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Developing a multivariate model for the prediction of concussion recovery in sportspeople: a machine learning approach

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ABSTRACT

Background Sportspeople suffering from mild traumatic brain injury (mTBI) who return prematurely to sport are at an increased risk of delayed recovery, repeat concussion events and, in the longer-term, the development of chronic traumatic encephalopathy. Therefore, determining the appropriate recovery time, without unnecessarily delaying return to sport, is paramount at a professional/semi-professional level, yet notoriously difficult to predict.

Objectives To use machine learning to develop a multivariate model for the prediction of concussion recovery in sportspeople.

Methods Demographics, injury history, Sport Concussion Assessment Tool fifth edition questionnaire and MRI head reports were collected for sportspeople who suffered mTBI and were referred to a tertiary university hospital in the West Midlands over 3 years. Random forest (RF) machine learning algorithms were trained and tuned on a 90% outcome-balanced corpus subset, with subsequent validation testing on the previously unseen 10% subset for binary prediction of greater than five missed sporting games. Confusion matrices and receiver operator curves were used to determine model discrimination.

Results 375 sportspeople were included. A final composite model accuracy of 94.6% based on the unseen testing subset was obtained, yielding a sensitivity of 100% and specificity of 93.8% with a positive predictive value of 71.4% and a negative predictive value of 100%. The area under the curve was 96.3%.

Discussion In this large single-centre cohort study, a composite RF machine learning algorithm demonstrated high performance in predicting sporting games missed post-mTBI injury. Validation of this novel model on larger external datasets is therefore warranted.

Trial registration number ISRCTN16974791.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ The severity of concussion is influenced by various factors, including injury history, symptom severity and neurological changes observed on MRI, yet predicting recovery time remains challenging.

WHAT THIS STUDY ADDS

⇒ This study demonstrates that a random forest machine learning model can predict the duration of sporting games missed following mild traumatic brain injury (mTBI) with high accuracy, sensitivity and specificity. The model integrates demographic data, injury history, MRI findings and Sport Concussion Assessment Tool fifth edition scores, providing a multifactorial approach to prognosis.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ The authors suggest that incorporating machine learning models into clinical practice could improve decision-making regarding return-to-play timelines for athletes with mTBI, potentially reducing the risk of premature return and subsequent injuries. This study highlights the need for further validation on larger, diverse data sets and could inform the development of more data-driven, individualised concussion management protocols.

INTRODUCTION

Background

Mild traumatic brain injury (mTBI), often referred to as concussion, is the most common cerebral injury pattern following sporting trauma (rugby and football). While it represents the least significant end of the spectrum of sports-related head injury, mTBI has multisystem effects and results in an average of 10 days period of recovery, before which players are generally advised not to return to sport.[1 2]

A premature return to sport, that is, a return to practice before the complete resolution of symptoms, places the sportsperson at significant risk.[3] In the short-term, players are at risk of delayed recovery due to unresolved, delayed reaction times because of the initial injury, contributing to an increased risk of a repeat concussion event.[3] The impact of repeated concussion events is demonstrated to be cumulative, with limited evidence suggesting worsening symptom severity with subsequent mTBIs,[4] with evidence suggesting potential subsequent chronic traumatic encephalopathy, particularly seen in boxing and football.[1 5] While appropriate management of post-concussion symptoms is important, predicting and determining the appropriate time frame for return to practice without unnecessarily prolonging time out of the high-level sport requires due consideration.

Various factors influence the severity of concussions. The findings of the literature vary, but overall, support that women, on average, take longer to recover and many studies have reported that younger age is associated with worse outcomes.[6] Multiple systematic reviews have found injury history and symptom severity statistically significant predictors of a prolonged return to play.[7] Many studies have illustrated that greater severity of acute and subacute symptoms following injury is associated with slower recovery.[8] The Sport Concussion Assessment Tool fifth edition (SCAT5) is a standardised tool for medical professionals to use as an adjunct to initial clinical assessment.[9] It integrates previously separate methods to assess symptoms (graded symptom checklist), cognitive status (five-word immediate recall, delayed recall, etc) and gross neurological functioning (speech, eye motion and pupil reaction, pronator drift and gait assessment; all assessed as 'pass' vs 'fail'). It has long been the gold standard for concussion assessment.[10]

While the mainstay of clinical assessment of concussion sufferers involves taking a history and assessing sportspeople's symptoms, imaging is not routinely undertaken. Imaging is predominately used for the detection of further trauma-related sequelae, which may require intervention beyond conservative management. CT is relatively insensitive to mTBI change, with MRI used as the gold standard imaging modality for prediction of clinical outcome at 6 months.[11] Hyperintense lesions associated with mTBI can be observed on the T2-weighted FLAIR (fluid-attenuation inversion recovery) images. FLAIR sequence is used to suppress signals from species with long T1 relaxation times, such as cerebrospinal fluid in the brain, making it particularly effective for visualising white matter lesions, particularly in the periventricular lesions. It offers superior sensitivity to detect subtle white matter changes often seen in mTBI, even following the resolution of symptoms.[12] Multiple T2/FLAIR white matter hyperintensities were reported to be the predominant finding of mTBI patients, which may be a marker of residual shear-strain injury to white matter.[13]

Objectives

Despite the widespread concern regarding the prognosis of athletes who have experienced mTBI and the identification of related factors and imaging findings, no study has yet established a predictive model incorporating multiple factors. Machine learning enables the evaluation of high-dimensional data, and several methods have been demonstrated to be beneficial in multiple medical predictive tasks.[14] Therefore, this study aims to develop a predictive model that integrates clinical history, symptom severity and imaging findings to estimate the duration of time out of sport following mTBI to guide clinical decision-making, ultimately aiming to reduce the risk of premature return to sport and optimise recovery strategies in athletes.

METHODS

Data

A prospective database was formulated based on the inclusion criteria of all athletes participating in contact sports who experienced a head injury categorised as a single/double mTBI (when assessed within 48–72 hours since injury), referred through our recruitment contacts in University Sports throughout the West Midlands and adjacent areas between 2016 and 2019, aged 18–40, who are fluent English speakers, who demonstrated an objectively normal neurological examination at the time of enrolment.

Exclusion criteria were as follows: cases that required hospital admission after the initial assessment, had intracranial blood/brain tissue injury/non-TBI-related pathologies on initial CT/MR scan, pregnancy, history of neurodegenerative pathology/any recent or ongoing illness affecting the central nervous system (eg, Parkinson's, multiple sclerosis, meningitis, epilepsy, neoplasm), a history of chronic alcohol/drug abuse, a formally diagnosed pre-existing neuropsychological impairment/learning disability or a contraindication for MRI (online supplemental file 1).[15]

Information was collected across four domains: sportspeople demographics, injury history, MRI report and SCAT5 score (table 1). MRIs were reviewed by a consultant neuroradiologist with more than 20 years of experience, blinded to the outcome. The number of sporting games missed due to injury was also recorded as a binary outcome (greater than five games, yes/no), which was deemed to reflect a significant time out of sport and, therefore, a surrogate of significant time out of sport. With different sports having a differing cadence of match frequency (eg, weekly/monthly), a regression problem would give heterogeneity across sports. Therefore, a binary classification is used here to better predict a significant time out of any sport.

All data was collected with informed consent and exported for analysis anonymously in accordance with local trust information governance policies.

Data handling

The concussion database was manually reviewed to remove several erroneous values, such as 'age of 180', which was presumed to be a typographical error. Missing variables (eg, blank height) were imputed using the 'missForest' random forest (RF) package. Cases with multiple (two or more) missing variables were removed (figure 1 summarises the overall data handling). Free-text-based MRI reports were categorised into the presence or absence of white matter hyperintensity changes.

Table 1 Features for model building

Domain	Features
Demographics	Age (years)
	Sex (M/F)
	Handedness (R/L/ambidextrous)
	Height (m)
	Weight (kg)
Injury details	Loss of consciousness (Y/N)
	LOC duration (s)
	Post-traumatic amnesia (Y/N)
	PTA duration (s)
	Additional head injury (Y/N)
	Cervical injury (Y/N)
	Number of prior concussions (excluding current)
	Number of concussions that resulted in LOC
	Number of concussions that resulted in confusion
	Number of concussions that resulted in difficulty remembering events that occurred immediately after injury
	Number of concussions that resulted in difficulty remembering events that occurred prior to the injury
MRI findings	Structural MRI white matter changes (Y/N)
SCAT5 questionnaire	Baseline SCAT5 Total Symptom Score
	Post-injury SCAT5 Total Symptom Score

LOC, loss of consciousness; PTA, post-traumatic amnesia; R/L, right/left; SCAT5, Sport Concussion Assessment Tool 5th edition score.

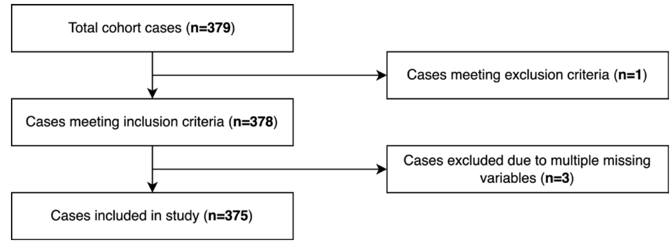

Figure 1 Summary flowchart of application of inclusion/exclusion criteria and data cleaning.

The analysis was framed as a binary classification problem with the outcome of the number of sporting games missed, greater than five, encoded as a Boolean value. Cases without a defined outcome, for example, unknown number of games missed, were removed.

The entire corpus was separated into outcome-balanced training and testing subsets in a 90:10% split. The training subset was used for machine learning model development using a simple holdout validation methodology.

Machine learning modelling

An RF machine-learning model was iteratively developed. Essential hyperparameters, such as ntree, mtry, nodesize, maxdepth and sampsize, were subject to manual optimisation to balance model complexity and generalisation. For the final model; ntree 500, maxdepth 5 and minimum node size 1 were selected. The model was constructed with the five aforementioned database domains as features, independently and as a composite model. Optimal cut-point thresholds were derived from receiver operator curves (ROC) by Youden's J.[16]

The derived RF models were assessed on the unseen testing subset. Model performance was principally assessed by discrimination (the model's ability to identify those missing more or less than five games) using the ROC area under the curve (AUC) and sensitivity and specificity.

Statistical analysis

All data handling, model training and statistical analysis were performed in R[17] V.4.4.0, using caret,[18] missForest[19] and pROC[20] libraries. Continuous variables were presented as mean and SD or median and IQR, and categorical variables were presented as frequency and proportion. Fisher's exact test was used for univariate testing, with Bonferroni correction for multiple comparisons. Performance metrics were as follows; accuracy (defined by overall fraction correct), sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and AUC. 95% CIs were by exact Clopper-Pearson interval (accuracy, PPV, NPV) and DeLong's method for AUC. A p value<0.05 was considered statistically significant. The TRIPOD+AI checklist was used to structure the report.[21]

RESULTS

Sportsperson characteristics

In total, 375 sportspeople were included. Mean age was 24.19±8.33 years, and 78.4% were men. 360 (96.0%) were right-handed, 9 (2.40%) were left-handed and 6 (1.60%) were ambidextrous. 22 (5.9%) had structural MRI white matter changes, while 53 (14.1%) missed more than five sporting games (table 2). Features were well balanced across training and testing subsets (table 3).

Machine learning model assessment

RF machine learning generated five models: one for each database domain and a composite model. The 'MRI findings' model yielded the highest accuracy (defined by overall fraction correct). However, the 'composite' model and 'injury details' models had the highest AUC (table 4).

A final composite model accuracy of 94.6% (95% CI 81.6% to 99.3%) based on an unseen testing subset was obtained. This yielded a sensitivity of 100% (95% CI 52.0% to 100.0%) and a specificity of 93.8% (95% CI

Table 2 Demographic features of sportspeople

Characteristics	Sportspeople (n=375)
Age of sportsperson (mean, year)	24.19±8.33
Sex of sportsperson (n, %)	
Male	294 (78.4)
Female	81 (21.6)
Handedness (n, %)	
Right	360 (96.0)
Left	9 (2.4)
Ambidextrous	6 (1.6)
Height (mean, m)	182.96±6.50
Weight (mean, kg)	88.97±13.09
Loss of consciousness (n, %)	47 (12.5)
Post-traumatic amnesia (n, %)	23 (6.1)
Additional head injury (n, %)	10 (2.7)
Cervical injury (n, %)	5 (1.3)
Number of prior concussions (median)	0 (IQR 0–2)
Structural MRI white matter changes	22 (5.9%)
Baseline SCAT5 Total Symptom Score	0 (IQR 0–6)
Sporting gamed missed >5 (n, %)	53 (14.1)

SCAT5, Sport Concussion Assessment Tool fifth edition.

86.3% to 93.8%) with a PPV 71.4% (95% CI 37.2% to 71.4%) and NPV 100% (95% CI 92.0% to 100.0%). ROC AUC was 96.3% (95% CI 92.6% to 100.0%) (table 4 and online supplemental file 2).

Figure 2 shows the ROCs demonstrating model components' relative sensitivity and specificity, with the final composite model demonstrating the optimal sensitivity and specificity parameters.

The composite RF model can use feature inputs to predict the likelihood of missing more than five sporting games following an mTBI. The output will indicate whether the sportsperson will likely miss more than five games (yes/no). A representative case is shown in figure 3.

Table 3 Feature balance across training and testing subsets

	Train (n=338)	Test (n=37)	P value
Male	264 (78.1%)	30 (81.1%)	0.91
LOC	43 (12.7%)	4 (10.8%)	0.85
PTA	21 (6.2%)	2 (5.4%)	0.94
Additional head injury	9 (2.7%)	1 (2.7%)	1.00
Cervical injury	5 (1.5%)	0 (0.0%)	0.88
MRI white matter changes	18 (5.2%)	4 (10.8%)	0.58
Games missed >5	48 (14.2%)	5 (13.5%)	0.94

LOC, loss of consciousness; PTA, post-traumatic amnesia.

DISCUSSION

Summary of findings

The present study aimed to develop a predictive model for estimating the sporting games that adult sportspeople would miss following mTBI, using a comprehensive data set encompassing demographic information, injury details, MRI findings and SCAT5 scores. The study used RF, a machine learning algorithm, to construct predictive models and assess their performance. The results demonstrate the utility of RF models in predicting return-to-play duration with high accuracy, sensitivity and specificity, particularly in the composite model that integrated multiple data domains.

Importance of predictive factors

Despite considerable variations among researchers, factors commonly associated with outcomes of mTBI in sportspeople include age, gender, prior concussions, mental health history, symptoms like loss of consciousness or memory problems and other individual characteristics.[6 22] This study incorporated diverse data domains such as injury history, MRI findings and symptom assessment scores (SCAT5), providing a holistic approach to model development capturing multiple facets that may influence recovery duration. This comprehensive approach aligns with the multifactorial nature of mTBI recovery, which involves complex interactions between individual characteristics, injury severity and neurological changes.

The relative weighting of each model feature to model performance aligns with prior research, with all categories demonstrating strong performance, particularly injury history (AUC 0.963). The presence of white matter hyperintensities on MRI ranked second (AUC 0.9), with the highest PPV. SCAT5 was relatively less (AUC 0.697), in keeping with its proposed purpose as a supplementary clinical assessment of the sportspeople. Despite the high individual component AUCs, the final composite model AUC does not improve on that of the injury history category. However, it does demonstrate the highest overall sensitivity and specificity. The individual model using injury details performed well mainly because this domain contained the most features, and future studies with a larger sample size might enable us to optimise the composite model.

MRI findings

Although well documented to correlate with mTBI and seen as potent negative predictors, MRI white matter hyperintensities are non-specific and subjective findings. MRI interpretation within this data set is particularly reliable due to the consistency of being interpreted by a single, highly experienced radiologist, thereby minimising the intrinsic subjectivity involved in radiological interpretation. More specific MRI modalities, such as functional MRI and diffusion tensor imaging, are

Table 4 Table representing the relative performance of each model

	Demographics	Injury details	MRI findings	SCAT5	Composite
Accuracy	0.811	0.946	0.973	0.784	0.946
Sensitivity	1.000	1.000	0.800	0.600	1.000
Specificity	0.781	0.938	1.000	0.813	0.938
PPV	0.417	0.714	1.000	0.333	0.714
NPV	1.000	1.000	0.970	0.929	1.000
AUC	0.887	0.963	0.900	0.697	0.963

AUC, area under the curve; NPV, negative predictive value; PPV, positive predictive value; SCAT5, Sport Concussion Assessment Tool fifth edition.

ongoing fields of investigation in assessing mTBI.[23] This imaging data is currently being collected at the same research centre for a subset of the cohort involved in this study. Incorporating additional MRI modalities as supplements to a prognostic machine learning model forms the basis of ongoing work.

Clinical implications

The composite RF model can process the features of the sportspeople and provide a binary prediction of the likelihood of missing more than five games. Based on the model's prediction, clinicians can make informed decisions about the sportsperson's recovery timeline. A prediction indicating that the sportsperson is likely to miss more than five games suggests a need for a more extended recovery period before returning to the sport, thus helping to prevent premature return and reduce the risk of further injury.

The study's findings have important implications for clinical practice and sports medicine. Predicting return-to-play duration following mTBI is crucial for optimising sportspeople's management and reducing the risk of recurrent injuries. The composite model's high accuracy and predictive validity suggest its potential utility as a decision-support tool for clinicians managing mTBI in sports settings. By incorporating demographic information, injury history, MRI findings and symptom assessment scores, the model provides a comprehensive approach to prognosis assessment, enabling individualised treatment strategies and informed decision-making regarding return to sport.

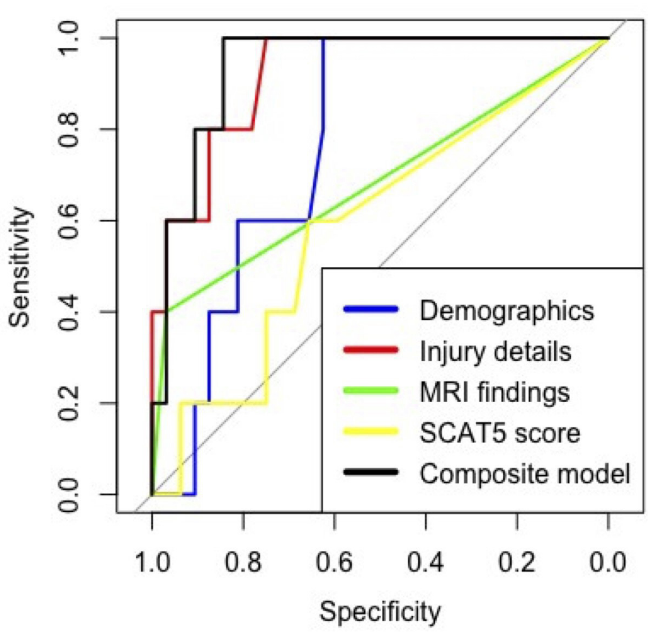

Figure 2 Receiver operating curves demonstrating the relative sensitivity and specificity of model components, with the final composite model demonstrating the optimal sensitivity and specificity parameters. SCAT5, Sport Concussion Assessment Tool fifth edition.

Limitations

This study has several limitations. First, the data set is relatively small and represents a single hospital site. Second, a highly simplistic training-validation splitting strategy was employed, which may increase the variability observed in the model's performance on the test set. Future work could consider k-fold cross-validation or similar methods to improve on this. Third, the casemix weighting (ie, games missed) may lead to a selection bias when extracting the unseen testing subset, potentially questioning the model's generalisation ability. Fourth, as with most large cohort studies, data was incomplete or variably collected, for example, head/cervical injury was not clearly defined and loss of consciousness could be self-reported/observed. The duration between concussions was quantified by the number of games missed (variable based on the type of sport) rather than the absolute number of days out of practice. Follow-up of sportspeople varied by the number and time frame of repeat appointments; despite best efforts to compute absent data, a degree of error is inevitable. Duration out of the sport, the preferred primary outcome measure, was insufficiently collected. Hence, the researchers preferentially used the better-recorded variable 'number of games missed'. This variable was

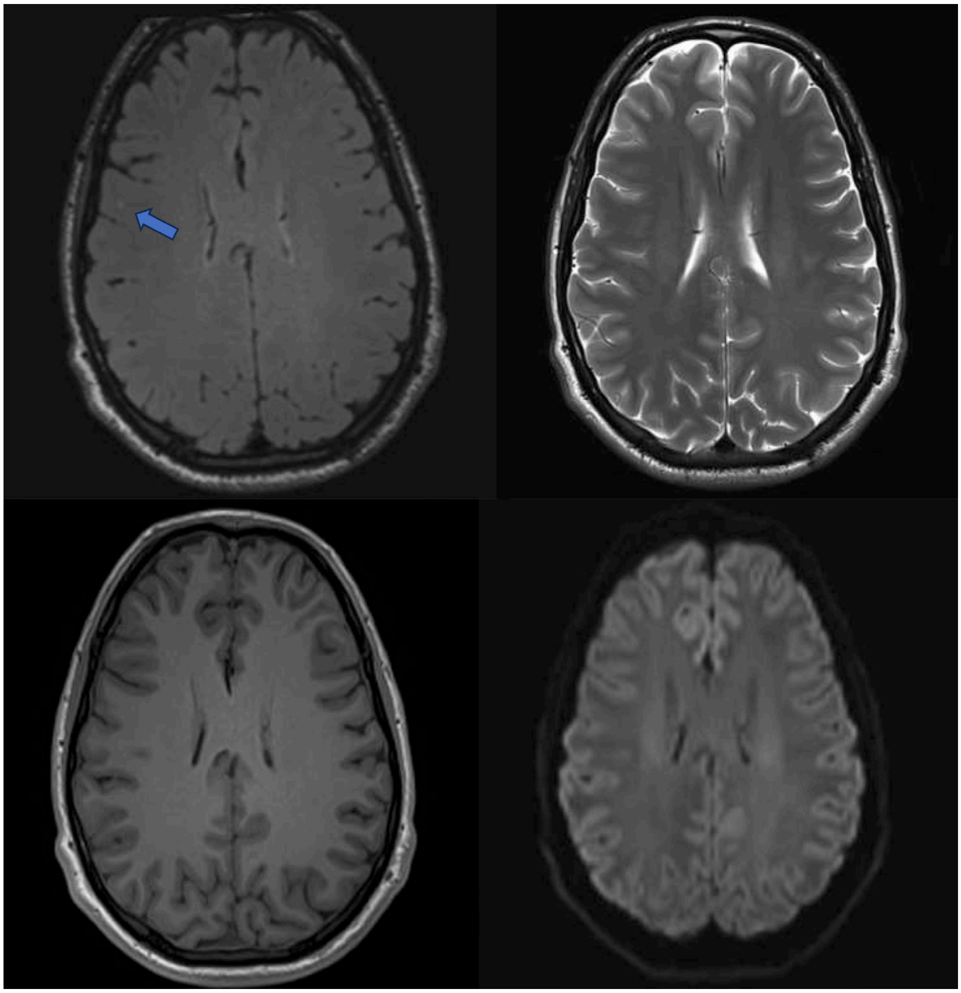

Figure 3 A representative case to illustrate the utilisation of the model. The MRI of an adult sportsperson who suffered from concussion. Small T2 hyperintense focus is shown in the right frontal lobe. Their total symptom score was 1. Their prognosis was predicted to be relatively good by the physician, but the random forest model predicted that they would miss more than five games. In the end, they missed over 20 games.

used as a binary classification (ie, ≤5 games missed or >5 games missed) to maximise the data points required for machine learning. Finally, although a promising ROC AUC, the proposed model has only thus far been internally validated. Plans to temporally validate the model are pending adequate duration to obtain a sufficient caseload. Future research should aim to externally validate the predictive model in diverse populations and prospectively evaluate its clinical utility in guiding return-to-play decisions following mTBI.

CONCLUSION

Overall, the proposed composite model demonstrates the ability to predict duration out of sport post-mTBI, demonstrating high accuracy, sensitivity and specificity. Existing literature has not yet explored the use of machine learning in mTBI prognostication, nor is there a published validated score for predicting duration out of sport following mTBI. Here, we have demonstrated a promising machine learning model with potential implications for optimising management and reducing the risk of recurrent injuries in sports settings. Ongoing work is required to validate this model externally.

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Contributors All authors contributed equally to this work. VS is guarantor. LCY and VS designed the concept. KY undertook data collection. EY implemented the methodology and performed statistical analysis. DD and AB provided support in data collection. LX and LCY prepared the manuscript. All authors gave substantial contribution to the work conception/data collection/analysis, critically revised the final version, approved the final version and agree to be accountable for all aspects of the work. Machine learning algorithms were used to build the prediction model.

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Competing interests None declared.

Patient and public involvement Patients and/or the public were involved in the design, or conduct, or reporting, or dissemination plans of this research. Refer to the Methods section for further details.

Patient consent for publication Not applicable.

Ethics approval This study was approved by the East of England—Essex Research Ethics Committee on 22 September 2017—REC 17/EE/0275; IRAS 216703. Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data may be obtained from a third party and are not publicly available. All analysed data from the study will be stored on NHS and University of Birmingham servers. These servers are housed on a network with restricted physical access, and data are stored under coded filenames. Network access is secured with passwords and restricted to a limited number of authorised personnel. Raw MRI data is stored on a separate DICOM server within a different network protected by its own firewall, accessible only by a few system administrators. Data spreadsheets will be stored on password-protected computers with coded filenames, while original paper files will be kept in locked filing cabinets. The datasets generated and/or analysed during this study will be available upon request from Professor Antonio Belli. He will be able to provide anonymised data with sufficient detail to reproduce the analyses for up to 10 years.

Author note AI use statement: Machine learning algorithms were used to build the prediction model.

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