Proof of Concept for an AI-Powered Pipeline in Paediatric Radiology

Louise Rigny [1], Pavithra Rajendran [1], Sebin Sabu [1], Shiren Patel [1], Susan Shelmerdine [1], Owen Arthurs [1]
[1] *DRIVE; Great Ormond Street Hospital NHS Trust*

Background

The evolution of artificial intelligence (AI) in clinical radiology has led to substantial advancements, reshaping clinical workflows and improving efficiency[1-2]. While significant progress has been made in areas such as adult imaging, specialties like breast imaging, oncology, and neuroimaging, paediatric radiology remains relatively underdeveloped[3].

Picture Archiving and Communication Systems (PACS) have facilitated the management, and reporting of patient imaging data, allowing radiologists to document findings effectively.

This study leverages AI models to reduce manual input and automate the collection of routinely gathered information in paediatric post-mortem image reporting.

We propose a proof-of-concept for an AI-driven pipeline focused on image classification tasks, utilizing post-mortem skeletal images from Great Ormond Street Hospital (GOSH) to predict image orientation and identify clinical abnormalities.

Methods

Dataset: 200 post-mortem skeletal images sourced from GOSH. Images labelled according to: **(1) anatomical orientation**—either "frontal" or "lateral", **(2) condition**—classified as "Normal" or "Abnormal," **(3)** gestational age (weeks) and **(4)** femoral length (mm) based on PACS radiology reports.

Training, validation, and testing subsets followed a split ratio of 50:20:10. Prior to model training, all images underwent resizing to a uniform dimension of 224x224 pixels, normalization and data augmentation. We implemented a baseline custom convolutional neural network (CNN) architecture (4 layers), alongside a modified version of the ResNet50 architecture to leverage transfer learning capabilities.

Performance evaluated using precision, recall, F1 score, accuracy for classification tasks and mean absolute error (MAE) for regression tasks.

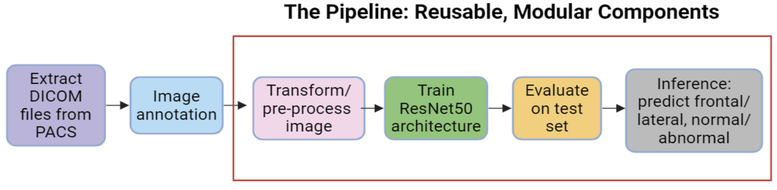


Fig 1. Overview of study pipeline.

Results

Use-case	Model	CPU	Dataset	Accuracy
Anatomical Orientation – Frontal/Lateral	CustomCNN	✔	Postmortem skeletal images (n=30)	54%
	Modified Resnet50 Classification	✔	Postmortem skeletal images (n=30)	90%
Condition – Normal/Abnormal	CustomCNN	✔	Postmortem skeletal images (n=38)	48%
	Modified Resnet50 Classification	✔	Postmortem skeletal images (n=38)	89%
Gestation age (weeks)	Modified Resnet50 - Regression	✔	Postmortem skeletal images (n=38)	MAE = 2.82
Femoral Length (mm)	Modified Resnet50 - Regression	✔	Postmortem skeletal images (n=38)	MAE = 5.4

Table 1. Overview of experiments and performance accuracy.

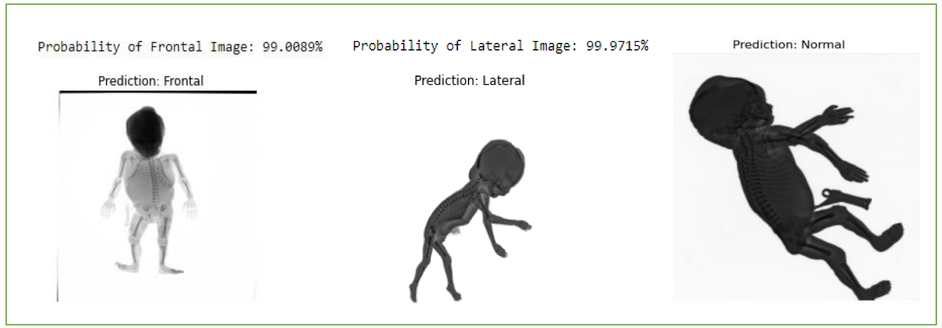


Fig 3. Prediction examples.

Discussion

This study presents a proof-of-concept for leveraging AI to automate aspects of paediatric post-mortem image reporting.

Resnet50 architecture demonstrated strong performance, achieving an **overall accuracy of 89% and 90%** for skeletal abnormality and anatomical orientations predictions, respectively, indicating effective identification for both classification tasks. Regression use-cases showed **a MAE of 2.82 for gestation age (weeks)** and **5.4 for femoral length (mm)**.

The integration of AI models into PACS has the potential to reduce manual input significantly by automating the collection and reporting of routinely gathered information, an important step toward enhancing in clinical workflows.

Previous work has shown AI's utility in streamlining radiological processes, but its application in paediatric radiology has been limited. This study extends AI's role in the field by focusing on automation within paediatric post-mortem imaging, setting a foundation for more comprehensive AI solutions in children's imaging[3].

Future work will aim to enhance the model's performance, expand the dataset, and explore more complex use-cases that offer greater clinical utility, such as automated report generation that can be tested in clinical practice.

Conclusion

This proof of concept underscores the potential of modular, reproducible pipelines in advancing AI applications in paediatric radiology at GOSH such as automated report generation and highlights the potential for broader operationalization.

References

1.Deep Learning in Radiology. Academic Radiology, 25(11), pp.1472–1480. doi:https://doi.org/10.1016/j.acra.2018.02.018.
2. Artificial intelligence in oncologic imaging. European Journal of Radiology Open, 9, pp.100441–100441. doi:https://doi.org/10.1016/j.ejro.2022.100441.
3. Artificial intelligence in paediatric radiology: Future opportunities. The British Journal of Radiology . 94(1117, p.20200975. doi:https://doi.org/10.1259/bjr.20200975.