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parts are included and if the images contain contrast agent or not. Further development of automated image quality assessment could also include image properties such as noise level and patient motion. Evaluation by a human observer is both time consuming and subjective. AI-based tools could help minimize both issues.

Conclusions

We have shown that it is feasible to develop an AI-based method to automatically perform a quality assessment regarding if correct body parts are included in CT scans, with a very high accuracy.

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