Image Classification for Spine fracture prediction from X-Rays

Introduction

This project endeavors to construct an efficient model tasked with categorizing spinal X-ray images to predict the presence or absence of cervical fractures. Such an application holds immense clinical significance, aiding healthcare professionals in diagnosing spinal conditions promptly and accurately. The dataset utilized for this undertaking, namely "spine-fracture-prediction-from-xrays," comprises a collection of X-ray images obtained from various sources consisting of two classes Normal and Fracture, which then provides a comprehensive representation of spinal conditions.

Dataset Description

The "spine-fracture-prediction-from-xrays" dataset encompasses a diverse array of spinal X-ray images, meticulously curated and categorized into two classes based on the presence or absence of fractures. This dataset, consisting of aroung 2000 images per class, undergoes rigorous preprocessing procedures to ensure optimal compatibility with the model architecture. Notably, the images are resized to a standard dimension, normalized to facilitate convergence during training, and partitioned into training, validation, and test sets where, 3800 were total training images, 200 were total validation images and 200 were test images.

Model Architecture

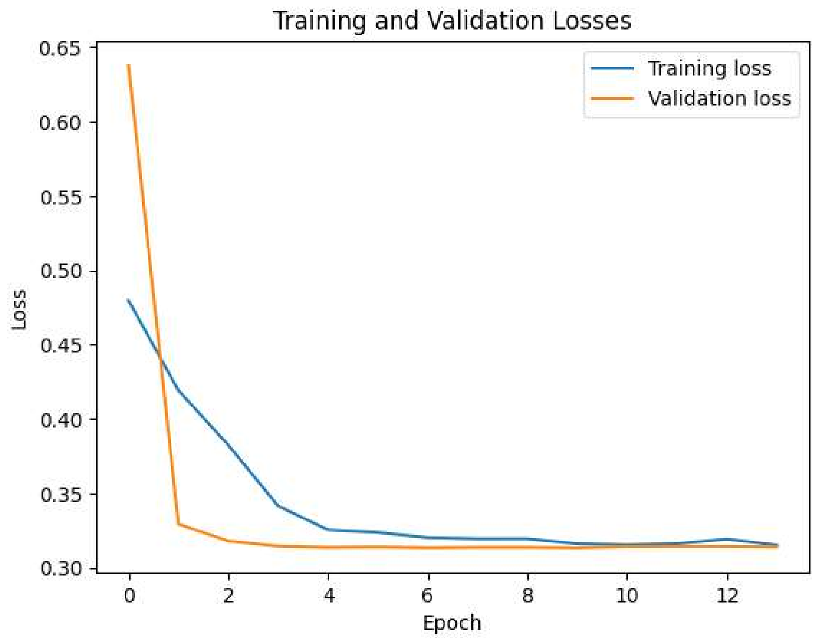
The MobileNet-based architecture employed in this project embodies a sophisticated design optimized for feature extraction and classification tasks. The model begins with a series of convolutional layers followed by batch normalization and ReLU activation functions. These initial layers serve to extract low-level features from the input X-ray images. Notably, the first convolutional layer convolves the input image with 32 filters of size 3x3, employing a stride of 2 for downsampling. Subsequent layers further augment feature extraction, gradually increasing the depth and complexity of learned features. Towards the end of the model architecture, global average pooling is employed to aggregate spatial information across feature maps, producing a compact representation suitable for classification. Subsequently, a dropout layer is introduced to mitigate overfitting, followed by a 1x1 convolutional layer to generate class predictions. Finally, the softmax function is applied to produce probability distributions over the target classes, enabling the model to make categorical predictions.

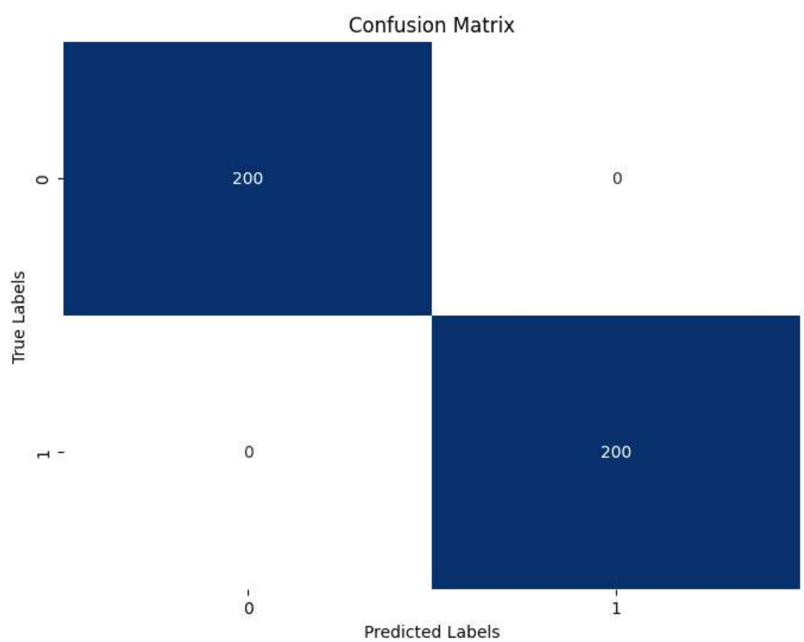
Training Process

The training regimen entails a meticulously orchestrated sequence of operations aimed at optimizing model parameters and minimizing classification errors. The model is trained using the Adam optimizer with a learning rate of 0.002. During training, the model undergoes iterative refinement, optimizing parameters to minimize the cross-entropy loss between predicted and ground truth labels. Additionally, early stopping is employed to prevent overfitting, halting training when the validation loss fails to decrease over a specified number of epochs. Throughout the training process, meticulous attention is devoted to logging essential metrics, including training and validation losses, facilitating comprehensive performance assessment and iterative model refinement.

Evaluation Results

Upon extensive training and evaluation, the model demonstrates commendable performance metrics indicative of its efficacy in cervical spinal fracture classification. Notably, the model achieves a testing accuracy of 100%, underscored by competitive precision, recall, and F1 scores across distinct classes was 1.00 for all. Detailed evaluation reveals nuanced insights into the model's proficiency, including its ability to accurately classify images across diverse categories. All in all, after extensive training and optimization, the model endeavors to accurately classify spinal X-ray images, aiding healthcare professionals in timely and accurate diagnosis, is if implemented in future.





Insight Gained

Detailed analysis of model predictions offers valuable insights into the strengths of this model. Specifically, examination of precision metrics elucidates the model's capability to accurately identify instances of spinal fractures, with 0 false negative and 0 false positive classifications. Such insights serve as invaluable guidance for iterative model refinement, aiming to bolster classification accuracy and robustness in real-world scenarios.

Conclusion

In conclusion, the MobileNet-based architecture leverages depthwise separable convolutions and bottleneck layers to achieve a balance between computational efficiency and predictive performance, making it well-suited for spinal fracture prediction from X-ray images. The developed model showcases promising performance metrics, indicative of its potential as a valuable diagnostic tool for healthcare professionals. By leveraging insights gleaned from comprehensive evaluation and iterative refinement, the proposed model stands poised to make meaningful contributions to the field of medical image analysis, facilitating timely and accurate diagnosis of cervical spinal conditions.