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Enhancing Equitable Study Distribution Using Reinforcement Learning

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Introduction/Background

Imaging organizations encounter heavy workloads requiring distribution among radiologists. Uneven study type distribution, cherry-picking and other factors can cause imbalanced workload distribution, which may lead to internal tension and burnout. We introduce an artificial intelligence model to assist in achieving workload balance. Our study compares PACS workload distribution between manual and AI-automated methods.

Methods/Intervention

We present a reinforcement learning model that distributes studies with the goals of maintaining fairness, respecting preferences, meeting priority deadlines, and balancing study value. The model takes requests from a PACS system including an exam and a list of active radiologists and returns an assignment recommendation. The model state is encoded as a 2D array, comprising information such as Relative Value Unit (RVU), due time, and the radiologists' workloads. The algorithm is rewarded if its recommendations meet the above goals and learns by maximizing cumulative rewards over time. Our model has two learning phases (Figure 1): offline learning using realistic simulations of small, medium, and large clinical settings, and online learning, where the model adapts to study distribution and radiologists' preferences in real-time. We performed a comparative study between AI-automated and manual assignment phases.

Results/Outcome

Five radiologists reviewed 481 studies in the manual and AI-automated phases. While the modality distribution was similar in both phases, the radiologists favored CR and CT over MR in the manual phase. Modality distribution was more balanced for all radiologists in the AI-enabled phase (Figure 2), and a 34% more equitable RVU distribution across modalities was observed for all radiologists (Table 1). MR RVUs read increased by 40% in the AI-automated phase, correcting the bias in favor of CR and CT from the manual phase.

Conclusion

We report a two-phase reinforcement learning-based study distribution framework that provides a balanced and efficient allocation of studies. We compared manual and AI-automated methods and showed a 34% reduction in the standard deviation of the RVUs read between radiologists when using the AI model.

Statement of Impact

We have demonstrated the impact of an AI-automated worklist on study distribution. We found a notable reduction in the RVU standard deviation and improved balance among modalities along with a reduction in cherry-picking.

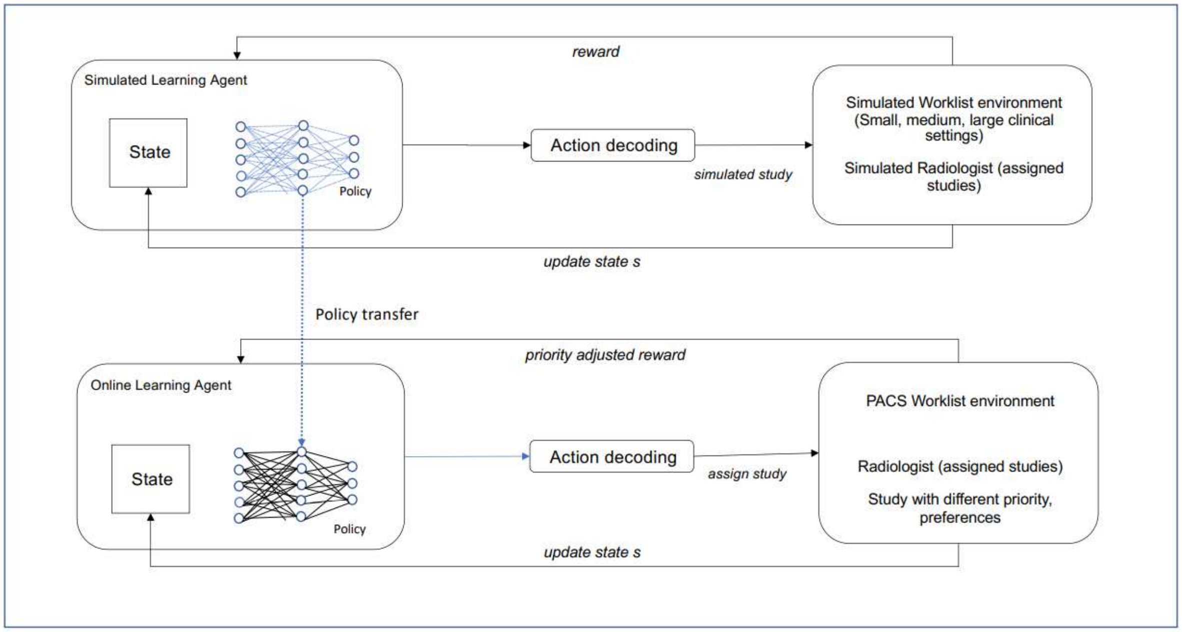

Fig 1 Study distribution learning architecture using offline and online reinforcement learning

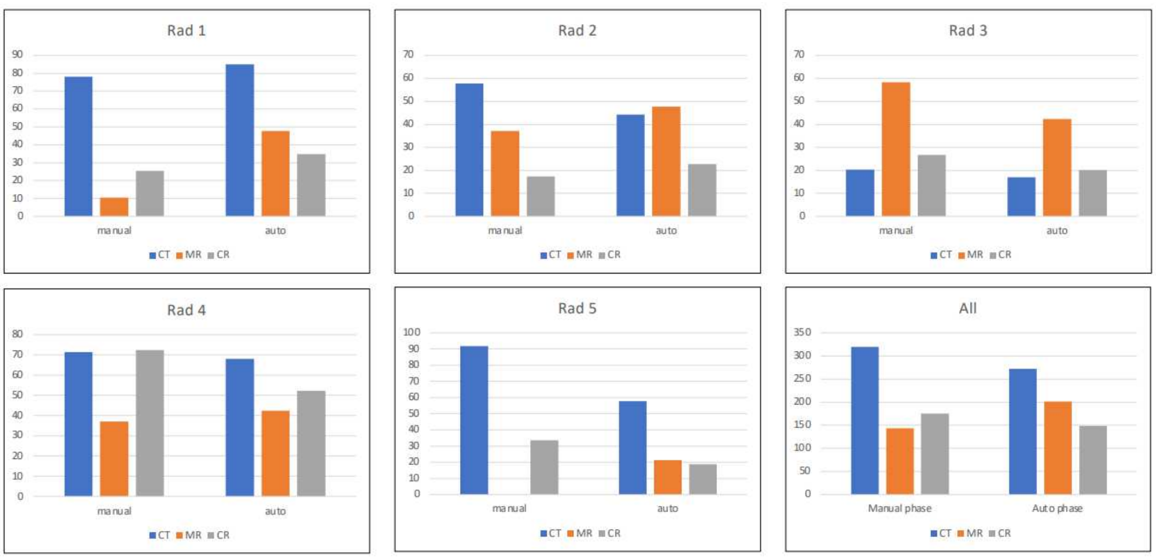

Fig 2 RVU sum of each modality of studies read by each radiologist per modality (manual phase, auto phase)

Study No (RVU)	CT	MR	CR	Total	STD(RVU)
Manual phase	94 (319.6)	27 (143.1)	131 (175.5)	252(638.4)	93.95
Auto phase	80 (272.0)	38 (201.4)	111(148.7)	229(622.1)	61.85

Table 1 Number of studies read and sum of RVU for each study modality

Keywords

Reinforcement Learning; Study Distribution; Radiologist Efficiency; Artificial Intelligence; PACS System; Online learning