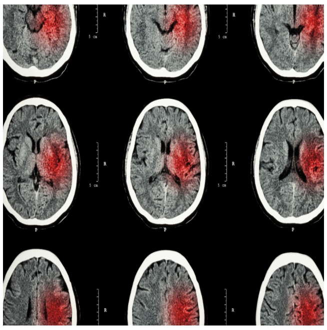
Predicting Early Haematoma Expansion: Nomograms vs. Machine Learning



Early prediction of haematoma expansion in hypertensive intracerebral haemorrhage (ICH) is critical for improving patient outcomes. Haematoma expansion can result in rapid clinical deterioration, increased mortality and long-term disability. Identifying patients at risk for early haematoma expansion allows clinicians to intervene more effectively, potentially reducing adverse outcomes. A recent study published in Academic Radiology compared the performance of a nomogram and several machine learning (ML) models in predicting early haematoma expansion. The goal was to determine the most reliable and practical tool for clinical application based on accuracy, calibration and clinical usefulness.

The Role of Radiomics and Nomograms in Haematoma Prediction

Radiomics involves extracting a large set of quantitative features from medical images, providing detailed information beyond visual assessments. In this study, a radiomics score (Radscore) was calculated from non-contrast CT scans. Radscore combined features such as shape, texture and intensity of haematomas, offering a data-driven method to quantify imaging characteristics. To develop a nomogram, this radiomics score was integrated with clinical predictors, including the initial Glasgow Coma Scale (GCS) score and blood pressure levels.

A nomogram is a statistical tool that visually represents a predictive model, simplifying risk assessment for clinicians. The nomogram developed in this study showed promising results, with an area under the curve (AUC) of 0.76 in the validation set, indicating moderate discriminatory power. However, while nomograms are valuable for their simplicity and ease of interpretation, they can be limited in complex datasets where non-linear relationships exist.

Machine Learning Models for Haematoma Expansion Prediction

Machine learning (ML) models were also employed to predict haematoma expansion in this study, including logistic regression (LR), random forest (RF), support vector machine (SVM) and extreme gradient boosting (XGBoost). These models processed the same radiomics features and clinical predictors as the nomogram but applied advanced computational techniques to identify patterns in the data.

Among the ML models tested, XGBoost demonstrated the highest predictive performance with an AUC of 0.85 in the validation set. This performance surpassed both the nomogram and the other ML models, including SVM and RF. XGBoost’s enhanced accuracy can be attributed to its ability to manage complex interactions among variables and reduce overfitting through gradient-boosting techniques. Random forest and SVM also performed well but fell slightly short of XGBoost in terms of accuracy and calibration.

A key advantage of ML models is their ability to process high-dimensional datasets, making them particularly suited for radiomics-based predictions. However, the increased complexity of these models can make them less interpretable than nomograms, which present results in a more straightforward visual format suitable for immediate clinical decisions.

Comparing Clinical Usefulness and Accuracy

To determine the clinical viability of each predictive approach, the study evaluated both the calibration of the models and decision curve analysis (DCA). Calibration measures how closely predicted probabilities match observed outcomes, while DCA assesses the clinical net benefit of using a model across various probability thresholds.

The nomogram demonstrated good calibration but lower accuracy compared to the ML models. The XGBoost model, however, showed superior calibration, accuracy and sensitivity. Specifically, XGBoost achieved a sensitivity of 89% and specificity of 68% in the validation set, making it the most effective tool among those tested.

DCA results further confirmed the advantage of ML models, particularly XGBoost, which provided greater clinical net benefit across a range of decision thresholds compared to both the nomogram and other ML models. The enhanced performance of ML models suggests they are better suited for identifying high-risk patients for early intervention, though the nomogram remains valuable in contexts where interpretability and simplicity are prioritised.

This comparative study demonstrates that both nomograms and ML models can effectively predict early haematoma expansion in hypertensive ICH patients. However, ML models, especially XGBoost, exhibited superior predictive accuracy, sensitivity and clinical usefulness compared to the nomogram. The ability of ML models to manage complex datasets and identify subtle patterns makes them highly effective tools for risk prediction in medical imaging contexts.

Nevertheless, nomograms retain value due to their simplicity and ease of interpretation, making them suitable for clinical settings where computational resources or expertise may be limited. Moving forward, integrating ML models into routine clinical workflows could significantly enhance decision-making processes and patient outcomes, though further validation across diverse datasets and clinical environments is recommended to confirm generalisability.

Source: Academic Radiology

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