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Letter to the editor

Mitigating biases in feature selection and importance assessments in predictive models using LASSO regression

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ABSTRACT

Yuan et al. developed a predictive model for early response using sub-regional radiomic features from multi-sequence MRI alongside clinical factors. However, biases in feature selection and assessment may lead to misleading conclusions regarding feature importance. This paper elucidates the biases induced by machine learning models and advocates for a robust methodology utilizing statistical techniques, such as Chi-squared tests and p-values, to uncover true associations. By emphasizing the vital distinction between true and model-specific associations, we promote a comprehensive approach that integrates multiple modeling techniques. This strategy enhances the reliability of predictive models in medical imaging, ensuring that outcomes are based on objective relationships and ultimately improving patient care.

Text

Yuan et al. developed a predictive model for early response by integrating sub-regional radiomic features from multi-sequence MRI with clinically relevant factors [1]. Radiomic features were extracted from tumor subregions using the K-means clustering method, followed by feature selection through LASSO (Least Absolute Shrinkage and Selection Operator) regression. However, this approach is susceptible to inherent biases introduced during feature selection and the assessment of feature importance. Such biases can lead to misleading conclusions regarding the underlying relationships between features and outcomes.

This paper aims to elucidate the reasons behind the biases induced by machine learning models in feature selection and feature importance assessments. We advocate for a more robust methodology that relies on statistical methods—such as Chi-squared tests and p-values—to identify true associations between target variables and features. By utilizing these statistical techniques, we can mitigate the influence of biased feature selection, thereby enhancing the reliability of predictive models and their clinical applicability. Through this analysis, we emphasize the need for rigorous validation of machine learning methods in medical imaging to ensure that predictions are based on substantial and unbiased associations, ultimately improving patient outcomes.

Researchers, including Yuan et al., must recognize the crucial distinction between true associations and model-specific associations [2,3]. Model-specific feature selections refer to the phenomenon where different models yield varying sets of features, even in the presence of underlying true associations. This inconsistency can lead to misleading interpretations of which variables are genuinely informative.

Understanding this difference is vital for ensuring the robustness and reliability of findings. The variability in feature selection across models highlights the importance of not solely relying on a single model's output for feature importance. Instead, researchers should adopt a more comprehensive approach, utilizing multiple modeling techniques and statistical methods to identify stable and consistent relationships. By doing so, they can reduce the risk of drawing incorrect conclusions based on model idiosyncrasies, thereby enhancing the validity of their research outcomes. Incorporating sensitivity analyses and cross-validation can further strengthen the reliability of feature selections and provide a clearer picture of the true influences at play.

LASSO regression is a popular technique in statistical modeling and machine learning for both regularization and feature selection. However, it can introduce specific biases in the feature selection process [4–7]. One significant issue is the shrinkage effect, where LASSO applies an L1 penalty to the regression coefficients, encouraging sparsity by setting some coefficients to zero. While this reduces model complexity, the penalty can disproportionately affect features with small but non-zero true effects. In particular, when features are correlated, LASSO tends to arbitrarily select one feature from a group while setting others to zero, leading to biased estimations of which features are truly important.

Correlation among features is another concern. LASSO does not differentiate between highly correlated variables and may favor one variable over another based solely on their interactions with the dependent variable in the sample. This behavior can result in situations where LASSO incorrectly suggests that only one of several correlated features is important, thus ignoring potentially significant predictors. Additionally, LASSO's performance is sensitive to sample size and noise in the data. In smaller datasets, it might randomly include or exclude certain features based on fluctuations in the data, leading to overfitting and the selection of features that may not generalize well, ultimately resulting in biased conclusions regarding feature necessity.

Another issue arises from boundary effects. When true coefficients are near zero, LASSO's tendency to force coefficients towards zero can lead to boundary bias. This means that features with small but potentially meaningful effects may be incorrectly shrunken to zero, under-representing their importance in the model. Moreover, the modeling assumptions inherent in LASSO contribute to its biases. The technique assumes linear relationships between features and the target variable,

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and if the actual relationships are nonlinear, LASSO may fail to capture those complexities. Consequently, this can lead to the misprioritization of certain features, further skewing the feature selection process.

Feature scaling is another critical consideration. LASSO is sensitive to the scale of the features; without proper scaling, features measured on larger scales can dominate the penalty term, resulting in biased assessments of feature importance. If features are not standardized, this may lead to the unintended exclusion of important features while retaining less informative ones, degrading the overall model accuracy.

While researchers have suggested combining ensemble methods or bias mitigation techniques [2–5] to address the feature selection biases of LASSO, it is also essential to incorporate robust statistical methods, such as Chi-squared tests or p-values, to validate the true associations between the features and the target variable [8]. This comprehensive strategy ensures that the selected features are genuinely informative and minimizes the effects of biases intrinsic to LASSO regression.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

Not applicable.

Code availability

Not applicable.

Authors' contributions

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CRediT authorship contribution statement

Yoshiyasu Takefuji: Conceptualization, Investigation, Validation, Writing – original draft, Writing – review & editing.

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Yoshiyasu Takefuji
Faculty of Data Science, Musashino University, 3-3-3 Ariake Koto-ku, Tokyo 135-8181, Japan
E-mail address: takefuji@keio.jp.