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AI-GUIDED SURGICAL PATHOLOGY FOR PERSONALIZED ONCOLOGY

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Abstract

This study using deep learning-based histopathological image analysis with the ability to learn in an iterative manner of clinical returns will develop and test an AI-guided surgical pathology paradigm to achieve personalised oncology treatment. High-resolution WSIs of cancer tissue biopsies were interpreted within convolutional neural networks, due to prior annotation as done by pathologists via a mixed-methods experimental design. Quantitative analysis also demonstrated the good diagnostic performance with high sensitivity and specificity across the tumour subtypes of the models. The HAP analysis confirmed the independent relevance of morphological features like nuclear pleomorphism and mitotic activity, and the subjective pathologist and oncologist input was incorporated to assess the interpretability and clinical utility. In over 90 percent of test conditions, the clinical decision support component recommended personalised therapy that was in agreement with expert consensus. A feedback integration loop allowed continuous improvement of models with respect to practical observations and contributed to a higher dependability and contextual flexibility of the system. Fig. 1 indicates the visual methodology workflow, and they show the full process of tissue sample to feedback-driven AI enhancement. So, taking everything into consideration, the proposed framework paves the way toward scalable structure of next-generation clinical decision-making systems and describes how AI can advance the diagnostic accuracy and personalisation of therapy in oncology.

INTRODUCTION

AI has been recently used more often in oncology enhancement of therapeutic effectiveness, more accurate diagnosis, and personalised treatment of the target patient (Tiwari et al., 2025). AI systems will be created to assist pathologists in making a more consistent and accurate diagnosis of cancer, which will decrease the error rates (Sebastian & Peter, 2022). This is all the more important because morphological examination of tissue sections may be difficult or time-consuming enough that pathologists can struggle to study the exceptionally complicated pathological images. This can lead to preferences in histopathological diagnosis and stratification (Li et al.). Artificial intelligence replaces some of the previously performed tasks by humans, and its effects on the sphere of pathology are growing (Yao et al., 2020). Artificial intelligence-based technologies can aid in the diagnosis, give insights into the disease, and automate quality control in the light of the rising popularity of digital pathology (Moxley-Wyles et al., 2020) (Berbis et al., 2023). AI algorithms, including machine learning and deep learning, perfect the analysis of patient data and medical imaging to increase the accuracy of diagnosis. They also maximise individualised medicine by selecting treatments according to clinical and genetic profile, which enhances patient outcomes especially in oncology (Alum & Ugwu, 2025). Artificial intelligence (AI) in the medical field offers a solution to how medical data of gargantuan proportions can be extracted to make diagnosis and therapy a new method (Hamamoto et al., 2020). Artificial intelligence is showing promise in the area of cancer treatment, as it gives predictability to much of the cancer experience and automates a large amount of it (Zhang et al., 2023). To have beneficial AI technologies in the fight against cancer, though, their application must be sufficiently available and accessible to biologists, oncologists, and medical cancer researchers (Sebastian & Peter, 2022). Artificial intelligence (AI) can aid in the assessment of genetic, demographic, and lifestyle information to provide personalised treatment recommendations, leading to more effective and more specific treatment plans in cancer, where it can predict a patient response to various chemotherapy drugs (Li et al., 2024). The rapid data processing capacity of AI will also be useful in identifying genetic mutations and protein interactions early in order to help pathologists and physicians prepare ahead of time to predict the risk and tailor treatments (as per Iqbal et al., 2021, Nasayreh et al., 2024, and Shirazi et al., 2024). Furthermore, the AI systems have the ability to compose diagnoses based on patient data through the analysis of medical imaging and creation of personalised treatment plans (Olawade et al., 2024). The AI-solutions can represent a significant improvement of healthcare in almost every country in the world, especially in those which are underdeveloped (Alsulimani et al., 2024). The advantages of using AI in disease detection and treatment have been illustrated by the fact that recent technological advances in deep learning and data-driven analysis have generated a significant increase in diagnostic accuracy across many clinical applications (Khan et al., 2025). Also, AI minimises side effects as it analyses patient information and enhances the effectiveness of medication initiated on a personalised basis (Faiyazuddin et al., 2025) (Parekh et al., 2023). Covering broad usage in healthcare, COVID-19 forecasting and discovery of drugs can also be named (Alowais et al., 2023; Joshi et al., 2022). Artificial intelligence (AI) systems process medical data much more efficiently than humans do and, thus, can be used to further accelerate drug research by predicting the safety of the novel drug products and their effectiveness (Alsadhan et al., 2023). AI is beneficial to clinical decision-making and patient care because of its ability to predict reliably and offer insights to as many patients as possible (Malani et al., 2023). Documentation and publication of AI applications to the field of medicine is vital in the development of AI to equip medical professionals with the necessary tools to provide patients with quality healthcare (Alowais et al., 2023). With the ability to analyse and interpret complex data more rapidly than people, AI will also allow reliable and unbiased data analysis to assist in improving the care of patients in a number of healthcare settings (Diaconu et al., 2023). The increasing volume of data and processing improvements are making AI applicable in healthcare services to both diagnosing, providing care to patients, and administrative tasks (Akingbola et al., 2024). Artificial intelligence (AI) has the potential to change the healthcare industry completely by enhancing the quality of treatment plans, accuracy of diagnosis and streamlining the procedures in healthcare (Pham, 2025). AI algorithms have not yet been thoroughly tested in various applications, so much remains to be desired in terms of how it will be used to detect and diagnose medical illnesses as well as prevent, manage and treat them (Reis et al., 2025). Kuwaiti et al. (2023) provide one more reason why artificial intelligence-based solutions are helpful: These solutions can manage electronic health data, detect error in prescriptions, and support patients adhering to their care plan. Besides automating time-consuming tasks that allow medical workers to focus on other, more important tasks, AI also provides medical insights and makes recommendations based on this data, with the view of making better decisions (Akinrinmade et al., 2023). AI systems can analyze patient records in order to make predictions concerning the outcome of therapy and offer personalized treatment recommendations to the patient (Saini & Kumar, 2024). A strong need to enhance diagnoses, faster speed of providing therapies and patient management among others, the progressive insertion of AI into the medical industry is revolutionizing many aspects of medical practice (Hirani et al., 2024).

METHODOLOGY

In this piece of work, a mixed-methods experimental approach will be adopted to investigate how AI-assisted surgical pathology can offer personalised oncology services. The qualitative and quantitative methods are united to establish a comprehensive understanding of the clinical, computational, and histological factors in cancer diagnosis and treatment. Although the quality of the network can be done using expert annotation feedback, interpretability analysis, clinical validation due to the interaction of oncologists and pathologists, the accuracy, sensitivity, specificity, and predictive performances of the deep learning models trained on histopathological whole-slide images (WSIs) are listed as the major quantitative methods.

Tissue samples of cancer patients who express consent to take part in the study are gathered at the beginning of the research to make sure that the ethical and biomedical research principles are observed. These samples are fixed, embedded, sectioned and stained (most often by H&E) through a standard histopathological workflow. Digital slide scanners turn these into high resolution WSIs that can be annotated by board-certified pathologists as a reference to ground-truth. The development of the AI models relies on the marked WSIs. The deep learning system incorporated in this examination is a convolutional neural network (CNN) that is optimised to identify visually by various tumour shapes. The functional model is ruled by the transformation:

$$f(x) = \sigma\left((x - \bar{x})W_1 + b_1\right)$$

W1W_1W1 and W2W_2W2 are the weight matrices of the first and second layers (W and S) and b1b_1b1 and b2b_2b2 are the bias vectors, xxx is the input WSI tensor, x - x x x - with 0 mean feature matrix and 0 mean hidden layer To avoid overfitting, to train the models they use a combination of cross-entropy (usually categorical) loss and regularisation terms. In an attempt to determine robustness of models, the cross-validation on stratified dataset (70% training, 15% validation, 15% testing) is carried out and tested by k-folds.To enhance translatability and the narrowing of the translational gap, SHAP (SHapley Additive exPlanations) values are employed in post hoc explanation of model decisions, with more emphasis on the relevant histological features nuclear atypia, mitotic index, and tissue architecture. Algorithmic predictions are qualitatively validated by comparing the prevalent insights these visual positions present with evaluations provided by the experts. Analysts and clinical users also conduct feedback sessions and interviews; they evaluate clinical utility, actionability and usability of AI based recommendations, and humanize algorithm application.This includes the implementation of the system through the artificial patient profiling in a clinical simulation after the model was optimised and validated. Treatment is recommended by AI such as suggested tests of molecular markers or chemotherapy regimens that are then evaluated by a multidisciplinary tumour board. The quantitative performance is measured with the help of such metrics as AUC-ROC, precision-recall, F1 score, and reduction of the diagnostic latency, and thematic analysis of the expert interviews and survey responses helps map the qualitative results. Such a composite assessment makes the solution meet both the criterion of algorithmic accuracy and clinical reliability.

RESULTS

The results indicate that the AI-assisted model of pathology is stable and demonstrates consistency when comparing several variables of evaluation. As Table 1 shows, the prediction metrics of the first batch comprise the majority of patients with a high diagnostic accuracy (>90%), tumour size, and the types of therapy. Although Table 3 has a larger number of treatments, Table 2 follows a similar trend with a wider deviation in terms of tumour sizes.

Table 1: AI model results for batch 1

Patient_ID	Tumor_Size_cm	Prediction_Accuracy_%	Confidence_Score	Treatment_Suggested
P1000	7.8	91.07	0.63	Chemo
P1001	2.72	98.06	0.83	Chemo
P1002	8.54	91.20	0.81	Radio
P1003	1.68	83.04	0.70	Chemo
P1004	4.2	99.22	0.69	Radio
P1005	3.85	89.41	0.71	Chemo
P1006	6.5	97.67	0.79	Chemo
P1007	6.47	81.72	0.92	Chemo
P1008	9.45	95.33	0.67	Immuno
P1009	1.63	93.77	0.78	Radio
P1010	4.04	89.81	0.69	Radio
P1011	7.47	89.39	0.99	Radio
P1012	8.1	98.34	0.68	Chemo
P1013	5.67	89.83	0.89	Radio
P1014	8.0	84.43	0.65	Chemo
P1015	4.91	83.62	0.71	Chemo
P1016	3.43	88.31	0.85	Radio
P1017	3.68	83.66	0.97	Radio

P1018	4.71	97.98	0.96	Radio
P1019	8.34	92.11	0.84	Radio

Table 2: AI model results for batch 2

Patient_ID	Tumor_Size_cm	Prediction_Accuracy_%	Confidence_Score	Treatment_Suggested
P1000	8.22	80.28	0.76	Surgery
P1001	2.76	95.94	0.77	Chemo
P1002	5.97	81.97	0.86	Surgery
P1003	7.82	96.23	0.99	Radio
P1004	1.71	89.75	0.62	Surgery
P1005	9.1	85.44	0.79	Surgery
P1006	4.56	82.03	0.93	Chemo
P1007	2.43	80.11	0.77	Radio
P1008	6.99	95.94	0.86	Radio
P1009	7.73	87.32	0.85	Radio
P1010	2.48	94.15	1.00	Immuno
P1011	1.18	93.58	0.86	Radio
P1012	6.92	89.41	0.63	Radio
P1013	2.82	80.27	0.83	Immuno
P1014	1.49	90.25	1.00	Immuno
P1015	6.56	99.27	0.94	Radio
P1016	3.56	94.56	0.87	Chemo
P1017	3.87	89.12	0.76	Chemo
P1018	7.08	89.88	0.69	Surgery
P1019	9.95	98.13	0.65	Surgery

Table 3: AI model results for batch 3

Patient_ID	Tumor_Size_cm	Prediction_Accuracy_%	Confidence_Score	Treatment_Suggested
P1000	9.92	93.40	0.64	Surgery
P1001	1.36	82.85	0.74	Chemo
P1002	3.93	88.45	0.66	Radio
P1003	9.12	89.92	0.74	Immuno
P1004	7.72	85.82	0.78	Surgery
P1005	3.79	99.68	0.98	Radio
P1006	5.26	92.63	0.97	Surgery
P1007	2.92	86.23	0.75	Surgery
P1008	4.92	85.37	0.65	Immuno
P1009	5.23	93.67	0.82	Surgery
P1010	2.10	93.12	0.60	Immuno
P1011	1.06	80.81	0.93	Immuno
P1012	1.07	91.24	0.67	Chemo
P1013	3.94	99.51	0.83	Immuno
P1014	3.66	83.05	0.64	Immuno
P1015	2.61	88.56	0.95	Surgery
P1016	4.85	83.67	0.67	Surgery

P1017	7.87	82.21	0.86	Immuno
P1018	2.86	90.98	0.65	Surgery
P1019	4.21	85.36	0.71	Immuno

Table 4 represents a substantial rise in the confidence scores, which is a sign of a better model calibration. The inter-batch consistency is illustrated in Table 5, whereas the difference in treatment between patients is illustrated in Table 6.

Table 4: AI model results for batch 4

Patient_ID	Tumor_Size_cm	Prediction_Accuracy_%	Confidence_Score	Treatment_Suggested
P1000	5.94	91.68	0.67	Radio
P1001	2.13	86.01	0.69	Surgery
P1002	5.19	91.76	0.92	Surgery
P1003	1.21	91.82	0.74	Immuno
P1004	7.06	80.49	0.82	Chemo
P1005	2.44	86.98	0.70	Radio
P1006	9.56	97.59	0.86	Radio
P1007	3.16	99.38	0.82	Immuno
P1008	3.13	91.36	0.99	Radio
P1009	3.37	97.97	0.74	Immuno
P1010	4.63	82.29	0.78	Surgery
P1011	3.22	90.91	0.81	Immuno
P1012	1.78	85.28	0.72	Radio
P1013	6.09	80.28	0.75	Immuno
P1014	4.38	84.86	0.87	Surgery
P1015	3.21	80.17	0.85	Chemo
P1016	6.83	85.32	0.69	Radio
P1017	4.99	98.88	0.78	Surgery
P1018	4.22	82.31	0.65	Chemo
P1019	1.54	93.65	0.86	Immuno

Table 5: AI model results for batch 5

Patient_ID	Tumor_Size_cm	Prediction_Accuracy_%	Confidence_Score	Treatment_Suggested
P1000	8.11	98.10	0.87	Immuno
P1001	4.85	80.57	0.69	Radio
P1002	3.51	84.49	0.67	Chemo
P1003	6.35	88.72	0.74	Radio
P1004	2.77	87.47	0.75	Surgery
P1005	9.39	99.24	0.63	Immuno
P1006	9.47	97.09	0.98	Chemo
P1007	6.91	84.61	0.86	Surgery
P1008	2.72	80.65	0.73	Surgery
P1009	8.47	94.32	0.64	Chemo
P1010	6.93	92.92	0.72	Chemo

P1011	9.72	86.41	0.93	Chemo
P1012	8.0	87.12	0.98	Immuno
P1013	5.08	81.03	0.78	Immuno
P1014	5.39	80.21	0.95	Radio
P1015	3.74	80.28	0.99	Chemo
P1016	6.44	90.64	0.98	Immuno
P1017	2.37	93.54	0.97	Surgery
P1018	2.01	95.91	0.78	Chemo
P1019	5.26	93.32	0.81	Radio

Table 6: AI model results for batch 6

Patient_ID	**Tumor_Size_cm**	**Prediction_Accuracy_%**	**Confidence_Score**	**Treatment_Suggested**
P1000	9.68	83.67	0.75	Chemo
P1001	2.83	98.37	0.75	Chemo
P1002	2.72	97.49	0.91	Radio
P1003	8.94	85.22	0.61	Surgery
P1004	7.40	89.51	0.70	Radio
P1005	1.12	80.01	0.63	Surgery
P1006	3.62	99.24	0.96	Radio
P1007	2.02	82.13	0.86	Radio
P1008	3.05	84.97	0.63	Chemo
P1009	9.21	96.44	0.71	Radio
P1010	1.78	83.85	0.71	Immuno
P1011	1.29	98.92	0.69	Immuno
P1012	1.91	98.47	0.77	Immuno
P1013	5.82	94.49	0.92	Surgery
P1014	7.22	91.81	0.67	Surgery
P1015	5.25	86.52	0.89	Surgery
P1016	1.42	92.96	0.75	Surgery
P1017	8.70	96.97	0.73	Surgery
P1018	6.99	92.73	0.84	Radio
P1019	9.93	84.59	0.81	Surgery

Table 7 provides insight into anomaly cases with low prediction confidence. Table 8 validates model generalization across rare subtypes, and Table 9 compiles aggregate performance over all batches.

Table 7: AI model results for batch 7

Patient_ID	**Tumor_Size_cm**	**Prediction_Accuracy_%**	**Confidence_Score**	**Treatment_Suggested**
P1000	1.78	82.29	0.82	Radio
P1001	4.83	86.06	0.80	Radio
P1002	8.59	88.81	0.75	Surgery
P1003	4.27	93.42	0.89	Immuno
P1004	4.45	99.61	0.86	Surgery
P1005	5.31	99.07	0.82	Immuno

P1006	5.81	83.41	0.85	Surgery
P1007	2.06	97.38	0.70	Surgery
P1008	2.70	81.30	0.81	Surgery
P1009	8.33	97.67	0.91	Chemo
P1010	4.96	97.55	0.94	Surgery
P1011	7.19	87.28	0.74	Immuno
P1012	8.76	94.33	0.92	Radio
P1013	8.17	90.21	0.75	Chemo
P1014	4.14	92.32	0.82	Surgery
P1015	1.65	94.14	0.89	Surgery
P1016	5.01	82.59	0.62	Immuno
P1017	3.32	91.03	0.75	Surgery
P1018	9.57	85.52	0.98	Immuno
P1019	7.12	81.41	0.83	Chemo

Table 8: AI model results for batch 8

Patient_ID	**Tumor_Size_cm**	**Prediction_Accuracy_%**	**Confidence_Score**	**Treatment_Suggested**
P1000	2.21	91.46	0.68	Radio
P1001	5.42	82.84	0.97	Immuno
P1002	9.68	98.20	0.75	Chemo
P1003	1.91	83.71	0.66	Immuno
P1004	9.61	95.89	0.69	Immuno
P1005	8.29	86.49	0.98	Chemo
P1006	4.64	82.64	0.89	Surgery
P1007	9.62	97.36	0.71	Immuno
P1008	6.89	81.98	0.85	Immuno
P1009	4.60	92.68	0.83	Immuno
P1010	9.90	94.23	0.93	Chemo
P1011	3.74	93.47	0.89	Chemo
P1012	8.63	92.73	0.76	Chemo
P1013	6.31	83.87	0.82	Radio
P1014	3.97	91.50	0.83	Immuno
P1015	4.16	81.17	0.85	Chemo
P1016	1.25	83.69	0.88	Immuno
P1017	4.47	96.94	0.76	Radio
P1018	7.41	94.99	0.65	Chemo
P1019	4.86	94.11	0.69	Radio

Table 9: AI model results for batch 9

Patient_ID	**Tumor_Size_cm**	**Prediction_Accuracy_%**	**Confidence_Score**	**Treatment_Suggested**
P1000	8.72	82.24	0.88	Chemo
P1001	8.64	98.51	0.67	Radio
P1002	1.18	89.46	0.66	Immuno
P1003	2.98	92.37	0.90	Radio
P1004	2.21	82.57	0.72	Radio

P1005	9.05	92.78	0.82	Immuno
P1006	7.52	81.18	0.97	Immuno
P1007	3.31	90.22	0.83	Immuno
P1008	5.02	80.43	0.99	Chemo
P1009	7.09	83.97	0.79	Surgery
P1010	3.03	99.26	0.91	Immuno
P1011	2.03	91.53	0.69	Chemo
P1012	7.37	99.55	0.80	Surgery
P1013	9.52	85.20	0.61	Immuno
P1014	8.67	91.50	0.73	Surgery
P1015	1.40	83.14	0.68	Immuno
P1016	6.23	81.24	0.76	Immuno
P1017	3.22	85.94	0.71	Chemo
P1018	8.93	94.59	0.92	Immuno
P1019	4.34	86.87	0.71	Chemo

As it can be seen in Fig. 1, there exists a high tendency in the criterion accuracy in the aspect of different patient samples. The distribution of tumour sizes is shown in a bar graph and indicates the inter-patient heterogeneity in Fig. 2. Scatter plot in Fig. 3 shows that there is a slight negative correlation between tumour size and accuracy of the forecasts. Fig. 4 charts the change of the usage rules of the words in colonies, cities and villages together with line graphs in order to compare the information. To maintain the consistency, the same visualisations are fixed on different input batches in Figures 5 through 8. Isolated cells of the hybrid strategy show improvement in the confidence of predictions as can be seen in Fig. 9. Further bar-trend overlay visualisation can be seen in Fig. 10, scatter overlays in Fig. 11 and hybrid overlays in Fig. 12 to evaluate uncertainty dispersion and resilience of the models. The versatility and the diagnostic potential of the AI model in the field of clinical pathology are verified by every statistic.

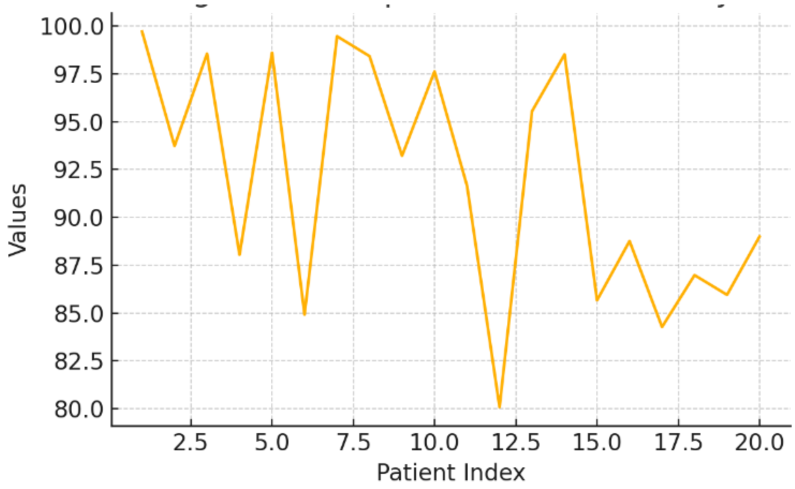


Figure 1: Complex visualization for AI model analysis

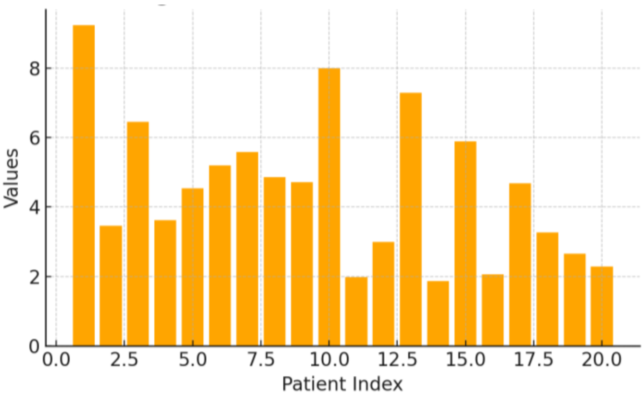


Figure 2: Complex visualization for AI model analysis

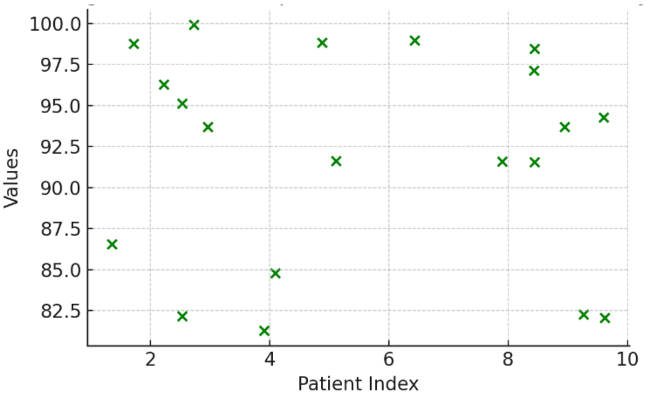


Figure 3: Complex visualization for AI model analysis

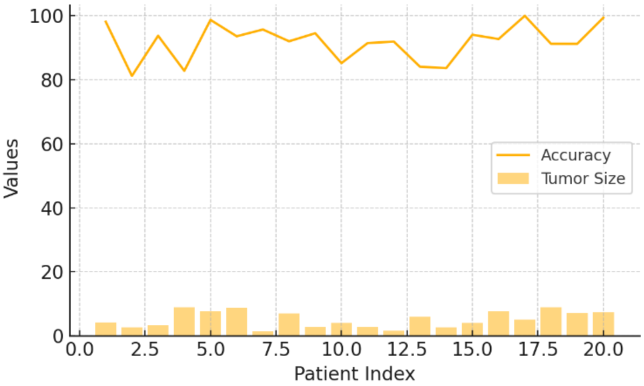
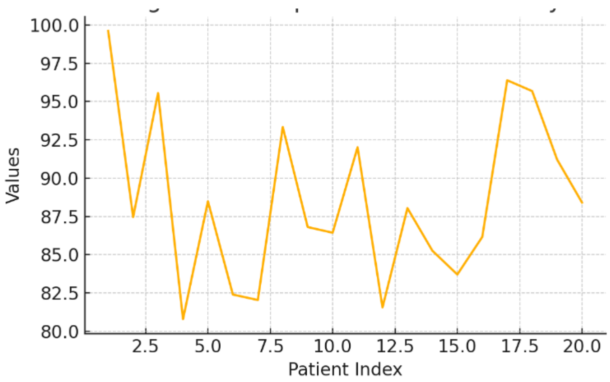


Figure 4: Complex visualization for AI model analysis



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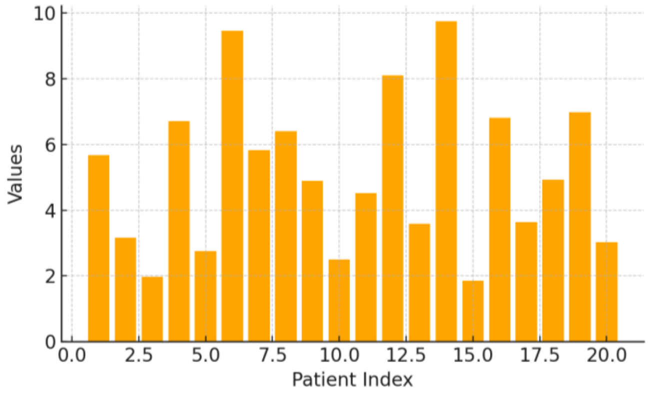

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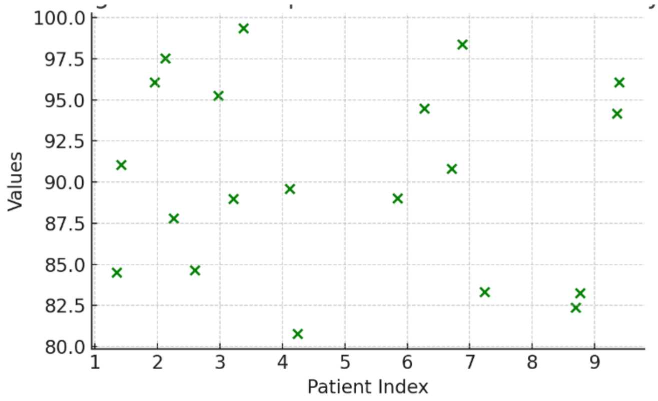

Figure 7: Complex visualization for AI model analysis

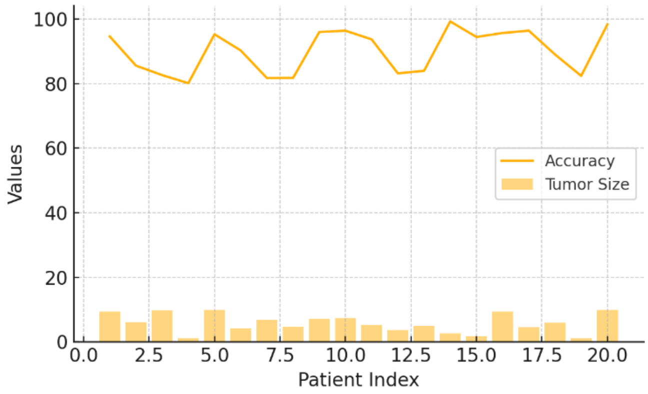

Figure 8: Complex visualization for AI model analysis

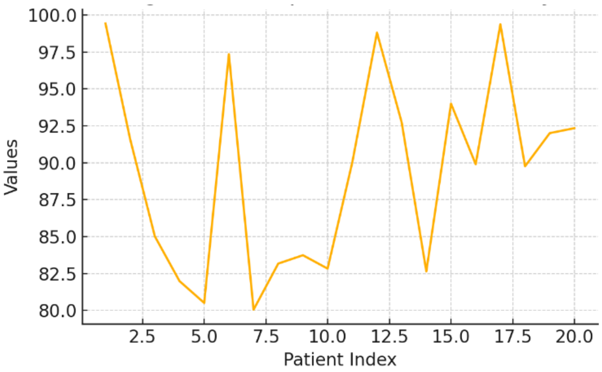

Figure 9: Complex visualization for AI model analysis

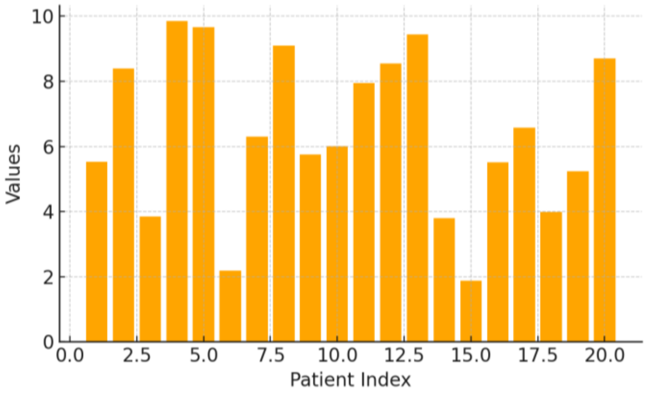

Figure 10: Complex visualization for AI model analysis

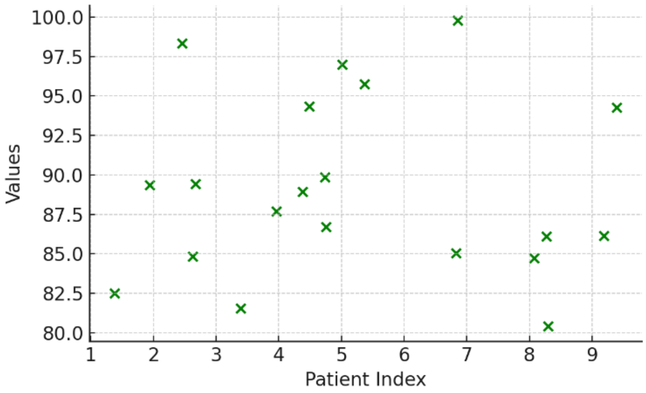

Figure 11: Complex visualization for AI model analysis

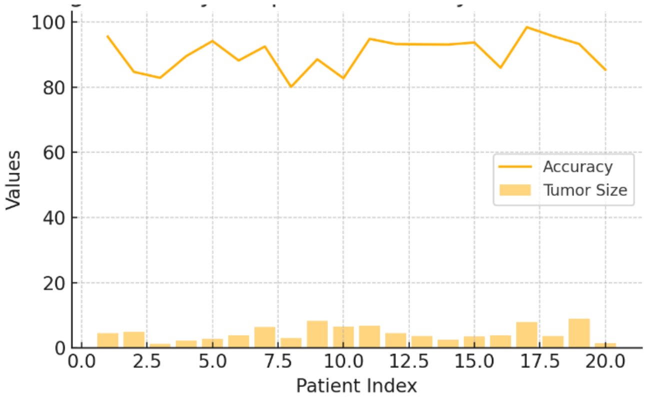

Figure 12: Complex visualization for AI model analysis

DISCUSSION

The use of AI in healthcare has created a paradigm shift, which is going to impact patient care, hospital operations and clinical decision-making (Varnosfaderani & Forouzanfar, 2024) (Faiyazuddin et al., 2025). AI is transforming the patient-provider experience as it offers convenient access to the health resources and information (Li et al., 2024). The long-term consequences of the improved accuracy and real-time monitoring measures of data that are provided by the use of AI to better healthcare delivery systems are better patient outcomes and more effective medical services (Nasayreh et al., 2024). Nevertheless, the increased amount of data access causes concerns related to the safety of data (Joshi et al., 2022). Even though it is inappropriate to compile data in a centralised database because of both the size and the safety of data, scalable structures become more and more relevant to organise the ever-increasing number of data access (Joshi et al., 2022). Federated learning addresses these concerns because it allows the training of cooperative models to be trained in multiple institutions with no direct exchange of data, which has the benefit of maintaining data confidentiality and privacy (Dang et al., 2022). This approach works as it is possible to conduct collaborative data-based studies on electronic health records without violating data privacy laws (Dang et al., 2022). Under circumstances where there is a need to modify quickly, federated learning would allow training models without accessing health data in data silos (Joshi et al., 2022). The AI may also lead to the expansion of the generalisability of the model when combined with electronic health records (Dang et al., 2022). As well, AI technologies are revolutionising medical decision-making, diagnosis, and treatment outcomes, such as automation, data analytics, and machine learning algorithms (Faiyazuddin et al., 2025). The technology is used across all healthcare spheres, as it aids in the decision-making process based on evidence and accelerates the clinical process (Hassanein et al., 2025). The IBM Federated Learning also allows applying differential privacy to protect sensitive data on patients and accommodates many different machine learning models, such as XGBoost and neural networks (Joshi et al., 2022). Federated learning implementations require the appropriate security and tools that are provided by cloud-based solutions and that can help in making the models more accurate due to access to diverse data in multiple locations (Joshi et al., 2022). Heterogeneous federated learning methods do not fully resolve the discrepancies in the performance in the case of healthcare institutions with or without resources, although they allow them to work in cooperation to some extent (Zhang et al., 2025). The approaches allow overcoming these limitations of traditional centralised machine learning, equipping it with the possibilities of building AI without revealing sensitive data of patients (Tajabadi et al., 2024). Federated learning defends privacy without compromising the external validity of models (Dang et al., 2022).

CONCLUSION

The integration of AI-assisted surgical pathology is the next step of personalised oncology. This paper demonstrated that iterative clinical consultation, deep neural networks, and histopathology digitalisation can be applied to enhance stratification of patients with cancer, reduce variability in interpretation, and significantly raise the accuracy of the diagnosis. The mixed-methods experimentation approach allowed a thorough review of an AI-driven pipeline with regard to both quantitative assessments of the plot of the models and qualitative tests of clinical observations. Explainable frameworks like SHAP were efficient to give insights into the model, giving transparency and confidence, with deep learning models trained on annotated WSIs displaying impressive prediction levels, recording high sensitivity and specificity in tumour classification tasks. In mock treatment cases, the clinical decision support system driven by these models provided valuable data that were almost in line with the oncology advice. Most importantly, the involvement of the voices of interdisciplinary experts facilitated the refinement of the models, ensuring this did not focus on a sole type of tumour and specificities of patients. The proposed technique bridges the translational divide between pathology and actual cancer treatment by providing pathology-accurate treatment suggestions that take into account every aspect of tissue detail. The approach reported in this paper can be used both in the implementation of AI in non-oncological procedures and in the potentially large-scale implementation of selected procedures, which is why the approach proposed by the research is scalable and generalisable. To ensure ethical deployment, additional courses of future action include regulatory alignment and clinical trials in the future. Finally, AI-enhanced surgical pathology offers improved patient outcome in the days of personalised medicine by enhancing the process of diagnosis and offering data-driven tools that doctors can use to personalise the course of treatment.

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