

Review Article

Machine Learning Prediction of Shunt Dependency After Aneurysmal Subarachnoid Haemorrhage

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Received: 7 February 2025; Accepted: 30 April 2025; Published: 26 July 2025; DOI: 10.5281/zenodo.22310481

Citation of this article: Prochazka K, Gallagher N and Teixeira B (2025) Machine Learning Prediction of Shunt Dependency After Aneurysmal Subarachnoid Haemorrhage. Curr Res Neurol Neurosurg, 8(1): 01-08.

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Abstract

Background: Chronic shunt-dependent hydrocephalus complicates a substantial minority of aneurysmal subarachnoid haemorrhage (aSAH) survivors. Early identification could guide external ventricular drain (EVD) weaning and shunt timing.

Objective: To review published machine learning (ML) models predicting shunt dependency after aSAH alongside the clinical scores and EVD-weaning strategies they are benchmarked against.

Methods: Narrative review of derivation and validation studies, systematic reviews and meta-analyses, and EVD-management cohorts identified through PubMed, Crossref and journal searches.

Findings: Traditional scores such as CHES and SDASH achieve areas under the curve (AUC) of roughly 0.75-0.82. ML models, including random forest and gradient-boosting classifiers, report AUCs of 0.80-0.92 in derivation cohorts, with pooled meta-analytic estimates near 0.79-0.80; one dual-centre external validation retained an AUC of 0.867. Most studies remain single-centre with heterogeneous predictors.

Conclusions: ML models modestly outperform traditional scores but need larger, externally validated, prospectively reported cohorts before routine adoption alongside standardised EVD-weaning protocols.

Keywords: Machine learning; Shunt dependency; Hydrocephalus; Subarachnoid haemorrhage; External ventricular drain

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Introduction

Aneurysmal subarachnoid haemorrhage (aSAH) remains a devastating cerebrovascular emergency, with roughly a third of survivors left dependent and mortality still approaching a quarter of cases despite modern neurocritical care [1]. Among the complications that shape recovery, chronic shunt-dependent hydrocephalus is one of the most consequential and most amenable to prediction. Acute hydrocephalus develops in a large proportion of patients in the first days after haemorrhage,

driven by intraventricular blood and impaired cerebrospinal fluid (CSF) resorption, and is typically managed with an external ventricular drain (EVD). A meaningful fraction of these patients fail to tolerate drain weaning and progress to chronic, shunt-dependent hydrocephalus requiring permanent CSF diversion, most often a ventriculoperitoneal shunt.

Predicting, at or soon after admission, which patients will become shunt dependent has obvious clinical value: it could guide the intensity and pace of EVD weaning, inform counselling, and support trial enrichment. Over the past decade this need produced a family of simple bedside clinical scores, most prominently CHES and SDASH, built from admission clinical and radiographic variables [2,3]. More recently, machine learning (ML) approaches — random forests, gradient-boosting machines, neural networks and other supervised classifiers — have been applied to the same prediction problem, promising to capture nonlinear interactions among a larger predictor set than a hand-crafted score can practically include.

This review is a narrative synthesis of the published literature, not a study of the authors' own patients. It surveys traditional clinical scores, the radiographic, CSF and clinical predictors that inform them, EVD weaning protocols and their relationship to shunt need, the ML models now being tested against this outcome, and the methodological limitations that currently constrain their clinical adoption. The rationale for pursuing better prediction is practical rather than purely academic: an EVD carries its own risks of infection, malposition and haemorrhage, and prolonging drainage while waiting to see whether a patient will tolerate weaning is not cost-free, while premature or overly rapid weaning risks a failed trial and clinical deterioration. A model, or a simple score, that reliably separated patients likely to need a permanent shunt from those likely to wean successfully

could therefore shorten intensive-care stay for one group while avoiding unnecessary weaning attempts in the other, and could also stratify patients for future interventional trials aimed at reducing shunt dependence itself.

Traditional Clinical Prediction Scores

The CHES score, derived in a large single-centre cohort, combines five readily available admission variables — CSF infection, hydrocephalus severity, extra-ventricular blood, and clinical and radiographic severity indices — into an early bedside estimate of shunt risk [2]. The SDASH score, derived independently at another centre, uses a similarly compact set of admission clinical and imaging variables [3]. Both have since been externally validated: a cohort of 214 patients found SDASH achieved an AUC of 0.816, materially better than the Hijdra and Barrow Neurological Institute scores and comparable to CHES [4].

Refinements have followed. Incorporating Huckman's ventricular index into a combined "CHES-Huckman" score improved discrimination in one cohort to an AUC of 0.751, formalising the intuitive link between early ventricular enlargement and eventual shunt dependence [5]. Other groups have derived competing prognostic models and preoperative risk-scoring systems from independent cohorts, generally identifying similar predictors — hydrocephalus severity, intraventricular haemorrhage, clinical grade, and rebleeding or infection — while reporting broadly comparable discrimination [6,7,8]. An editorial commentary has framed this proliferation of scores as an unresolved "quest," noting that no single score has achieved dominant, universally reproduced performance across settings [9]. Part of the difficulty is that these scores were each derived in a single centre's practice environment, with its own thresholds for EVD placement, weaning pace and threshold for permanent shunting, so a score that discriminates well at its home institution may calibrate poorly elsewhere even

when its raw discrimination, measured by AUC, appears preserved. This distinction between discrimination and calibration recurs throughout the traditional-score and ML literature alike, and is one of the central methodological themes of this review.

Table 1: Traditional clinical scores for predicting shunt dependency after aneurysmal subarachnoid haemorrhage reviewed here [2,3,4,5,6,7,8].				
Score / model	Derivation cohort	Key admission variables	Reported AUC	Source
CHES	Single centre, Germany	CSF infection, hydrocephalus, extra-ventricular blood, clinical/radiographic grade	~0.75-0.82 on validation	jabbarli2016
SDASH	Single centre, Germany	Clinical grade, hydrocephalus, IVH, aneurysm location	0.816 (external validation)	diesing2018; garciaarmengo2021
CHES-Huckman	Single centre	CHES items plus Huckman ventricular index	0.751	said2023
Mijderwijk prognostic model	Single centre	Clinical and radiographic predictors	Comparable to CHES/SDASH	mijderwijk2019
McMahon stronger predictive model	Single centre, US	Expanded prognostic variable set	Improved over prior models	mcMahon2025
Kim preoperative risk score	Single centre, Korea	Preoperative clinical /radiographic risk factors	Not directly comparable (risk categories)	kim2019

Radiographic, CSF and Clinical Predictors

Across both score-based and ML studies, a consistent set of predictors recurs: clinical severity at admission (Hunt-Hess or World Federation of Neurosurgical Societies grade), the amount and distribution of subarachnoid and intraventricular blood, acute hydrocephalus requiring EVD, radiographic ventricular indices such as the Evans and Huckman indices, CSF characteristics including protein and red-cell content, and complications such as rebleeding, infection and vasospasm [10,11]. Ventricular measurements taken

serially, rather than at a single admission time point, appear to add incremental predictive value, consistent with the observation that shunt dependence reflects an evolving CSF-dynamics process rather than a fixed baseline risk [5]. Machine learning models exploiting dynamic, repeatedly measured variables — intracranial pressure trends and cumulative CSF drainage volume among them — have shown measurably better discrimination than models restricted to static admission-only variables, reinforcing the same point [12]. CSF laboratory characteristics, though less consistently reported than imaging or clinical grade, add a further dimension: elevated CSF protein and persistent red-cell counts have repeatedly featured among independently significant predictors in cohort studies of shunt-dependent hydrocephalus, presumably reflecting the burden of blood breakdown products interfering with arachnoid granulation resorption of CSF, the presumed final common pathway to chronic hydrocephalus [10,11]. No single predictor, however, has proved sufficient alone; every reasonably performing score or model instead combines several of these domains.

Machine Learning Approaches and Model Performance

Several groups have now trained supervised ML classifiers on this outcome. A distributed random forest model trained on 386 patients, of whom 12.9% became shunt dependent, achieved an AUC of 0.88 with 73% sensitivity and 92% specificity [13]. A head-to-head comparison of ML models against CHESS and SDASH in 292 patients found ML using admission data alone reached an AUC of 0.80, "excellent" by conventional thresholds, compared with 0.77-0.78 for the traditional scores — a real but modest improvement [14]. A dual-centre study using a landmark design at day 21, combining static and dynamic variables, reported an internal AUC of 0.894 and, in a genuinely external 102-patient validation cohort, retained

an AUC of 0.867, with risk-tier stratification separating patients into groups with 5.3%, 35.7% and 64.7% observed shunt-dependence rates [12]. Imaging-based deep learning applied directly to preoperative CT has also been explored as a complementary, less feature-engineered approach [15], and explainable ML frameworks using SHAP-based attribution have been used to make model outputs more interpretable to clinicians in related aSAH outcome-prediction tasks [16].

Table 2: Machine learning studies predicting shunt dependency after aneurysmal subarachnoid haemorrhage reviewed here [13,14,12,15,17,18]; n = 6 primary/synthesis studies.				
Study	Design	Cohort size	Best model	Reported AUC
Muscas 2020	Single-centre derivation	386	Distributed random forest	0.88
Frey 2023	Single-centre, ML vs CHESS/SDASH	292	ML (admission data)	0.80 vs 0.77-0.78
Zheng 2026	Dual-centre, external validation	228 + 102	Random forest, dynamic features	0.894 internal / 0.867 external
Han 2026	Multi-centre, i maging-based	Not stated	Deep learning (CT-based)	Not directly comparable
Javadnia 2025	Systematic review/meta-analysis	5 studies pooled	Pooled estimate	0.79 (95% CI 0.78-0.81)
Hajikarim loo 2026	Systematic review/meta-analysis	6 studies, 2096 patients	Pooled estimate	0.80-0.92

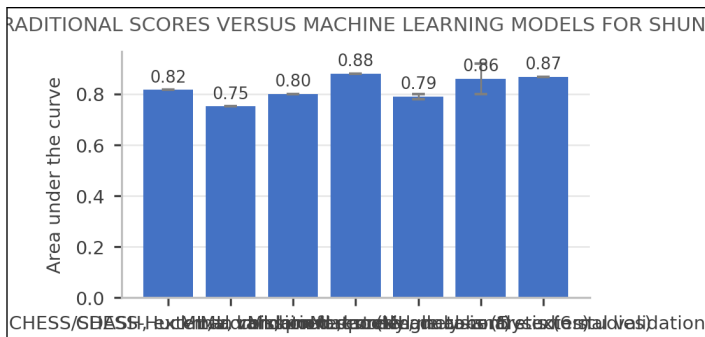


Figure 1: Discrimination (AUC) of traditional clinical scores versus machine learning models for predicting shunt dependency after aneurysmal subarachnoid haemorrhage: SDASH external validation, 0.816 [4]; CHES-Huckman combined score, 0.751 [5]; ML using admission data only, 0.80 [14]; single-cohort random forest, 0.88 [13]; pooled meta-analysis of 5 studies, 0.79 [17]; pooled meta-analysis of 6 studies, up to 0.86-0.92 range [18]; dual-centre external validation, 0.867 [12].

Two recent systematic reviews and meta-analyses now summarise this literature. One, pooling five studies, found a pooled AUC of 0.79 (95% CI 0.78-0.81) with moderate heterogeneity, no significant difference between linear, tree-based and deep-learning model families, and better discrimination in models built from more than ten input features (pooled AUC 0.82) than fewer (0.78) [17]. A second, pooling six studies and 2096 patients, reported pooled AUC ranging from 0.80 to 0.92, with accuracy, sensitivity and specificity each spanning roughly 0.70-0.92 [18]. Together these reviews suggest ML consistently reaches, and sometimes modestly exceeds, the performance of traditional scores, without yet establishing a single superior algorithm or feature set. Model choice itself appears to matter less than feature richness and outcome definition: gradient-boosted trees, random forests, logistic-regression-based scores and even deep neural networks trained on tabular clinical data have produced broadly overlapping AUCs in head-to-head comparisons, whereas studies with larger, more carefully curated predictor sets and larger sample sizes consistently outperformed those with sparser inputs. This pattern argues that further gains in this field are more likely to come from better data — richer, prospectively collected,

multicentre datasets with standardised outcome definitions — than from more sophisticated algorithms applied to the same modest single-centre datasets already available.

External Ventricular Drain Weaning and Its Relationship to Shunt Need

Because chronic shunt dependence is often only confirmed after a failed attempt to wean or clamp the EVD, weaning protocol itself is both a confounder and a potential predictor in this literature. A pooled analysis found gradual EVD weaning associated with a lower risk of subsequent shunt dependency than rapid weaning [19], yet other single-centre before-after studies found the opposite: switching to an intermittent-drainage, rapid-weaning strategy reduced ventriculoperitoneal shunt rates from 35% to 13% and shortened stay [20], and a prospective multicentre study across six centres likewise found rapid weaning associated with a lower hazard of shunt placement (HR 0.52) [21]. A standardised, criterion-based gradual-weaning protocol in another cohort achieved an 11% shunt rate against a benchmark of roughly 21% [22], and quantitative modelling of EVD output dynamics, rather than a fixed weaning schedule, has itself been proposed as a predictor of eventual shunt need [23]. Similar weaning-outcome relationships have been reported outside pure aSAH cohorts, including intraventricular haemorrhage [24] and drainage-volume analyses in mixed subarachnoid haemorrhage populations [25]. A recent narrative synthesis of this conflicting evidence concluded that rapid weaning generally shortens stay without clearly increasing shunt risk, but that the underlying trial evidence remains observational [26]. This heterogeneity matters for ML studies: models trained on cohorts managed under different weaning protocols are implicitly learning institution-specific practice patterns as well as biology.

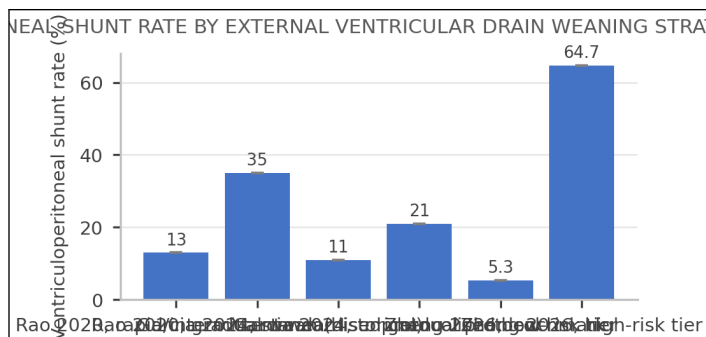


Figure 2: Reported ventriculoperitoneal shunt rate by EVD weaning strategy and by ML-derived risk tier: rapid/intermittent versus gradual wean, 13% vs 35% [20]; standardised gradual protocol versus an unprotocolled benchmark, 11% vs 21% [22]; ML-derived low- versus high-risk tiers, 5.3% vs 64.7% [12].

Limitations of Machine Learning Prediction

Despite encouraging discrimination, the ML literature in this area shares recurring weaknesses. Cohorts are almost uniformly single-centre and modest in size, typically 200-400 patients, limiting the complexity of model that can be safely fit without overfitting. True external validation, in a geographically or temporally distinct cohort, remains rare — the one dual-centre study to report it showed only a small AUC decrement, but this remains an isolated example rather than the norm [12]. Calibration, arguably as important as discrimination for clinical decision-making, is inconsistently reported across studies, and heterogeneous outcome definitions (which shunt-dependence threshold, and over what follow-up window) complicate cross-study comparison, as reflected in the moderate heterogeneity seen in pooled meta-analyses [17]. Reporting quality more broadly falls short of methodological standards such as TRIPOD, which call for explicit description of model development, validation and calibration [27]. Finally, because shunt decisions are themselves shaped by local EVD-weaning practice, models risk encoding institutional practice rather than purely biological risk, an issue that prospective, multicentre, protocol-standardised studies will be needed to resolve.

Conclusion

Machine learning models for predicting shunt dependency after aneurysmal subarachnoid haemorrhage now consistently match, and in several derivation cohorts modestly exceed, the discrimination of established clinical scores such as CHES and SDASH, with pooled meta-analytic AUCs approaching 0.80 and derivation-cohort AUCs reaching the low 0.90s. Dynamic, repeatedly measured variables — ventricular indices and EVD-drainage parameters among them — appear to add real incremental value over static admission-only predictors. However, the evidence base remains dominated by small, single-centre derivation studies with sparse external validation, inconsistent calibration reporting, and outcome definitions entangled with heterogeneous, non-standardised EVD-weaning practice. Larger multicentre cohorts, prospective and externally validated model reporting aligned with TRIPOD standards, and explicit accounting for local weaning protocol are the principal steps needed before ML-based shunt-dependency prediction can be recommended for routine bedside use.

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