PREDICTING NEED FOR URGENT ENDOSCOPY IN PATIENTS WITH ACUTE GASTROINTESTINAL BLEEDING

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AIMS: **To d**evelop a model to predict a) Source of GIB –Upper vs. Lower, b) Need for urgent endoscopy, and c) Disposition in patients with acute GIB

BACKGROUND: The ability to reliably predict need for an urgent endoscopy and intensive care monitoring in patients with acute GIB could potentially improve outcomes and prevent unnecessary complications by allowing appropriate allocation of scarce resources and optimizing costs.

METHODOLOGY: Modern machine learning methods, such as artificial neural networks (ANN)[4,5] and support vector machines (SVM)[6] with learning capabilities analogous to human learning have been utilized to predict outcomes in a wide variety of settings.[3,7,8] Training these models with a set of correctly entered input variables allows classification functions that generalize for all possible inputs. This can then be utilized to predict output for any given input. Both ANN's and SVM's have demonstrated robust generalization ability and high classification accuracy in a wide variety of applications.

For purposes of this study, relevant clinical data (Table 1) was collected retrospectively on a cosecutive sample of 117 patients representing both acute upper and lower GIB. Endoscopic data was utilized to confirm the source and to ascertain if the patient would have benefitted from urgent endoscopy. Criteria utilized to ascertain need for an urgent endoscopy (defined as immediately upon resuscitation) were: **a)** non-white-based ulcer, **b)** red blood on nasogastric lavage, and **c)** history of cirrhosis. On the other hand, findings such as white-based ulcers and non-bleeding Mallory-Weiss tears were classified as not requiring an urgent endoscopy. Both endoscopic and clinical data were utilized to calculate Rockall scores to help ascertain disposition.

RESULTS: We utilized the SVMTorch package and Matlab coding of a standard ANN with backpropagation to implement the classifiers. Learning parameter settings were not extensively optimized, nor was extensive evaluation through multi-fold cross-validation performed due to the limited dataset. Training was performed on a randomly selected subset of 78 patients.

FIGURE 1: ANN ARCHITECTURE F
(20 INPUT NODES, 15 HIDDEN NODES, 1 OUTPUT NODE)

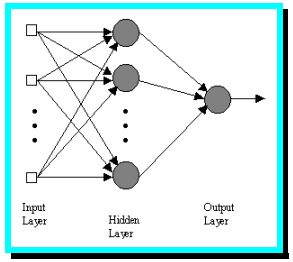

TABLE 1: CLINICAL INPUT VARIABLES

Presentation
- Hematemesis/Coffee Grounds
- Hematochezia/Melena

Demographics
- Age

Comorbidities
- CVD/COPD
- Risk of Stress Ulcer
- Cirrhosis
- ASA/NSAID use
- Prior history of GIB

Clinical Exam
- BP, HR, Orthostasis
- NG Lavage

Laboratory Data
- Drop of Hct
- Platelet count
- Creatinine, BUN/Cr ratio
- PT/INR

TABLE 2: PREDICTION VARIABLES

Source of GIB: Upper, Lower
Emergent Endoscopy: Yes, No
Disposition: Home, Regular Floor, Telemetry, ICU

TABLE 3: PREDICTION RESULTS

Missclassifications	ANN	SVM
Source	2.95 (7.56%)	3 (7.69%)
Emergent Endoscopy	13.2 (33.82%)	10 (25.64%)
Disposition	14.65 (37.56%)	11 (28.21%)

Testing was performed on the remaining (unseen-before) 39 patients. The architecture used for the ANN is shown in Figure 1. For SVM we used both polynomial and gaussian kernels. Table 3 summarizes the results for each prediction variable and for each classifier. Both models yielded similar performance, with the SVM model being slightly better. The best results were obtained for the prediction of source of GIB. Predictive results for "Disposition" were poorer representing a harder classification problem with 4 output. We speculate that the amount of training and testing data is rather small for this 20-dimensional classification problem. Nevertheless, these results in a very small representative sample clearly demonstrateing the potential of this approach.

CONCLUSION & IMPLICATIONS

With increasing medical knowledge and broad technological advances, diverse clinical tools will play an increasingly important role to help guide therapy.[8-13] While such tools may not replace experience and clinical acumen, they may aid and standardize clinical care of patients, improve outcomes, optimize healthcare costs and prevent adverse complications. The application of the ANN as a clinical tool in patients with GIB needs further validation in prospective randomized studies to test if it truly helps reduce mortality and results in cost savings among patients with acute GIB. Validation of such a model could potentially lead to application of this model to varied clinical scenarios.

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