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Peer Review

Review of: "Mining Double-Line Spectroscopic Candidates in the LAMOST Medium-Resolution Spectroscopic Survey Using a Human-AI Hybrid Method"

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This article is well-organised and effectively motivated. The style is direct and accessible, greatly facilitating readability. The methodology is described adequately, proposing a human-AI hybrid method aimed at partially replacing visual inspection in the identification of spectroscopic binaries (SBs) among thousands of potential candidates. The authors address the perceived 'black-box' nature of machine learning (ML) methods in big data analyses, which is mitigated by incorporating human inspection. The balance between traditional techniques, such as the cross-correlation function (CCF), and ML is well-discussed and effectively implemented throughout the work. The results are highly relevant to the field, with a notable fraction of the 7096 SB2 and 1903 SB3 candidates identified for the first time in this study.

The following are my comments:

The training dataset relies predominantly on synthetic spectra generated using stellar atmospheric models. While practical, synthetic spectra may not fully replicate the variability or noise characteristics present in real observations. Incorporating real examples of SB2 and SB3 systems could improve the model's ability to generalise to actual observations. However, the authors rightly highlight that even in large datasets such as LAMOST-MRS, the verified numbers of SB2 and SB3 systems are insufficient for comprehensive training. With this fundamental limitation in mind, the use of a synthetic dataset would benefit from incorporating realistic noise, spectral line blending, and near-threshold flux ratios (as shown in Fig. 6). These enhancements could improve the robustness of

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the model against challenging cases, such as SB3 candidates. Techniques such as oversampling, undersampling, or cost-sensitive learning could also mitigate the class imbalances noted in the discussion.

The authors assume the spectra confirmed by human validation as 'ground truth', but human validation is not free from biases. For instance, detections may vary based on individual expertise. Moreover, subtle borderline cases might be overlooked, leading to inconsistencies in validation.

Previous studies that exploit LAMOST data are properly cited. Some recent works, such as those by Kovalev et al. (2024; 8105 binary candidates) and Liu et al. (2024; 4848 binary candidates), could further contextualise the findings and enable additional cross-matching. Also, the *Gaia* DR3 data products could enhance the analysis and validation of candidates by exploiting parameters such as 'ruwe' or 'radial_velocity_error', to name just a couple.

In addition to efficiency improvements, a quantitative comparison of computational costs between traditional and hybrid methods would be valuable. As mentioned above, the current training dataset limits the ability to analyse the model's performance based on S/N values.

Overall, the article makes a strong contribution to the field, combining methodological innovation with practical application and demonstrating excellent exposition and style. Future work could focus on addressing the limitations of the synthetic dataset and further exploring the implications of S/N variability and human validation biases.

Declarations

Potential competing interests: No potential competing interests to declare.