Piloting A Machine Learning Model for Automatic Blood Film Analysis

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INTRODUCTION

- Blood film analysis is an integral part of the haematological diagnostic service but is time-consuming and labour intensive.
- The Bart's Life Science team have developed a novel deep learning model[1] using vision transformers for the automatic analysis of blood cells, which could significantly speed up and enhance the diagnostic process. However, integrating artificial intelligence (AI) into clinical practice has significant challenges such as data privacy, model interpretability and real-world performance.
- The project coincides with the Barts Digital pathology project to digitise all pathology images.
- A secondary goal is to outline the regulatory requirements and local governance pathways to streamline future AI deployment within the trust.

PROJECT AIMS

- To test a machine learning AI tool developed for the interpretation of blood films.
- To validate the AI tool in a live healthcare setting.
- To explore the regulatory environment and clinical workflow in deploying an AI model.
- To draft a regulatory document outlining the legal regulations and local governance processes for future AI project deployment.

METHODS

Scoping for deployment

1. Stakeholder discussions with clinical lead, laboratory leads and board director.
2. Logistics assessment regarding existing clinical workflow, physical infrastructure, data storage platforms and IT integration.
3. Literature review on regulatory requirements and other existing AI models.
4. Securing research management and ethics board approvals.
5. Understanding model infrastructure including factors affecting performance, class imbalance in training and validation datasets.
6. Design of validation studies to assess performance of AI model and generate evidence for clinical use.

Validation study

1. 132 blood films were randomly selected from Feb-March 2025 from archived medical review films.
2. The slides were digitised using the 3DHistech Pannoramic 250 Flash III digital scanner with x40 objective and 1.6x C-mount adapter (total magnification 82x).
3. Subsections were manually identified, annotated and extracted using QuPath v0.5.1.
4. A total of 1320 images (2433x2072 pixels) were generated to date, with 161 images containing blasts vs 1159 with no blasts.
5. The models were run on all images and the sensitivity, specificity, accuracy, and AUROC curves were computed.
6. Subgroup analysis was performed to assess how different cell types and variation in image characteristics affect model performance.

REFERENCES

1. Piazesse et al, (2025). BloodImage: Leveraging Vision Transformers for Automated Identification of Blasts in Microscopic Blood Images of Leukemia Patients. Manuscript under review.

FINDINGS

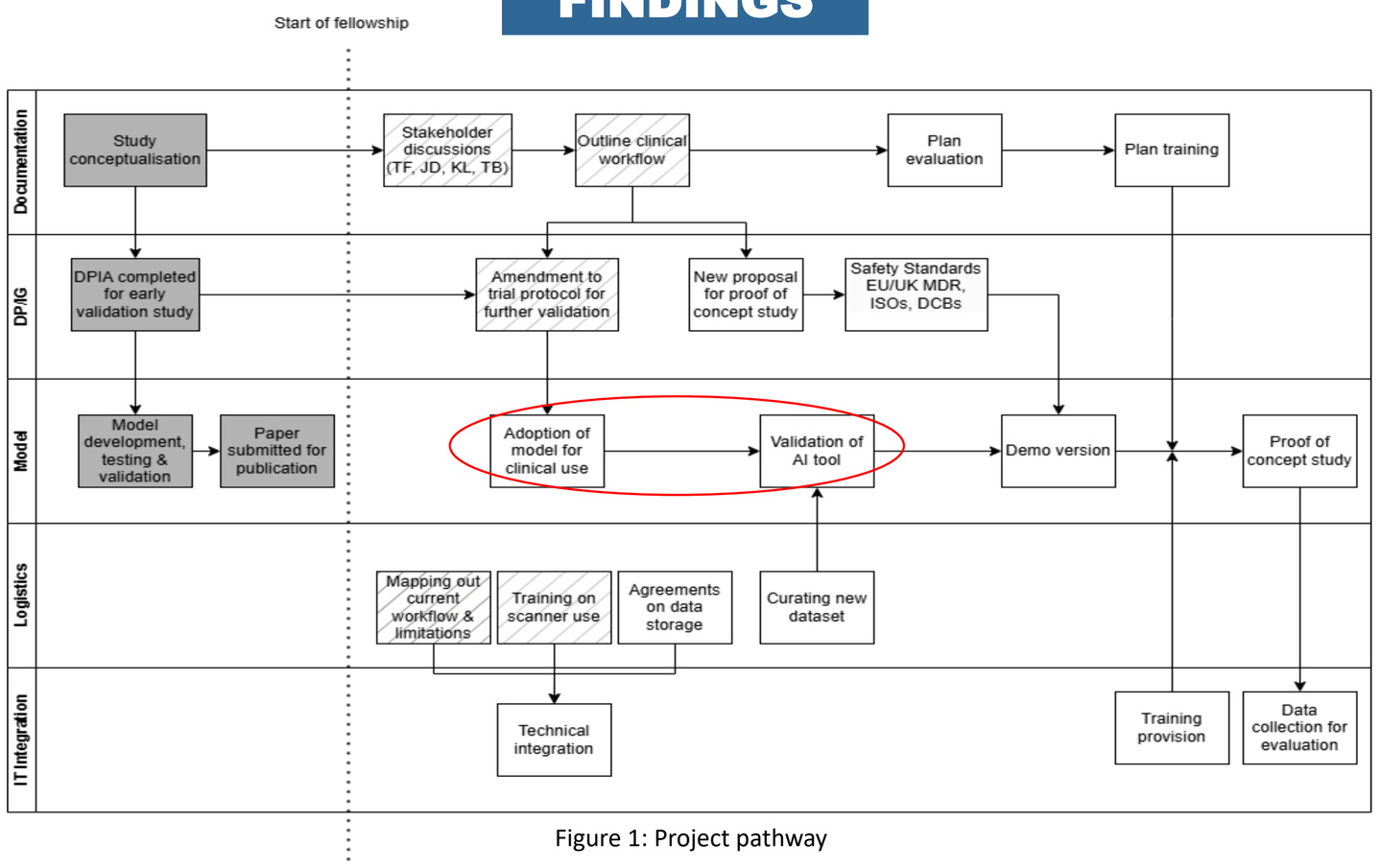

Figure 1: Project pathway

Models	Sensitivity	Specificity	Accuracy
VIT1	0.82 (↓0.10)	0.54 (↓0.21)	0.56 (↓0.30)
VIT2	0.77 (↓0.16)	0.66 (↓0.12)	0.66 (↓0.20)
VIT3	0.83 (↓0.06)	0.63 (↓0.12)	0.65 (↓0.18)
VIT4	0.70 (↓0.10)	0.81 (↓0.02)	0.80 (↑0.04)

Figure 2: Model performance (Relative to original dataset)

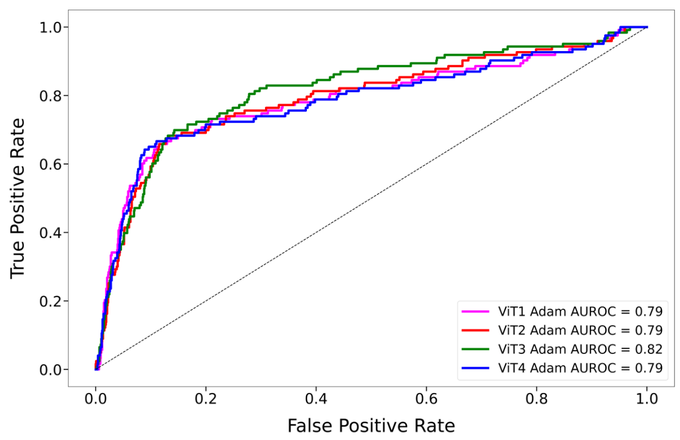

Figure 3: AUROC Curves

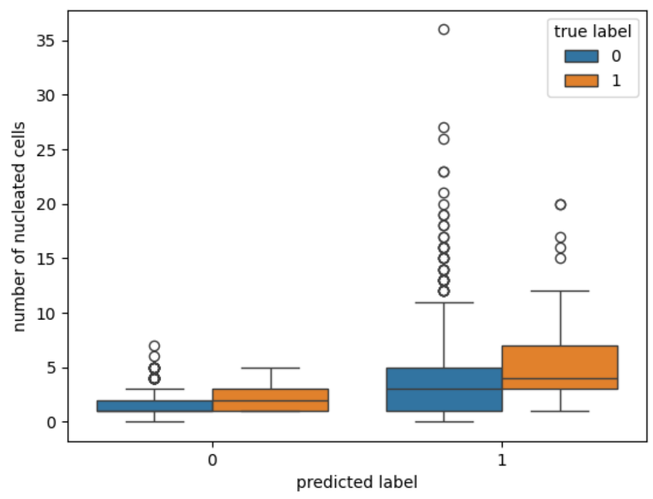

Figure 4: Subgroup analysis

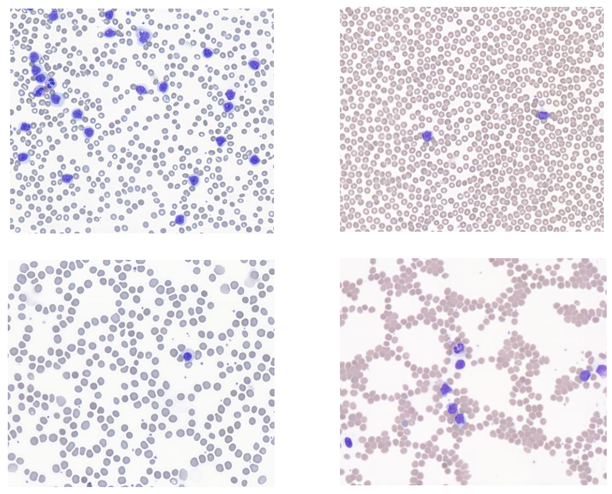

Figure 5: Assessment of film morphology.

DISCUSSION

1. Model performance is good but underperforms on validation studies using a new dataset compared to the original validation dataset. Reasons for this could include:
   - New features not previously seen in training data.
   - Class imbalance
   - Overfitting
2. Most prominent features identified that affect performance are high cell counts and new cell types.
3. AUROC performance is not the only metric for a desirable model, as different sensitivity/specificity thresholds may be more desirable in real life (e.g. avoid missing true positives)

FUTURE WORK

- To diversify the range of cell types used to train the model.
- Optimising model performance and functionality.
- Curate digitised blood film collection for subsequent projects.
- Collaboration with external partners to access additional datasets.
- Overcome local logistical hurdles and development of a clinical pathway for the deployment and adoption of AI models.

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