Prediction tree for severely head-injured patients

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Prediction tree techniques are employed in the analysis of data from 555 patients admitted to the Medical College of Virginia hospitals with severe head injuries. Twenty-three prognostic indicators are examined to predict the distribution of 12-month outcomes among the five Glasgow Outcome Scale categories. A tree diagram, illustrating the prognostic pattern, provides critical threshold levels that split the patients into subgroups with varying degrees of risk. It is a visually useful way to look at the prognosis of head-injured patients. In previous analyses addressing this prediction problem, the same set of prognostic factors (age, motor score, and pupillary response) was used for all patients. These approaches might be considered inflexible because more informative prediction may be achieved by somewhat different combinations of factors for different patients. Tree analysis reveals that the pattern of important prognostic factors differs among various patient subgroups, although the three previously mentioned factors are still of primary importance. For example, it is noted that information concerning intracerebral lesions is useful in predicting outcome for certain patients. The overall predictive accuracy of the tree technique for these data is 77.7%, which is somewhat higher than that obtained via standard prediction methods. The predictive accuracy is highest among patients who have a good recovery or die; it is lower for patients having intermediate outcomes.

Key Words  •  head injury  •  prognosis  •  Glasgow Outcome Scale  •  prediction tree

Prediction of outcome for the severely head-injured patient has received much attention in recent years but remains difficult to achieve. An accurate prediction rule enhances the formulation of appropriate therapeutic and management plans, and can also provide a basis for family counseling. Such rules have been constructed using mathematical/statistical models that describe and quantify the relationships between possible prognostic factors (for example, age, motor score, and oculocephalic response) and outcome.

Previous attempts at modeling have used the same set of prognostic indicators for all patients. It is quite likely, however, that the set of important indicators differs among various patient subgroups. In other words, one would expect interactions between prognostic factors and outcomes. For instance, initial motor score may have a stronger influence on outcome in younger than in elderly patients. Another problem is that the previous prediction models do not provide any information about the critical point of each indicator. For example, it is known that age is negatively correlated with good outcome in a continuum, but it is not known if there is a most critical level for age, separating high-risk and low-risk individuals. Such information can be useful in therapeutic planning and for stratification in clinical trials, among other applications. Because of these problems, a general and more flexible method for relating prognostic information to outcome is desired. This paper uses data from a large head-injury database to construct a prediction tree. The tree structure shows that the sequence of important prognostic factors varies among patients. Such trees can easily be used to predict outcome in new patients.

Clinical Material and Methods

Patient Population

The data base contained information from 617 patients with severe head injury (not following commands and Glasgow Coma Scale (GCS) scores of < 9) who were admitted to the neurosurgical service of the Medical College of Virginia between May, 1976, and December, 1989. Patients with gunshot wounds of the head or those who arrived brain-dead were not included. Of these patients, 555 had a known 12-month outcome. The mean age of the patients was 30.9 years, the mean GCS score was 6.3, and 74% were males. The
characteristics of this patient series were similar to those described extensively in previous reports.1-4,16

Patient Management and Outcome

All patients in this database were managed according to a previously described protocol1-4,16 with emphasis on ventilatory support and control of intracranial pressure (ICP) below 25 mm Hg. The initial neurological assessment was performed in the emergency room after cardiopulmonary stabilization. Subsequent neurological examinations were performed on postinjury Days 1, 4, and 14, and in survivors at 3, 6, and 12 months. Outcomes were classified at 3, 6, and 12 months, according to the five Glasgow Outcome Scale (GOS) categories: good recovery, moderately disabled, severely disabled, vegetative, and dead. The distribution of outcomes of these 555 patients at 12 months postinjury is shown in Table 1. Only a small number of patients remain in the vegetative state at 12 months postinjury. Therefore, the severely disabled and vegetative categories were combined prior to data analysis.

Statistical Methods

We have studied 23 prognostic factors that may be related to outcome in head injury. These factors are listed in Table 2. The ICP was obtained during monitoring in the neurosurgical intensive care unit, but all other values were recorded at admission.

In the past, we have used logistic regression7,15,17 and discriminant analysis5,15 to model outcome as a function of prognostic information. Although reasonably effective in predicting outcome, these models were restricted to using the same set of prognostic indicators for all patients; hence, they lacked flexibility. Also, these methods did not provide prognostic variable thresholds — critical levels beyond which the risk of a poor outcome is substantially increased or decreased.

The prediction tree approach1 is an alternative to the traditional methods for prediction. It relies on statistically optimum recursive splitting of the patients into smaller and smaller subgroups, based on the critical levels of the prognostic variables. The splits are designed to produce maximum separation among subgroups and minimum variability within subgroups with respect to the outcome variable. The resulting tree structure is easily diagrammed, and a new case in which the prognostic variable levels are known can be run down the tree to predict outcome. Prediction trees take account of the fact that different relationships exist between variables in different patient subgroups. For instance, if the data is first split based on age, then the next split for younger patients may involve a factor different from that for older patients. Even if the split variable for the younger and older groups is the same, the actual threshold may differ.

Prediction trees are visually more informative and are easier to interpret than the mathematical expressions produced by the other methods. Not only can a prediction tree be used in prediction of outcome, but the threshold points can be useful in developing therapeutic strategies for individual patients.

Results

A prediction tree for 555 severely head-injured patients, based on their known 12-month GOS outcomes, is presented in Fig. 1. The oval in this hierarchical diagram denote intermediate subgroups, subject to further splitting. The name of the corresponding split variable is recorded within each oval, and the actual split values (thresholds) are indicated in the branches.
Prediction tree for severely head-injured patients

Fig. 1. Prediction tree based on 555 severely head-injured patients. The predicted 12-month outcomes (defined by the Glasgow Outcome Scale) are: G = good recovery; MD = moderately disabled; S = severely disabled; V = vegetative; and D = dead. **Ovals** denote intermediate subgroups subject to further splitting; **squares** denote terminal prognostic subgroups. The numbers below the squares represent the prognostic rank of each subgroup based on the proportion of good (G/MD) outcomes.

The terminal prognostic subgroups are represented by squares; within each square, the predicted 12-month outcome and the total number of patients having that pattern in the tree are given. The subgroups, ranked according to the proportion of good outcomes (good recovery plus moderately disabled), are numbered 1 to 8 as denoted below the squares. Thus, for example, Subgroup 1 is the group with the best prognostic pattern, while Subgroup 8 is the group with the worst prognostic pattern.

The patients are first split on the basis of their pupillary response. Patients with a bilaterally normal response are separated from patients having unilaterally or bilaterally absent responses. Subsequent splits in these two major branches of the tree show somewhat different patterns. As expected, the bilaterally normal patients tend to have reasonably good outcome, unless they are elderly or have an intracerebral lesion. Two of the earliest splits for the bilaterally normal cases are based on age, suggesting that age has a greater effect on outcome in these patients. Patients with a unilaterally or bilaterally absent pupillary response tend to have a poor outcome, with motor response and age appearing in subsequent splits.

Prediction of outcome for a patient is accomplished by simply running that patient down the prediction tree, according to the values of the prognostic factors. For example, a patient with a bilaterally absent pupillary response and a motor score of 2 or less would be placed in Subgroup 8. The predicted outcome for such a patient is severely disabled, vegetative, or dead. A 55-year-old patient with a bilaterally normal pupillary response and no intracerebral lesion would fall into Subgroup 2, and the expected outcome is good recovery or moderately disabled.

We have calculated the proportion of cases correctly
TABLE 3
Summary of prediction tree based on 555 severely head-injured patients.*

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>12-Month GOS Outcome</th>
<th>Prediction Rate (%) by Subgroup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Good</td>
<td>Moderate</td>
</tr>
<tr>
<td>1</td>
<td>110</td>
<td>19</td>
</tr>
<tr>
<td>2</td>
<td>21</td>
<td>9</td>
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<td>3</td>
<td>12</td>
<td>7</td>
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<td>6</td>
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<tr>
<td>7</td>
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<td>3</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>total</td>
<td>192</td>
<td>76</td>
</tr>
</tbody>
</table>

*Overall prediction rate is 77.7%. GOS = Glasgow Outcome Scale; veg = vegetative.

classified in each subgroup, in each outcome category, and for the entire data set. These findings are summarized in Table 3. Predictive accuracy is much higher for good recovery and death than for the intermediate outcomes. Previous investigators have also found it difficult to predict intermediate outcomes with a high degree of accuracy. A similar trend is evident among the accuracy rates for the subgroups. Note that subgroups 1 and 8 have the two highest predictive accuracy rates, while Subgroup 5 has the smallest. The overall predictive accuracy was 77.7%.

Although 23 prognostic factors were considered in this analysis, only four were actually used in construction of the prediction tree. Three of these, pupillary response, motor score, and the age on admission, have been shown to be effective predictors of outcome in previous studies. Mass lesion data also play an important role in determining outcome in some patients. The other prognostic factors, although not meaningless, are less closely associated with outcome. We found that, for each split, a short list of “competitor” splits describes the best alternative splits at that point. For example, pupillary size, ocularcephalic response, eye response, and \( pO_2 \) level appear often as competitors in the analyses; consequently, these variables may well possess some predictive power, even though they do not appear in Fig. 1.

The primary benefit of the prediction tree technique remains the illustration of the important prognostic variables and their thresholds as related to patient outcomes. Another benefit is that it shows some common prognostic patterns, ranked in terms of likely outcomes.

**Discussion**

One would expect interactions between prognostic factors and outcomes in head injury. For instance, the effect of different motor scores is likely to vary among different age groups. Therefore, we believe that recursive partitioning is a promising strategy for identifying subgroups that might be missed by traditional prediction methods. Besides, a prognostic tree is a visually useful way to look at the prognosis of head-injured patients.

We have constructed a prediction tree for severely head-injured patients and have examined its predictive accuracy. The subgroup accuracy rates range from 57% to 90%, but the higher accuracy of prediction was attained in subgroups where good outcomes (Subgroup 1) or bad outcomes (Subgroup 8) predominate. One interesting and important pattern emerges from the examination of accuracy of the method. For subgroups with poor prognosis (that is, Subgroups 5 to 8) the proportion of good outcomes is relatively large, while the proportion of poor outcomes in the subgroups with good prognosis (Subgroups 1 and 2) is considerably lower. In other words, the results indicate proportionately more pleasant surprises than unpleasant surprises.

Although the prediction tree in Fig. 1 contains eight terminal subgroups, the sample sizes for several subgroups are rather small (for example, there are fewer than 40 patients in Subgroups 2 and 7); hence, it is difficult to obtain precise estimates of the predictive accuracy in these subgroups. It would also be inappropriate to construct larger trees for these data, since the subgroup sample sizes would become even smaller. However, a tree with too few terminal subgroups fails to consider all of the important prognostic variables. It is believed that the tree in Fig. 1 accurately depicts the relationships between the prognostic factors and outcome. It should be mentioned that a larger tree with more subgroups can be constructed if the number of patients is much larger. In such cases, as implied, other factors such as \( pO_2 \), systolic blood pressure, or body temperature could appear in the tree following the important factors shown in Fig. 1. Of course, the larger the tree, the more difficult it is to visualize the prognostic patterns. The statistical problem of determining the “optimum” number of splits has been addressed by Breiman, et al. 2

As previously stated, the overall predictive accuracy of the prediction tree is 77.7%. We wished to compare this rate with those obtained using more traditional methods of prediction. Accordingly, stepwise logistic regression and stepwise discriminant analyses were performed on the head-injury data, using the same prognostic factors employed in the prediction tree. The overall predictive accuracies obtained were 74.2% for logistic regression and 74.6% for discriminant analysis. Note that these rates for 12-month outcomes are lower than the previously published figures for 3-month and 6-month outcomes. The prediction tree technique achieved the highest predictive accuracy of the three approaches. Moreover, this technique is a nonparametric procedure which does not require the restrictive statistical assumptions of the other two methods. Finally, prediction trees give the best visual representation of the prognostic patterns determined from the data.
Prediction tree for severely head-injured patients

Previous investigators have noted that reclassification of an original sample provides an overly optimistic estimate of predictive accuracy. Therefore, we would expect the prediction tree model to be somewhat less accurate when predicting outcomes in an independent set of patients. Moreover, the accuracy rate is expected to be different if the proposed prediction tree is used to predict outcomes of patients from other centers. Among other confounding factors, the therapeutic approaches used in different centers are not necessarily identical, and considerable disagreement is expected among physicians in determining the GOS score. Prediction of outcome in head injury will remain a somewhat subjective exercise, and the tree technique is meant to supplement, not to replace, the physician's clinical judgment and other prediction schemes.

These methods could be utilized in many other clinical investigations. Another important neurosurgical application would be the construction of a prediction tree to identify patients with an increased risk of mortality or morbidity after subarachnoid hemorrhage, using factors such as age, computerized tomography results, site of aneurysm, and GCS score.

References

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