Seeking an Optimal Approach for Computer-Aided Pulmonary Embolism Detection





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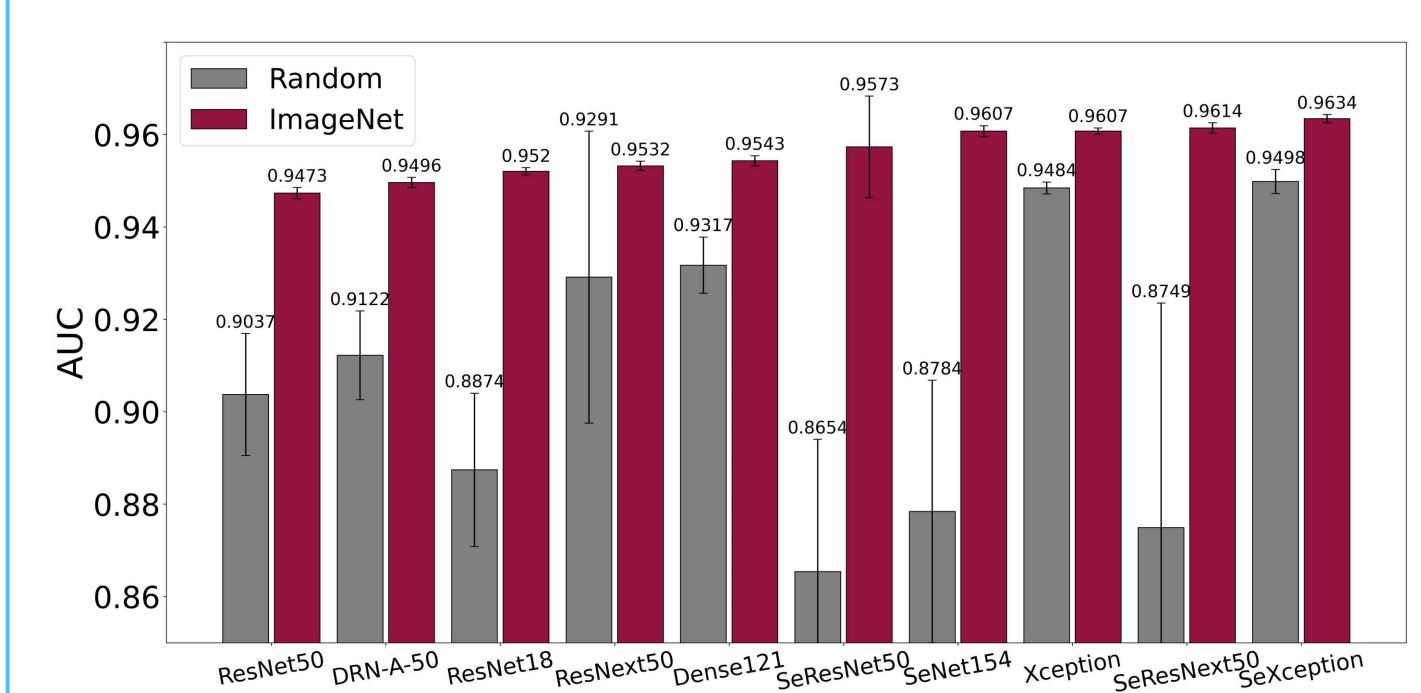
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GitHub: https://github.com/jlianglab/CAD_PE_Detection

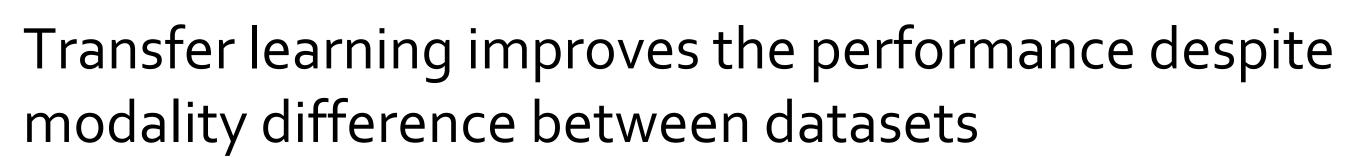


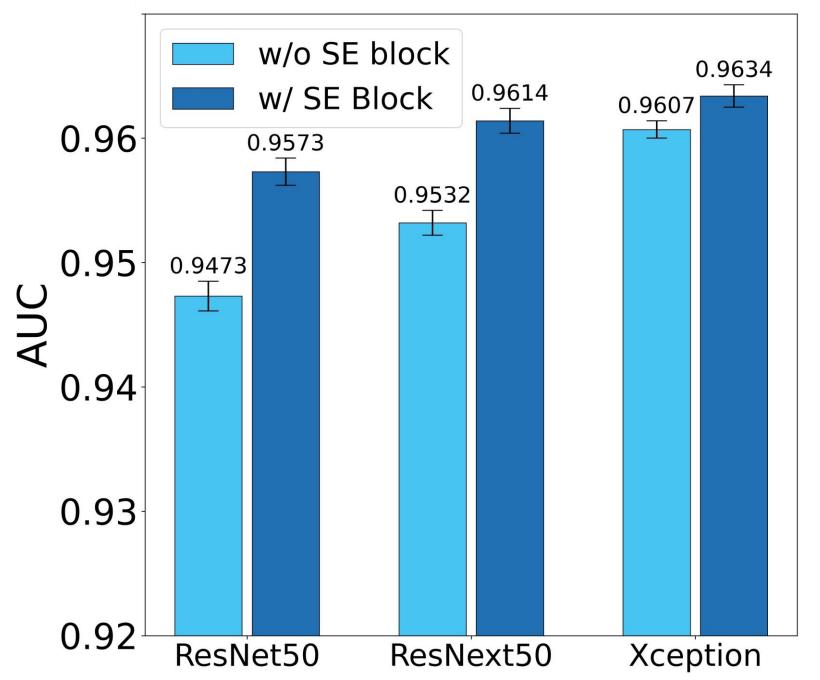


Motivation: Pulmonary embolism (PE) represents a thrombus ("blood clot"), usually originating from a lower extremity vein, that travels to the blood vessels in the lung, causing vascular obstruction, and in some patients, death. we present a comprehensive analysis of competing deep learning methods applicable to PE diagnosis using CTPA at both the image and exam levels.

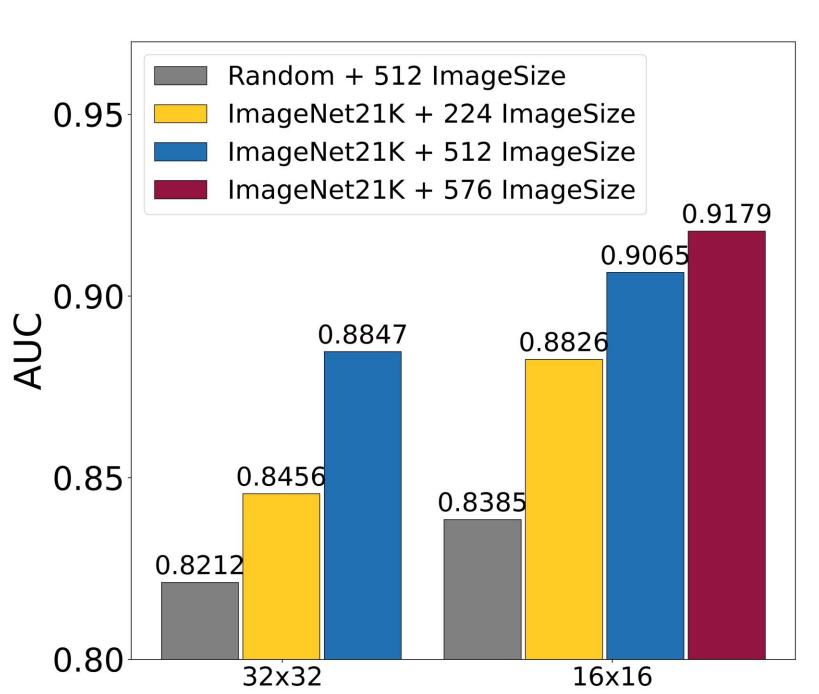
Contribution: Extensive experiments that compare architectures, model initialization, and learning paradigms; Optimal approach for detecting PE, achieving an AUC gain of 0.2% and 1.05% at the image and exam levels, respectively, compared with the state-of-the-art performance.



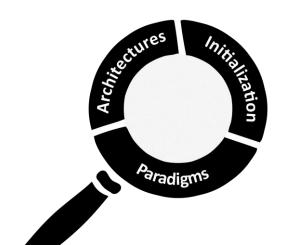




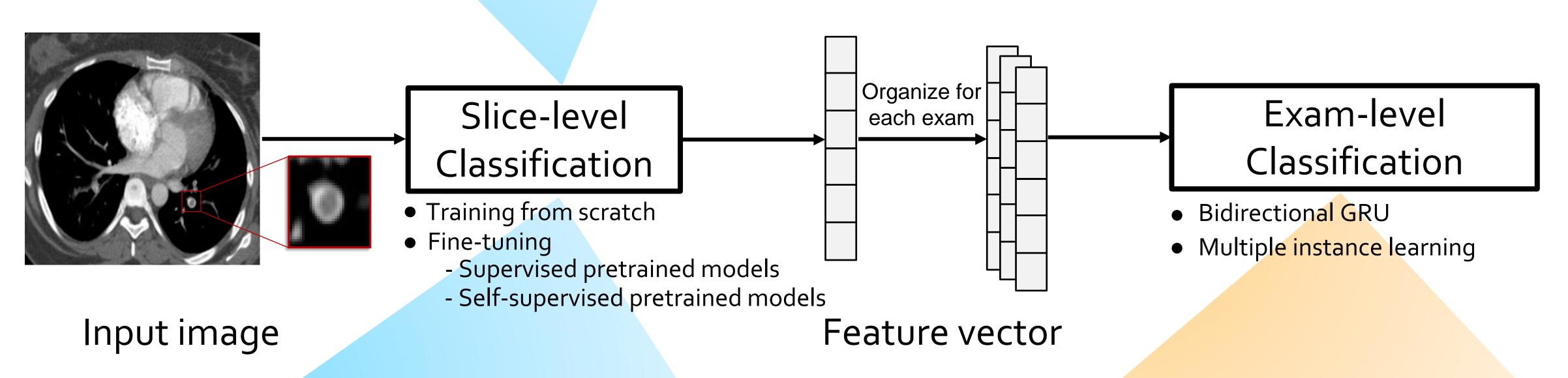
Squeeze & excitation blocks enhance CNN performance



Vision transformer performs inferiorly compared with CNN



What deep learning architectures, model initialization, and learning paradigms should be used for CAD applications in medical imaging?



Transfer learning with self-supervised methods performs better than supervised model

0.96
Supervised Pretraining
Learning From Scratch
0.94
0.92
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Conventional classification (CC) marginally outperforms the Multiple instance learning (MIL) for exam-level data. Multiple Instance Learning Conventional Classification 0.8912 0.89^{-} 0.8859 0.8852 0.883 0.8807 O 0.88 0.8773 0.87 0.86 SeResNext50 Xception SeXception