Prostate Cancer Classification Using EfficientNet B0

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Project 2

Introduction

This project was developed as part of the Bioengineering 224B course and addresses the "Prostate Pathology Slide Image Classification" challenge hosted on Kaggle. The goal of the competition is to build a binary image classification model capable of distinguishing between cancerous and non-cancerous tissue patches extracted from high-resolution whole-slide images (WSIs) of radical prostatectomy specimens. These slides are a critical component of the clinical diagnostic pipeline and have been labeled by expert pathologists.

Each whole-slide image is processed through a standard histopathology workflow. The prostate specimens are fixed, stained with Hematoxylin and Eosin (H&E), sectioned, and scanned at high resolution. The resulting gigapixel images are then divided into smaller patches to make them suitable for deep learning. In this task, each patch is a 224 by 224 RGB image captured at 20x magnification and stored in PNG format. These patches are annotated with binary labels, where 1 denotes the presence of cancer and 0 indicates non-cancerous tissue.

Dataset and Preprocessing

The dataset used in this study includes such labeled patches along with their corresponding metadata provided in a CSV file. The dataset was split into training and validation subsets using an 80 to 20 ratio to ensure that the model had enough data for effective learning while preserving a representative validation set. A custom PyTorch Dataset class was implemented to load the images and apply transformations. During training, the images were augmented using random horizontal and vertical flips and color jittering to improve robustness and generalization. All images were normalized and converted into tensors for processing by the neural network.

Sample Patches from the Dataset

To better illustrate the dataset, Figure 1 shows two example patches used for training. These images are 224×224 pixel RGB patches extracted from scanned prostate tissue slides at 20× magnification.

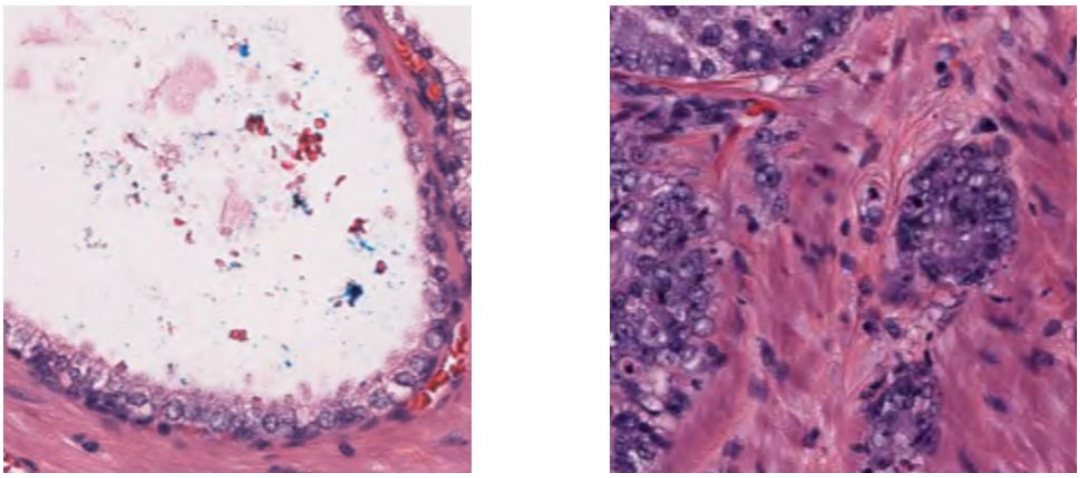

Figure 1: A non-cancerous tissue patch (train/0001.png, label = 0, left) and a cancerous tissue patch (train/0003.png, label = 1, right).

Model Architecture and Training

EfficientNet B0 was chosen for its balance of accuracy and efficiency. This lightweight convolutional neural network has shown strong performance across a variety of image classification tasks while maintaining a low computational footprint. For this application, the classifier layer was modified to output a single value for binary classification. The output was passed through a sigmoid activation function to yield a probability score.

The model was trained using Binary Cross Entropy with Logits Loss and optimized using the Adam algorithm with a learning rate of 0.0001. Training was conducted using a batch size of 32 on an NVIDIA RTX 3060 GPU, which significantly reduced the time required to complete each epoch. The model was trained for 15 epochs. After each epoch, the training loss was recorded, and the model was evaluated on the validation set using F1 score and accuracy as metrics. The model weights were saved whenever the validation F1 score improved, ensuring that the best version of the model was preserved for inference.

Results

The best performance was observed at epoch 12, where the model achieved a validation F1 score of 0.9181. The training loss decreased steadily over the course of training, starting around 0.42 and reaching below 0.05 by the final epoch. The validation accuracy remained consistently high, while the F1 score showed stable improvement, indicating that the model generalized well to unseen data.
These trends are visualized in the figures below. The first shows the reduction in training loss over epochs, and the second illustrates the progression of validation F1 and accuracy scores.

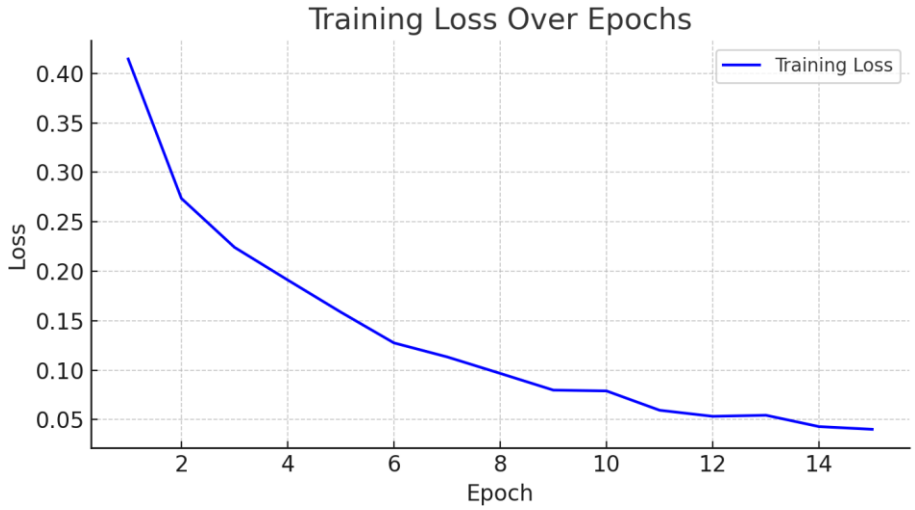

Figure 2: Training Loss Over Epochs

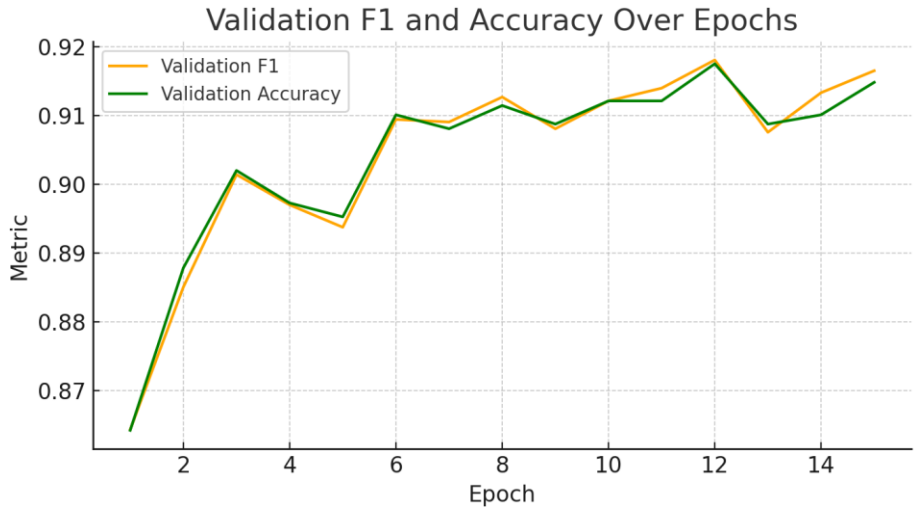

Figure 3: Validation F1 and Accuracy Over Epochs

Conclusion

This project demonstrates the feasibility and effectiveness of using transfer learning with EfficientNet B0 for prostate cancer image classification. The model performed reliably without overfitting and required minimal tuning to achieve strong results. The decision to visualize training loss separately from validation metrics made it easier to interpret learning behavior and track progress. Overall, the model exhibited solid performance across both probability calibration and binary classification accuracy.

In conclusion, this project presents a successful application of deep learning to the classification of histopathology images. By leveraging a pretrained EfficientNet B0 model, employing meaningful data augmentation, and carefully tracking performance, the final pipeline achieved high accuracy and strong F1 scores. These results reflect the potential of computational pathology methods in supporting clinical decision making. Future work may involve extending the approach with interpretability tools or adapting it to new staining protocols and tissue types.

Code availability

The code and results for this project are available in the following GitHub repository:
https://github.com/fnsangiul/224b-project2