing:end; B23 12345 01
2023-05-16 01:00:00; Processing:end; B23 12345 02

2023-05-16 15:03:17; Block archived; B23 12345 01
2023-05-16 15:15:01; Block archived; B23 12345 02
2023-05-16 16:06:01; Staining:start; B23 12345 01 01
2023-05-16 16:08:01; Staining:start; B23 12345 02 01

2023-05-16 10:49:01; Scanning:start; B23 12345 01 01
2023-05-16 10:52:01;Scanning:start; B23 12345 02 01

2023-05-19 07:45:52; Block retrieved; B23 12345 01

Figure 4: Missing Capturing Points

Hanna and Pantanowitz outline the history of barcodes in pathology [10]. They presented different types of codes including 2-D data matrix codes which is also used at the Haukeland pathology lab. Additionally, they detail how hospitals have improved the scanning performance with barcodes and improved efficiency. They explain how scanning could fail and mentioned some measures to reduce the risk of failure. Some of these challenges such as print quality are

also relevant to the OCR solution proposed. One significant benefit of incorporating barcode based tracking system is the potential to eliminate mistakes in labeling and enhance patient safety, leading to a decrease in adverse incidents [10]. However it is problematic to scan large number of barcodes at the same time. Since image processing techniques have been improved over the years, it can also be used for tracking laboratory samples at pathology lab.

In 2009, Buese looked at adapting lean workflow models to histology labs [11]. He introduced the concept of lean manufacturing, which is characterized by unitary production, minimal waste, and customer-driven production processes (referred to as "lean"). He initially provided a historical background of workflow methods, tracing their origins back to the automotive industry and illustrated how these management techniques evolved to encompass concepts of quality control and total quality management. Buese demonstrated the application of these methods in histology labs. The article summarizes the findings from 25 histology facilities that implemented management tools. Based on this data, it is extrapolated that labs handling over 20,000 cases annually derive greater benefits from incorporating these methods, although all 25 hospitals observed an improvement in performance. The article concludes by proposing 13 changes to enhance workflow in histology labs.

In Zayas et. al., [12], a peer-reviewed analysis of 123 articles related to automation approaches in various industries is conducted to identify opportunities for workflow automation in healthcare. The authors highlight specific characteristics which promotes automation. The paper presented different tasks that can be automated at different stages such as low-, semi- and fully automated tasks. The level of automation achieved is closely related to the clarity and precision within which the task is defined.

Object centric process mining [13] can deal with divergence (multiple instances of the same activity within a case) and convergence (one event may be related to different cases) related problems. However, it does not offer a solution for tracking cassettes and slides carrying laboratory samples in pathology workflows or their subsequent analysis.

Zhou et. al., introduced an efficient and accurate scene text detector (EAST) in [14]. EAST is a fully convolutional neural network designed to achieve both efficiency and accuracy. The authors provided detailed information about the image processing pipeline and explain the decisions made regarding neural network training, including the choice of loss function, optimizer, and number of batches. To evaluate the performance of EAST, quantitative and qualitative experiments were conducted using three publicly available benchmark datasets: ICDAR 2015, COCO-Text and MSRA-TD500. The results showed that the proposed algorithm outperformed existing methods in terms of enhanced performance while also running significantly faster when applied on the standard benchmark dataset [14]. In our work, we have tweaked existing techniques for character recognition and incorporated them into process engineering to streamline pathology workflows.

5. Proposed Method: Specimen Tracing with OCR

In order to address the issue described in Sect. 3, we present a character recognition image processing component, which serves as a lightweight tracing mechanism. This component exploits the human-readable information that is attached to the process artefacts (i.e. blocks

and slides), see Fig. 3. We expect this approach to be applicable for any physical process, that has not yet adopted Barcode or RFID technology, because it only relies on the human-readable textual information, which we expect to be present anywhere human workers are involved. Moreover, we illustrate how the image processing component can be incorporated into existing workflow execution and process mining environments, where it provides improved traceability.

5.1. Image Processing Component

Image processing is the central part of our proposed solution for improving the tracing capabilities within the pathology lab. The goal of image processing is to analyse, manipulate, and extract meaningful information from digital images. It is used for extracting relevant features, and enabling automated interpretation. Image processing often involves pre-processing steps where certain aspects of the image are manipulated beforehand. This field can be divided into the subcategories: text extraction, facial recognition, and vision systems. Our method focuses on text extract, also referred to as *OCR*, i.e. "turning the text into analysable, editable, and searchable data." [15]. Machine learning has been successfully applied in OCR. However, existing machine learning tools for image processing either need to be trained using a large dataset which requires a lot of heavy computing power, or need to be fine-tuned with custom image processing techniques. Our proposed framework includes an image processing component which has been fine-tuned based on two techniques. These techniques have been selected based on a sample dataset containing images of containers with a number of cassettes.

These two techniques are optimized for pathology cassette detection. Two different image processing pipelines have been used; one is built using various functionality from OpenCV [16]; and another one is built using a neural network. Fig. 5 depicts these two processing pipelines: (i) Cassette reader pipeline with *Edge Detection (ED)*; and (ii) Cassette reader pipeline with *Efficient and Accurate Scene Text detection (EAST)*.

The cassette reader pipeline with edge detection (Fig. 5 left) applies filters and customized contour detection for reading cassettes. It takes an image of a container with many cassettes as input and applies gray scale filter and bilateral blur filter to smooth out noise. The pipeline includes a sharpening step where objects boundaries are detected using an adaptive threshold which binarize the image into black and white pixels. This sharpening technique increases the outline of cassettes edges. The pixels are then eroded to remove noise. Contour detection is also used for noise removal of small contours, and then contour detection is applied again for locating and reading cassettes information. This pipeline uses Tesseract [17], or more specifically PyTesseract which is a wrapper for Google's Tesseract-OCR Engine for text recognition. The Tesseract-OCR is already trained for text recognition, and therefore it simplifies the task of extracting the textual information from cassettes. We have chosen Tesseract as it is open source and freely available, even though the performance may not be the best when compared with other commercial software [18].

The cassette reader pipeline with EAST (Fig. 5 right) is a neural network based approach using a fully convolutional network [14]. EAST requires an image resolution to be a multiple of 32 and therefore the pipeline checks for the resolution and adapts to the requirement by padding each side with black pixels if required. In this pipeline, the output of the neural network is parsed until the vertices of each piece of text is extracted. At this point, all 4 text fields of each

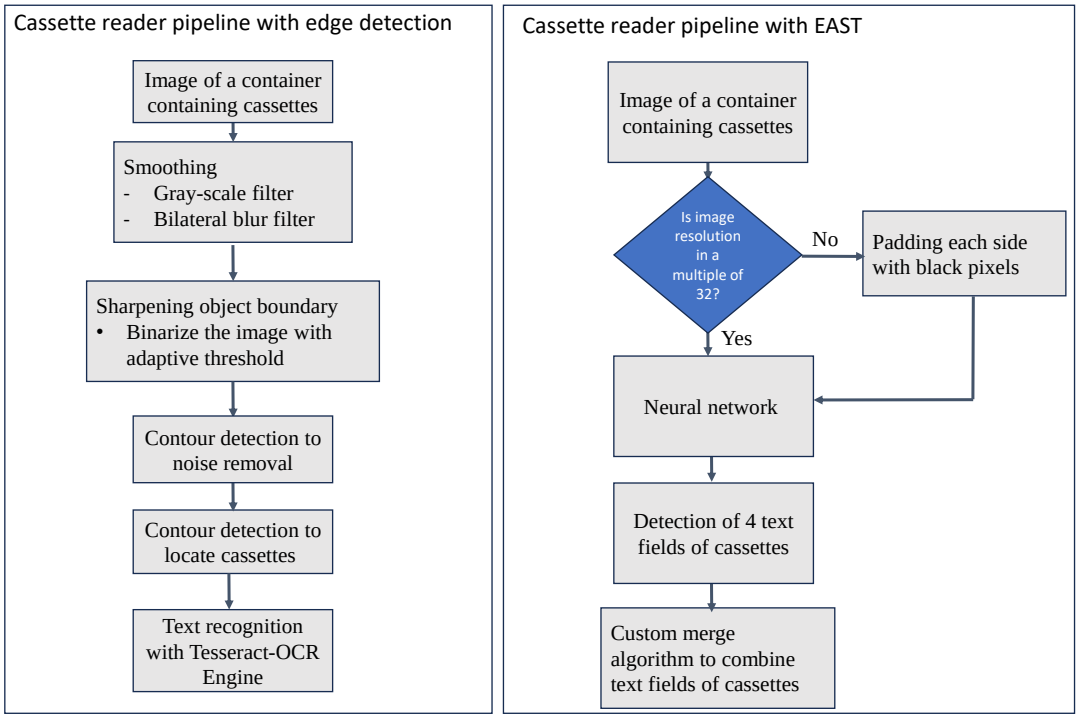


Figure 5: Two versions of image processing pipelines

cassette are extracted. However, to detect the boundary of all the text on each cassette, a custom merging algorithm is employed. This merge algorithm checks the distances between the box and pads them dynamically based on the image resolution until all text fields are merged or removed in case if they are found to be too small. The cassettes are then considered located. Fig. 6 shows a screenshot of the results of image processing component.

5.2. Architectural Integration

The purpose of the image processing component is to identify cassettes and record their locations at various checkpoints in the process flow. The image processing component offers two major functionalities: tracking and locating cassettes. Both functionalities are exposed via a REST API and thus can be incorporated into arbitrary frontends.

The cassette tracking API takes an image file and a parameter deciding over processing pipeline as inputs. The API outputs a JSON object containing the coordinates of recognized cassettes and texts field contents. Moreover, the application creates respective events in a log file every time a cassette is recognized and when a cassette is retrieved from the archive. This specialized log file is merged with the main event log to form a comprehensive event log.

Fig. 7 shows how this component fits into the general framework of our project. The LIS serves as the primary operative information system and also as a kind of process execution engine since it is aware of the Pathology workflow. The data generated by the LIS serves as the

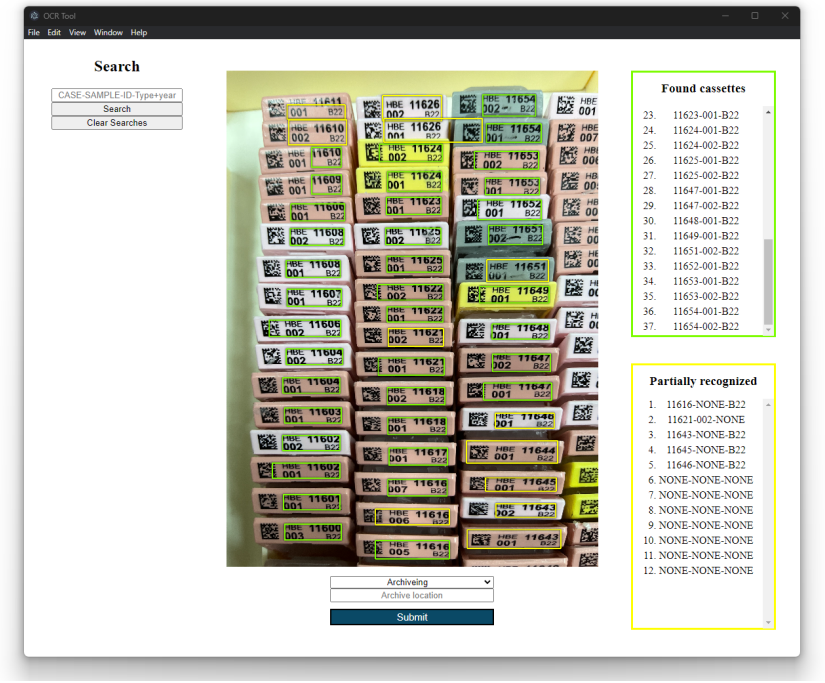


Figure 6: A Screenshot of the output of the Prototype

foundation for the creation of a cleansed event log, which is provided by an *Extraction, Load & Transform (ELT)* component. Details about this component can be found in [3]. The event log is the basis of the process mining activities and succinct simulation and optimization components. The novel part, here, is the image analysis component. It simultaneously serves as an operative system as well as an analytic system.

6. Evaluation

The performance of the image processing component is crucial for the applicability of our proposed approach. Table 1 and 2 below present the results obtained from image processing pipeline with edge detection and EAST for the identification of cassettes in four representative images. These images were captured at equal distances. The images were taken using an iPhone 13 with a resolution of 3024x4032. The evaluation and processing of the images were done on a windows machine. To achieve the DPI resolution required by Tesseract the images were taken from a close proximity. It also ensures that no details from the images were lost. Consequently, a full image of tray containing 150 cassettes were not feasible to use, instead smaller tiles containing between 37 and 49 cassettes were used. The results are expected to scale with cameras that are able to capture images with similar text sizes and higher resolutions. The only difference would likely be an increase in runtime with larger image sizes.

Cassettes are classified into different categories based on the OCR tool's performance. Fully recognized cassettes refer to cases where the OCR tool successfully reads all the data present on

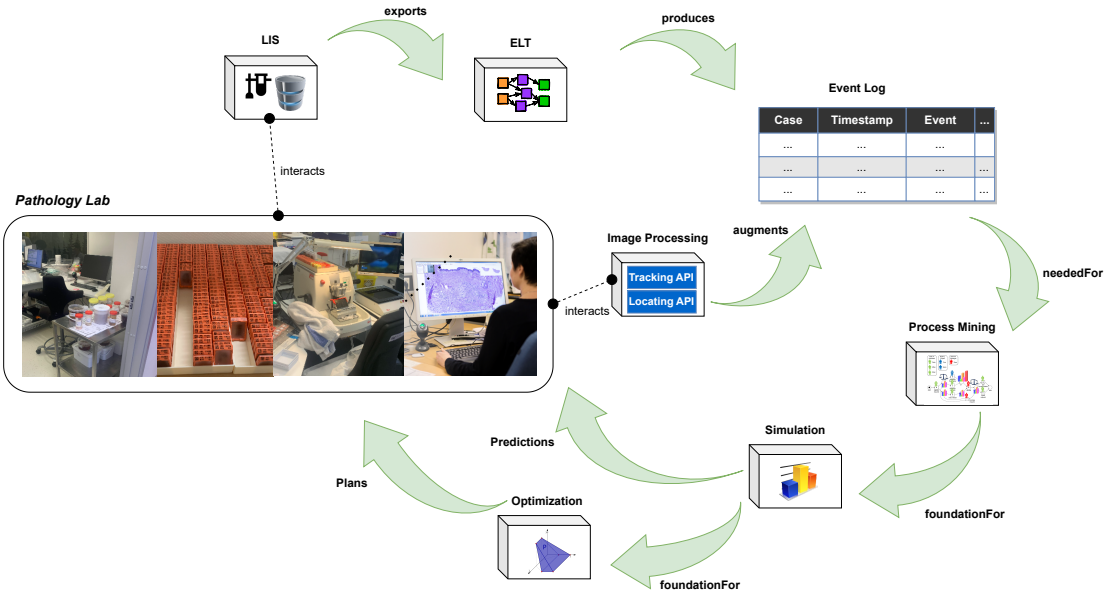


Figure 7: Architectural Overview

the cassette. Partially recognized cassettes indicate instances where the OCR tool only partially recognizes or fails to recognize some of the text on the cassettes, although the cassette itself is successfully located. False detections occur when the system highlights an area that does not contain a cassette, possibly due to noise or erroneous detections. OCR errors correspond to cases where the data on a cassette is recognized, but there are errors in the data itselfr.

Table 1
Results from edge detection

		Recognized			Errors		Times		
Image id	Cassettes in image	Total	Fully	Partially	False detection	OCR error	OCR runtime	Error correction	Total
1	37	22	16	6	1	0	00:06	02:51	02:57
2	49	37	19	18	0	1	00:08	03:45	03:53
3	37	32	9	23	3	0	00:07	03:38	03:45
4	44	39	3	36	0	1	00:08	04:46	04:54

The edge detection model demonstrates an overall accuracy of 77.84% (130/167) in cassette detection, while EAST achieves an average accuracy of 93.41% (156/167) in localizing cassettes. However, this accuracy improvement comes at the cost of an average runtime increase of 22.01 seconds compared to edge detection. Some instances of false detections have been observed in our experiments, wherein the program erroneously identifies a cassette that does not actually exist. To estimate the time required for manually sorting cassettes, we conducted observations

Table 2
Results from EAST detection neural network

Image id	Cassettes in image	Recognized			Errors		Times		
		Total	Fully	Partially	False detection	OCR error	OCR runtime	Error correction	Total
1	37	35	27	8	1	0	00:30	01:41	02:11
2	49	49	37	12	0	0	00:34	01:24	01:58
3	37	34	18	16	1	1	00:26	02:26	02:52
4	44	38	25	13	0	1	00:26	02:34	03:00

in the archive room alongside a lab technician on a randomly selected day. Within a fixed time span, it was determined that, on average, 10.78 cassettes are sorted per minute when the process is performed manually.

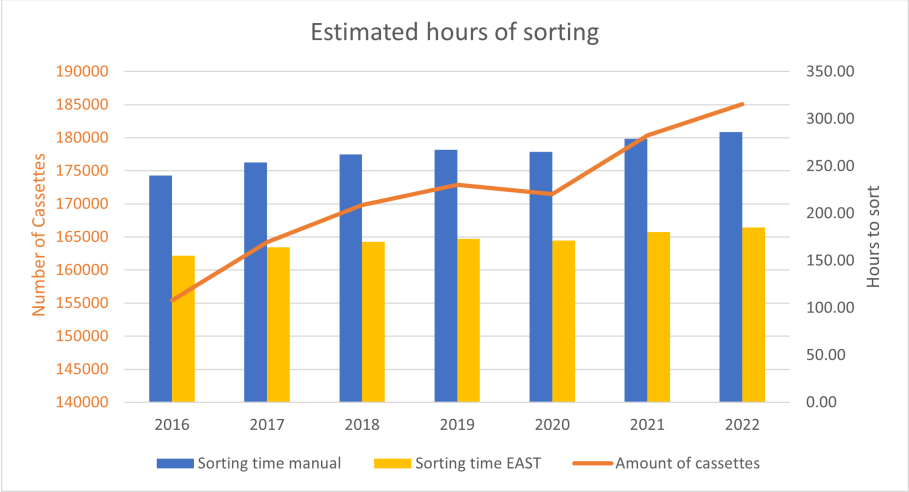


Figure 8: This graph shows an estimate of the sorting times saved and the amount of cassettes increasing each year

The graph in Fig. 8 presents the progress of produced blocks by the lab over time. The bar chart below shows an estimate of the number of hours the lab technicians have dedicated to sorting, based on the data gathered through observation. There is also an estimate of how much time would have been saved if they utilized the EAST based sorting in its current state, including the time for manual error correction.

In 2022, the pathology lab sorted 185065 cassettes. If the sorting process were conducted at the average manual speed measured here, which amounts to 647 cassettes per hour, it would require approximately 286 hours of work. However, by implementing the EAST-based sorting method with manual error correction, which currently achieves an average speed of 1000.333 cassettes per hour, it would be possible to complete the sorting within 185 hours. This would allow the pathology lab to reduce sorting time by 101 hours, resulting in a 35.32% decrease in time spent on sorting activities, while simultaneously enhancing traceability.

7. Conclusion

In this paper, we have presented an automated tracking system for lab samples using image processing and its integration with a process execution engine. The technique we presented for tracking lab samples will contribute to process improvement, as the tracking data can be used to leverage process mining output. Empirical evaluations were conducted to assess the effectiveness of the proposed method. Accurate recognition of text from the labels of lab samples is crucial for this project, thus two different image processing techniques were tested: one is based on edge detection and the other is based on a neural network for text detection named EAST. The image processing pipeline with EAST outperformed the edge detection method, achieving an accuracy score of 93.31%. Although EAST exhibited a slightly longer runtime compared to the edge detection method, its accuracy is higher.

Furthermore, a comparison of sorting time with and without the image processing tool was performed. The experimental results demonstrated that utilizing EAST for sorting enabled the processing of 54% more cassettes within a given time frame compared to the current manual sorting approach. Based on our calculations, employing EAST for sorting would have saved a total of 101 hours in 2022, corresponding to 35% reduction in sorting time. Although the evaluation shows promising results, there is scope for improvement. The current accuracy of the system necessitates manual oversight and error correction. Taking into consideration the current runtimes of 1 minute and 56 seconds, a theoretical maximum of achieving 100% accuracy and full automation would enable the sorting of approximately 86.38 cassettes per minute, resulting in a substantial 701% increase in the number of cassettes sorted per hour. However, it is important to note that this calculation assumes consistent runtimes and anticipates technological advancements that can surpass the current error rate observed in manual sorting. The primary drawback of the current models resides in their limited OCR performance, estimated at 62% (97/156). Consequently, the remaining 38% of cassettes would require manual labeling. Nevertheless, despite this suboptimal performance, the EAST model continues to outperform manual sorting in terms of efficiency.

In future work, we plan to explore the development of a custom machine learning model specifically designed for cassette detection, instead of relying on off-the-shelf solutions. Developing a custom machine learning model will require a substantial volume of training data, containing labeled images of cassettes and slides captured from various angles.

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