Department of Industrial Systems Engineering and Management | IE3100R Systems Design Project

DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE (AI) ASSISTED SCREENING MODEL FOR ABNORMALITIES IN THE SMALL BOWEL USING MACHINE LEARNING ALGORITHM

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Executive Summary

In collaboration with SingHealth, the project aims to develop an AI-assisted screening model for small bowel abnormalities post-capsule endoscopy (CE) in order to address the current problems in the diagnosis process, specifically the tedious and error-prone manual screening process. The detection model utilized deep learning algorithm to produce promising results in accuracy. However, further experimentation is required to meet clinical standards and ensure integration into clinical practice, emphasizing ongoing collaboration between clinicians and developers for successful implementation. this endeavor has provided our team with invaluable insights and practical experience in the medical field, particularly in the realm of endoscopy. Lastly, our involvement in this project has enabled us to refine the following skillset:

Machine learning, Python, Project management, Data analytics, Statistical analysis, Problem-solving, Team collaboration, and Effective communication.

Company Background

SingHealth, the leading government-owned healthcare institution in Singapore, plays a crucial role in providing affordable, accessible, and high-quality healthcare services. Supported by the Health Services Research Center (HSRC), who we worked closely with, SingHealth is actively involved in medical research, education, and professional healthcare training. Additionally, the HSRC collaborates with Changi General Hospital's Department of Gastroenterology and Hepatology, aligning with the focus of the project on endoscopy.

Problem Statement

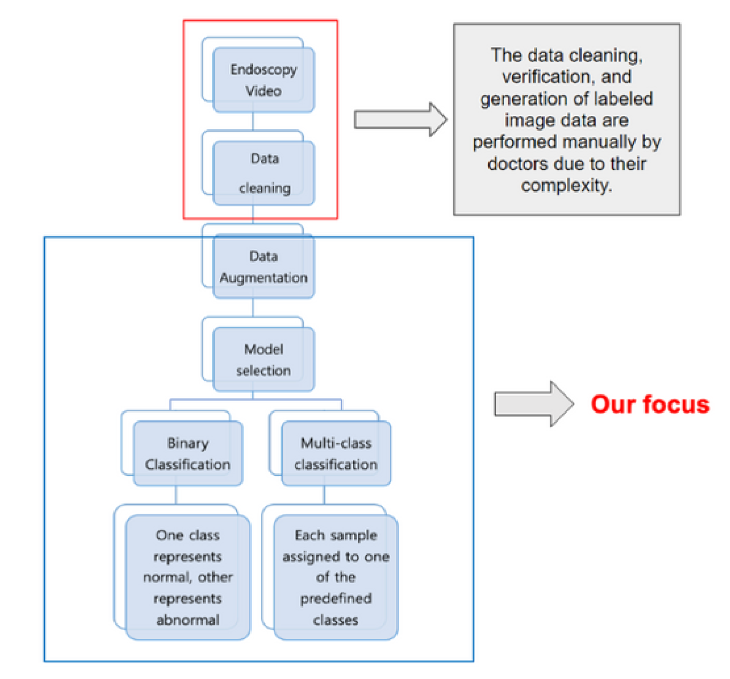
Time Consuming

- Post hoc manual verifications
- Repeated several times
- Each video is about 8 to 11 hours long
- Clinicians experiencing burn outs

Error Prone

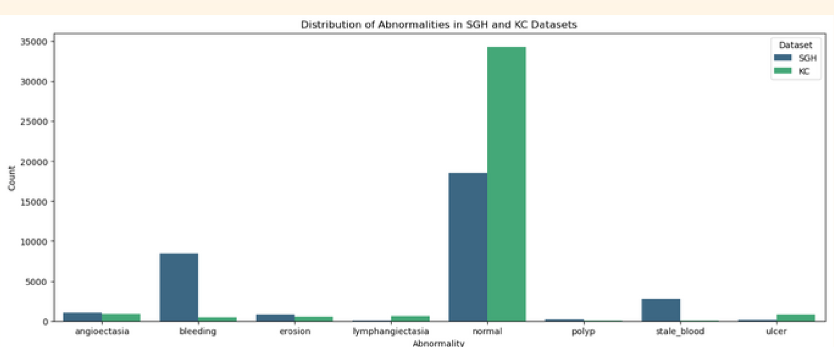
- Subtle manifestations of anomalies
- Abnormalities with similar appearances
- High variations in assessments due to inter and intra observers

Solution



Our proposed solution is to automate the screening process by developing an AI assisted screening model which takes in the CE videos, rendering it down into frames, before identifying abnormalities that may be present within these frames. It will be a dual-functional model consisting of a binary classification model used to differentiate between normal and abnormal states in small bowel CE images, and a multi-class classification model which categorizes abnormalities into different severity levels or types.

Methodology



There is class imbalance amongst abnormalities, resulting in under-representation. As part of the data preprocessing process, we synthetically generate new images using existing CE frames via image augmentation to use as training data.

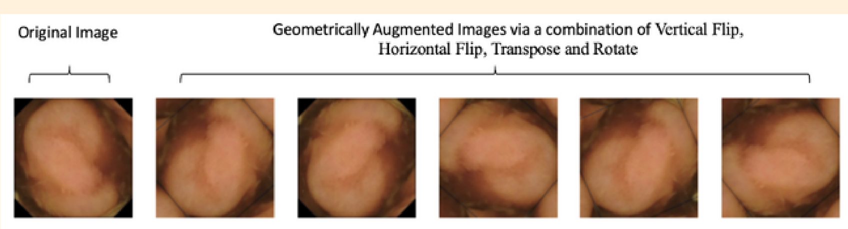
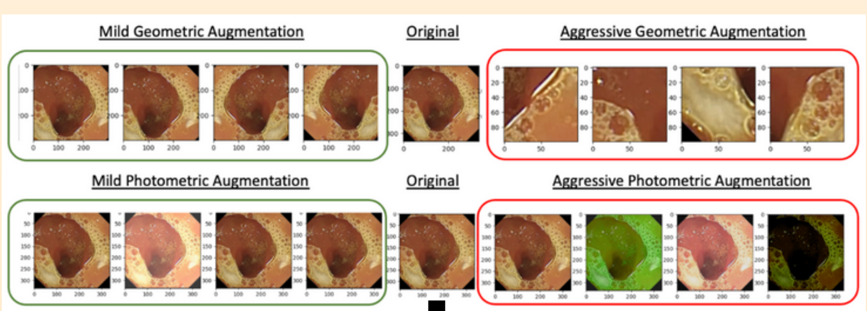
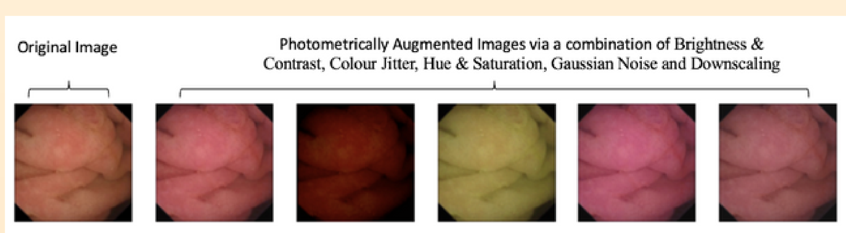
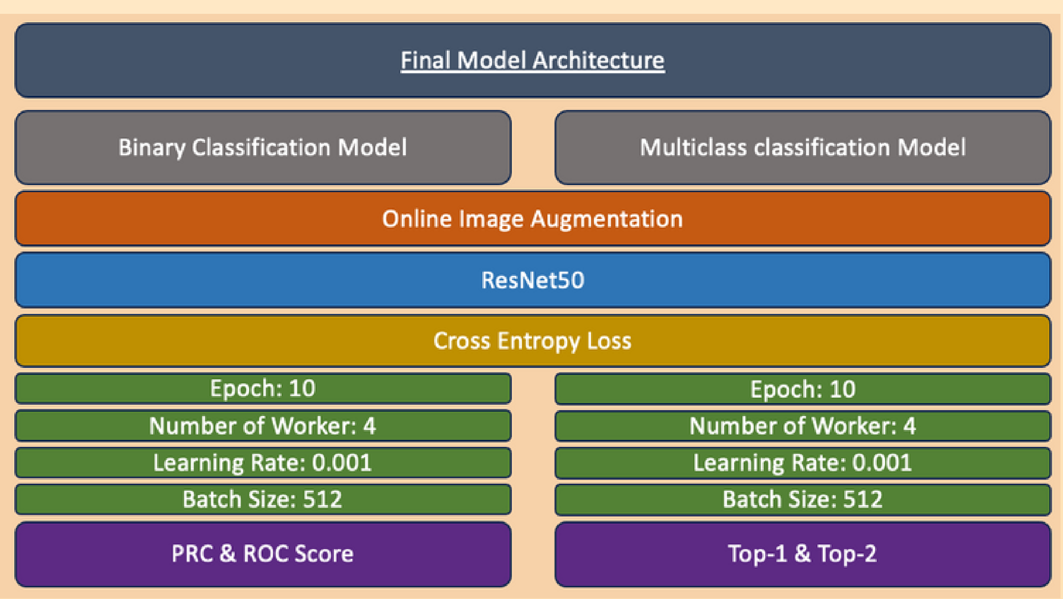


Image augmentation can be done via geometric transformations, photometric transformations.





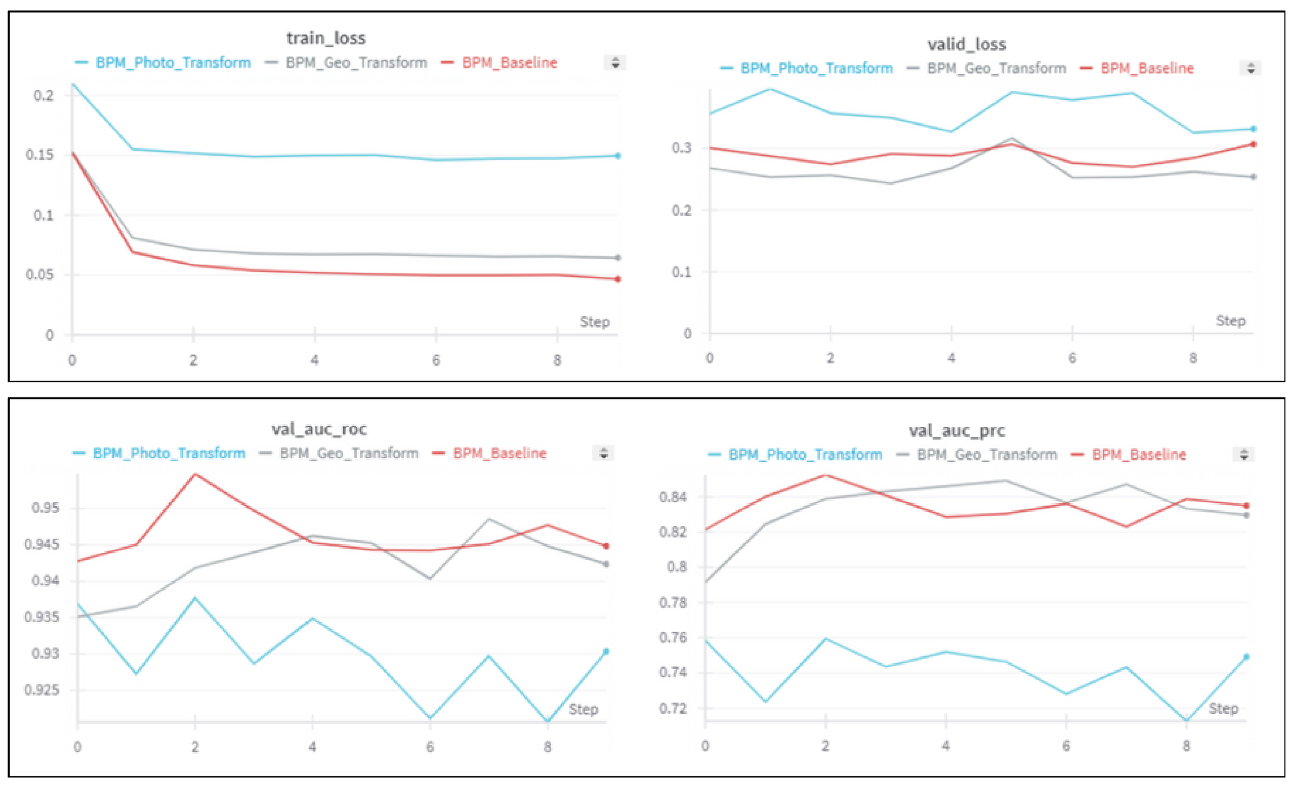
Our model also uses a mild augmentation strategy as it generally preserves the essential features of the original image, ensuring that the augmented images remain semantically similar to the originals. This maintains the integrity of the training data. It also reduces the risk of overfitting by introducing smaller, more controlled variations, encouraging the model to learn more generalized and robust representations of the data.



After thorough research and testing, these are the final model architectures. The selection of architecture is based on what is readily available, as well as the Singhealth hardware capabilities. We acknowledge that future iterations of the model could potentially utilise different models architectures.

Results

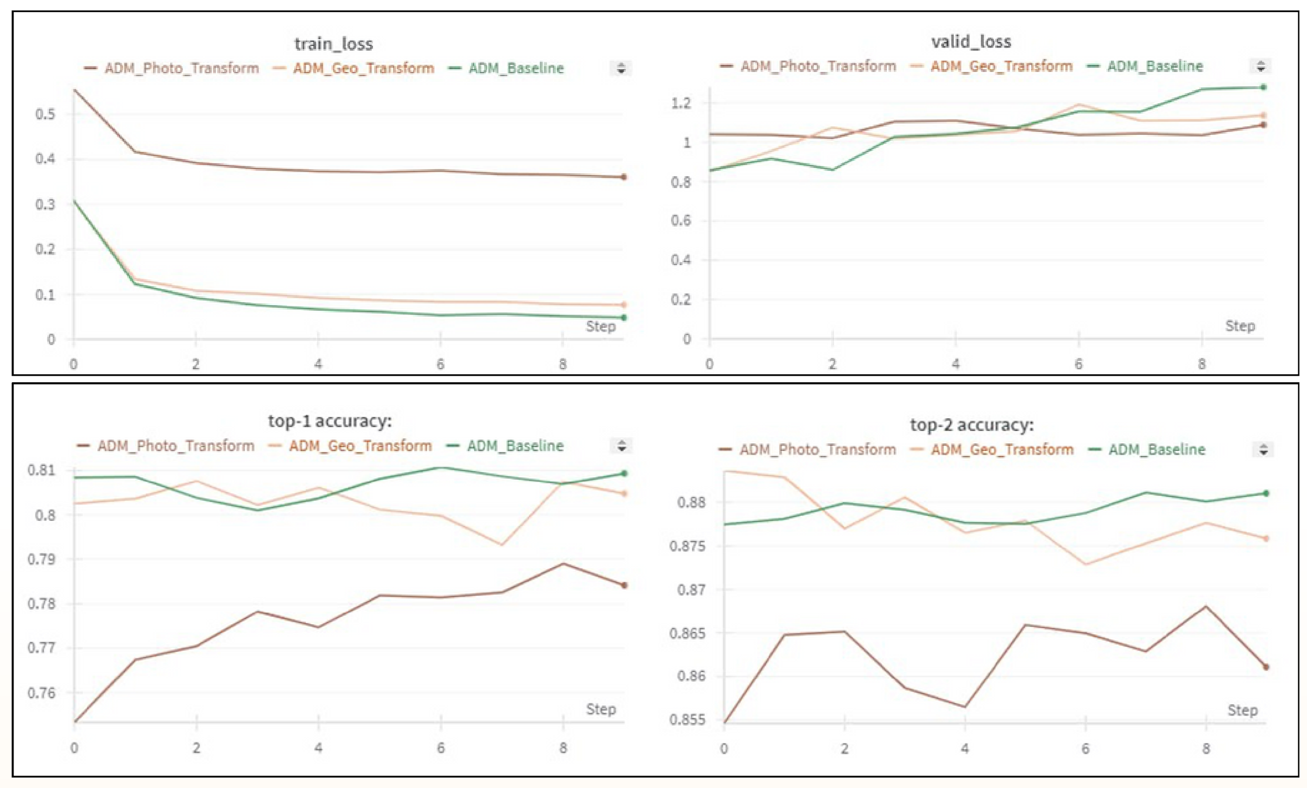
Binary Classification Model



The baseline binary classification model has the lowest training and validation loss. AUC ROC value is also the most favorable for the baseline binary classification model, and the baseline model is also the best performing model based on comparison of the PRC AUC.

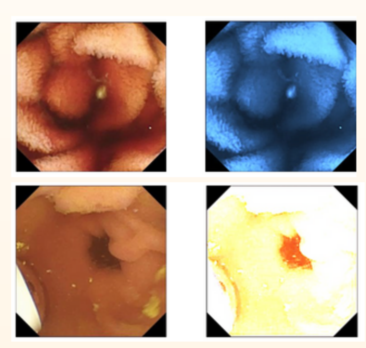
Multiclass Classification Model

The baseline model had the lowest training loss while the model with photometric augmentations applied had the lowest validation loss. baseline muti-class model consistently has a higher top-1 and top-2 accuracy as compared to the others

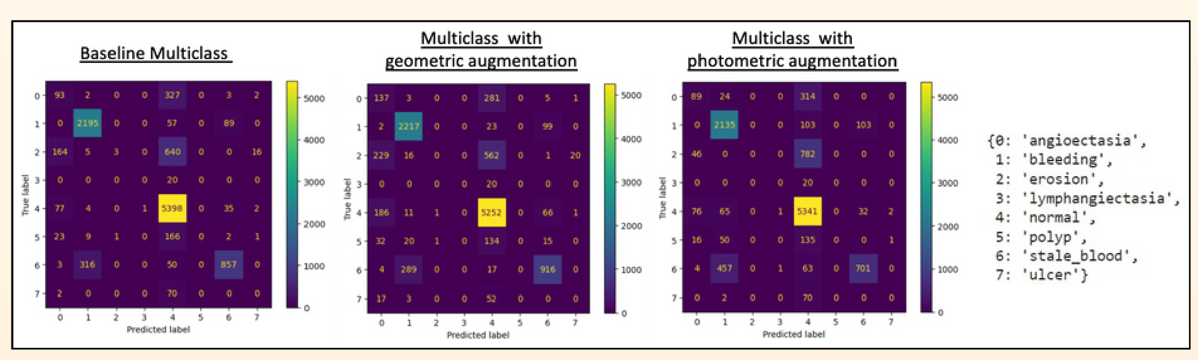


Discussion

It is observable that the validation loss is consistently higher than the training loss. Moreover, training losses were almost stagnant after the first epoch. This is a good indication of overfitting. In addition, any augmentation strategies should improve our model performance in theory. It is plausible that our augmentation strategies have to be more targeted towards a specific abnormality or image type.



Certain abnormalities have specific fixed features. For example in blood, it usually exists in shades of red. Hence, any changes to colour may train the model inaccurately. As a result, this renders some augmentation functions ineffective.



Using Angioectasia (Class 0), it had better prediction performance when geometric augmentation was employed with 137 correct predictions as compared to 93 using the baseline model, and deteriorated when using photometric augmentation, with only 89 correct predictions.

Future Direction

Improved Functionality

A multilabel model that accommodates situations where an image may exhibit characteristics of more than one abnormality. Clinicians can use this additional feature if they want to know the probability of more than one abnormality appearing in a single frame.

Combination of Augmentation Strategies

Tailoring a combination of geometric and photometric augmentation for specific abnormalities can potentially improve the performance of the models. This also ensures that the model is not overly biased, resulting in a model that is more adaptable, robust, and capable of handling diverse tasks.

Bounding Boxes

Bounding boxes target specific areas within an image, allowing models to focus on distinct objects while reducing the interference of irrelevant background noises and elements. This targeted approach enhances the precision in identifying and categorizing the objects. I also enhances the efficiency of training workflow.