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Expert system for prediction of avalanches

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Many statistical as well as classical methods have been developed as guidance tools for forecasting avalanches. Statistical methods are based on strict mathematical procedures (i.e. mathematical expression used to build the system) and classical methods are mainly based on reasoning and lack in analytical explanation. To overcome the problems posed by both the methods, a data-based expert system has been developed for the Chowkibal–Tangdhar road axis in Pir Panjal range of NW Himalaya. The expert system has been developed using situation-based rules which make it highly flexible and compact. In addition, an inductive incremental learning feature has been included in the model. The developed expert system predicts a day as avalanche day, with degree of avalanche danger as practised for operational avalanche forecasting in NW Himalaya, or as a non-avalanche day. It has been tested independently with two types of avalanche occurrence namely, actual avalanche occurrence reports available and these reports combined with the expert forecaster's assessment of the situation. This is mainly to overcome the loss of avalanche occurrence information due to bad weather conditions during winter. Independent testing of the expert system with actual avalanche occurrence reports available combined with the expert forecaster's assessment of the situation may help largely to ensure whether the system is in agreement or disagreement with the assessment of the expert avalanche forecasters. The developed expert system was tested independently for the past five winters. The independent test results show that the expert system predicts more than 80% days correctly for both types of avalanche occurrence information. The results are encouraging and the expert system is in good agreement with the assessment of expert avalanche forecasters.

Keywords: Avalanche, avalanche prediction, expert system.

TWO predominant methods for forecasting avalanche danger are the conventional and statistical methods[1,2]. Conventional avalanche forecasting is practised as a mix of deterministic treatment for snow and weather parameters and inductive logic to reach an actual forecast decision[1]. The statistical methods utilize past measured data of snow, weather and avalanche occurrence to distinguish avalanche days from non-avalanche days. The statistical

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methods include discriminant analysis[3], nearest neighbour method[4] and a combination of different statistical methods[2]. Operational avalanche forecasting based on the above methods is widely practised in India and worldwide.

Statistical methods are mainly based on strict mathematical procedures (i.e. dependent on mathematical expression used to build the system) and to completely transfer the forecaster's logic in the statistical model is a difficult and challenging task. However, avalanche forecast purely based on statistical methods is rarely practised. Classical methods lack analytical explanation and substantially depend on domain expert knowledge and experience, and are subjectively influenced. Therefore, classical methods are difficult to understand easily. Any avalanche forecast system based on a combination of both the methods, i.e. statistical as well as classical, may be more productive in assisting the avalanche forecaster to make better forecast decisions. This is because it may allow inclusion of domain expert knowledge and it may be easy to understand the model decision-making process.

One of the many possible ways to include the reasoning of the expert avalanche forecaster in any avalanche prediction model is to develop an expert system using rules. We propose an expert system for prediction of avalanches which includes both the procedures, i.e. classical procedure to form rules and analytical procedure to reach a forecast decision. The developed expert system predicts a day as avalanche day with degree of avalanche danger, or as no avalanche day. The developed expert system has been tested independently for the past five winters and results are briefly discussed.

The present study area falls in the Pir Panjal range of NW Himalaya, which is characterized as warm temperature, deep snow cover and heavy snow precipitation[5]. The Chowkibal–Tangdhar (CT)-axis is the only road connecting the districts of Tithwal and Kupwara, the road axis passing over the Pir Panjal range at Nasta–Chun pass, at an altitude of 3120 m msl. Movement along this road axis become hazardous due to the lurking danger of avalanches during winter. To provide necessary guidance to the people and to collect snow, weather and avalanche occurrence data, an observatory named stage-II was set up on the CT-axis in the early 1990s. The winter study team collects snow, weather and avalanche occurrence data twice daily at 0830 and 1730 h. Data of the past 12 winters (1991–92 to 2003–04, exclusive of missing data of winter 1994–95) recorded at stage-II are utilized in this study. The data of seven winters (1991–92 to 1998–99) were utilized to develop the expert system, which was tested independently for the next five winters (1999–2000 to 2003–04).

The loss of avalanche occurrence information during winter cannot be ruled out completely[3,6]. To overcome the loss of avalanche occurrence information, expert forecaster's assessment of the situation was taken independent of the actual avalanche occurrence reports available in the dataset. This is required because we rarely get complete avalanche occurrence reports on a specific area of interest during heavy snowstorm or immediately after it. Such days create suspicion about their category, i.e. avalanche day or non-avalanche day, and are mainly days in which avalanche warnings were issued in the past, i.e. expert forecasters assessed them most likely as avalanche days. Suspicious days of the past were assigned the appropriate class label, i.e. avalanche day or non-avalanche day. The expert avalanche forecaster's assessment of the situation was mainly based on long-term experience, the snow and weather conditions on suspicious days and field snow stability tests. After supplementing the expert forecaster's assessment of the situation for suspicious days, we are left with the two types of avalanche occurrence information, i.e. actual avalanche occurrence reports available and these reports combined with the expert forecaster's assessment of the situation.

The model was developed and calibrated utilizing actual avalanche occurrence reports of past seven winters only (1991–92 to 1998–99) and tested independently with both types of avalanche occurrence information mentioned earlier, for test winters (1999–2000 to 2003–04). The model was deliberately developed with the actual avalanche occurrence reports available to avoid any ambiguity that may be introduced in the model by developing it with the actual avalanche occurrence reports available combined with the expert forecaster's assessment of the situation. However, it may be relevant to develop the model using the latter[2]. Before employing any such scheme careful assessment of model performance is necessary. Thus, independent testing of the model with actual avalanche occurrence reports available combined with the expert forecaster's assessment of the situation will allow us to test the model with respect to the assessment of the expert avalanche forecasters, i.e. whether the model is in agreement or disagreement with the expert forecasters.

The expert system can be used to simulate the decision-making process of the expert avalanche forecaster. The pragmatic expert based on his experience, intuition and knowledge reaches a forecast decision, which largely depends on inductive logic and reasoning. However, experts are unable to explain their decision-making process completely[7]. The decision-making process of any expert avalanche forecaster involves recalling of memory for the past similar situations, logically relating them with the present situation (i.e. forecast day) and drawing inferences about avalanche danger situation.

The expert system presented here, has been developed using 'if, then' rules. Each rule represents the input condition and logic required to reach on decision, i.e. data needed to reach a specific decision and criterion used to evaluate the data. Thus, each rule provides a relationship between the antecedent and consequent part of the rule. In our case the antecedent part of any rule is the condition

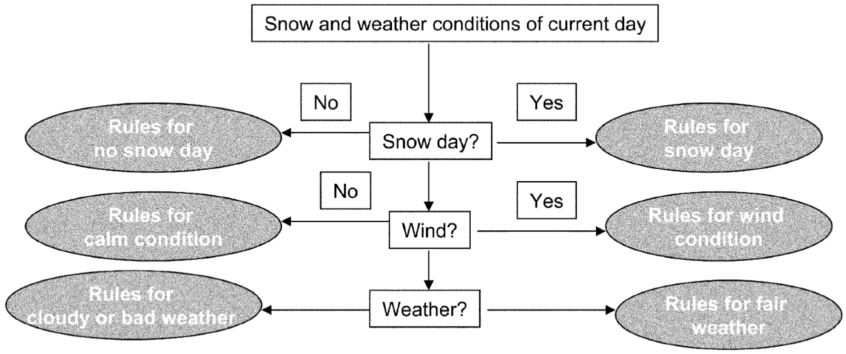

Figure 1. Strategy followed for development of rules in the expert system.

Table 1. Variables used for development of expert system

Variable	Unit
Maximum temperature	°C
Minimum temperature	°C
Average wind speed	km/h
Cloudiness	Octa
New snow depth	Centimetre
New snow depth in the past 24 h	Centimetre
New snow depth in the past 48 h	Centimetre
New snow depth in the past 72 h	Centimetre
Snow cover depth	Centimetre
Sunshine	Hours

in the input space (i.e. variables) and the consequent part of each rule is rule weight. The rule weight is computed statistically from the past similar situations and can be thought of as equivalent to the logical importance of a rule. It is computed from past similar situations and depends on avalanche days (i.e. proportion of avalanche days). Rule weight of each rule in our case is a measure of how a particular rule contributes to the logical model as whole and can never exceed 1.0 (see below). In logical sense, rule weight can be viewed as the knowledge extracted from the data.

The rules in our case represent conditions on the variables and a combination of these. The variables chosen for development of the expert system are the same as reported earlier by many avalanche researchers[3,4,6]. The criteria for forming rules are based on experience and reasoning, i.e. different sets of rules for snow day (new snow depth in the past 72 h > 0.0 cm) and no snow day (new snow depth in the past 72 h = 0.0 cm), observed weather, average wind speed, etc. The strategy followed, in general, to form rules in the expert system is shown in Figure 1.

Each day in the past dataset represents a unique situation, i.e., two situations may rarely be identical, if not impossible. Therefore, to develop an avalanche prediction scheme, forming rules for each existing situation in the past database is difficult and complexity of such a system may increase continually with increasing size of the dataset. Further, it is difficult to know in advance how many situations in the dataset have to be coupled together to form a rule and how many rules will be sufficient to develop a successful expert system.

To overcome the above-mentioned problems, we developed an expert system with the help of situation-based rules, i.e. the system based on the input conditions automatically generates the rule set for each new situation encountered at the input (i.e. forecast day). However, the general criteria to form rules for different variables (Table 1) and a combination of them are well defined. Situation-based rules provide expert system a high degree of flexibility and compactness.

Based on the input value of each variable, the expert system specifies the condition for searching past similar situations and computes the rule weight. The condition for searching similar situations may be the current value or range around the current value of each variable depending on the situation, i.e. snow (snow day, no snow day), average wind speed (calm condition, windy condition) and weather (fair weather, cloudy or bad weather), etc.

In addition to situation-based rules, the heuristic rule has been included in the model. This rule decides whether the irregularity has been filled to initiate the avalanche activity in the area or not. This rule has been developed partially analysing past avalanche occurrence data and after consulting experienced forecasters. If heuristic condition is not met for any day, then the model directly predicts a day as no avalanche day, i.e. no avalanche danger.

We outline below how the model works in real situations and the rules generated based on maximum temperature and new snow depth in the past 72 h (Table 1).

Rule 1. If maximum temperature $\geq A1$ and $\leq A2$, then W_1 is the proportion of avalanche days. W_1 is the rule weight of rule 1.

Rule 2. If new snow depth in the past 72 h = 0 and snow cover depth $>H1$ and $\leq B1$, then (rule for no snow day).

W_2 is the proportion of avalanche days in the past. W_2 is the rule weight of rule 2.

Else, if new snow depth in the past 72 h > 0 and $\leq C1$ and snow cover depth $>H1$ and $\leq B1$, then (rule for snow day).

W_2 is the proportion of avalanche days. W_2 is the rule weight of rule 2.

In the above rules, $A1$ and $A2$ are the range around the current-day value of maximum temperature; $H1$ defines the heuristic condition, $B1$ is the current-day value of snow cover thickness (necessarily $B1 > H1$), and $C1$ is the current-day value of new snow depth in the past 72 h.

For any input situation for which the heuristic condition is met, the expert system generates a rule set, as above, and computes the rule weight accordingly. Rules in the expert system represent the variables and a combination of these, and the rule weight of each rule can be thought of as support (i.e. logical importance) of each variable towards avalanche occurrence. The rule weight of all rules is added to decide the rule weight of the expert system. The rule weight of the expert system indicates whether variables favour avalanche days or not, in a logical model as whole. The process can be thought of as equivalent to the decision-making process of an expert avalanche forecaster. While forecasting, the expert analyses each variable and assigns logical importance to it coupled with his experience, knowledge and intuition. He then assembles the information conveyed by all the variables logically to reach a forecast decision. To make decisions in a similar fashion as the expert avalanche forecaster, we add up all the rule weights. However, it can be argued that the rule weights can be multiplied. Multiplying the rule weights of different rules is not reasonably correct and may lead to the worst model. This is because at any given day, one variable may not favour an avalanche day while all others may be in favour of it. The rule weight of the expert system is calculated using following expression.

$$W = \sum W_i,\ i = 1 \ldots n, \text{ where } n \text{ is number of rules.}$$

The developed expert system was run for each day of model development data and rule weight of the expert system was retained along with the observed avalanche activity. The threshold value of the rule weight of the expert system was decided for which it performs best for the classification of avalanche day and non-avalanche day in the model development data. The threshold value of the rule weight of the expert system was chosen as the decision criteria of the expert system. Based on this value, the expert system predicts any day in the test dataset as avalanche day or no avalanche day as follows.

$$Y = \begin{pmatrix} 0, \text{ if } W \leq W_{\text{th}}, \text{ No avalanche day} \\ 1, \text{ if } W > W_{\text{th}}, \text{ Avalanche day} \end{pmatrix},$$

where Y is output of the expert system, W the rule weight of the expert system for any day (i.e. forecast day) and W_{th} the threshold value of the rule weight.

Prediction of any day as avalanche day or no avalanche day in operational avalanche forecasting does not provide sufficient information, about the existing avalanche danger (Table 2). To achieve this, our aim was to develop an expert system for operational avalanche forecasting (Table 2). The avalanche days with the rule weight of the expert system for model development data and avalanche warning bulletins issued in the past were analysed. Different threshold values of rule weights of the expert system were chosen considering the distribution of the rule weights and avalanche warnings issued in the past. The expert system predicts avalanche danger under different scales based on the threshold values of the rule weight of the expert system as follows:

$$Y = \begin{pmatrix} 0, \text{ if } W \leq W_{\text{th}}^1, \text{ No avalanche danger situation} \\ 1, \text{ if } W_{\text{th}}^1 < W \leq W_{\text{th}}^2, \text{ Low avalanche danger situation} \\ 1, \text{ if } W_{\text{th}}^2 < W \leq W_{\text{th}}^3, \text{ Medium avalanche danger situation} \\ 1, \text{ if } W_{\text{th}}^3 < W \leq W_{\text{th}}^4, \text{ High avalanche danger situation} \\ 1, \text{ if } W > W_{\text{th}}^4, \text{ All around avalanche danger situation} \end{pmatrix},$$

where W_{th}^1, W_{th}^2, W_{th}^3 and W_{th}^4 are threshold values of rule weights for low avalanche danger situation, medium avalanche danger situation, high avalanche danger situation and all around avalanche danger situation respectively (Table 2) and W is the rule weight of the expert system for any input situation (i.e. forecast day). Logically, a large value of rule weight of the expert system for any day means greater avalanche danger (i.e. all variables favouring avalanche occurrence). Thus, threshold rule weights associated with different avalanche danger scales are logically bound by the following condition:

$$Y = 1 \text{ and } W_{\text{th}}^1 < W_{\text{th}}^2 < W_{\text{th}}^3 < W_{\text{th}}^4,$$

since, low avalanche danger is at a minimum level and all around danger is at the highest level of avalanche danger.

The developed expert system was tested independently for past five consecutive winters consisting of 550 records, with both types of avalanche occurrence information mentioned earlier. To test any forecast system rigorous comparison of day-to-day forecasts with actual observations is necessary. Any day with at least one avalanche along the road axis has been taken as an avalanche day[3,6] to verify the model with the actual avalanche occurrence reports available. For verifying model performance with actual avalanche occurrence reports available combined with the expert forecaster assessment of the situation, the expert's assessment (i.e. avalanche day/no

Table 2. Practised avalanche danger scales and suggested precautions in India

	Avalanche danger scale
Degree of danger	Avalanche release probability from different types of slopes, on sequences and suggested precautions.
Low avalanche danger	Generally favourable condition. Triggering is generally possible only with high additional loads and on few extreme slopes. Only sluffs possible and reach the valley in small sizes. Valley movements are safe. Movement on slopes with care.
Medium avalanche danger	Partly unfavourable condition. Triggering is possible from most avalanche-prone slopes with low additional loads and may reach the valley in medium size. Avoid steep slopes. Routes should be selected with care. Valley movements with caution. Movements on slopes with extreme care.
High avalanche danger	Unfavourable condition. Triggering possible from all possible avalanche-prone slopes even with low additional loads and reach the valley in large size. Suspend all movements. Airborne avalanches likely.
All around avalanche danger	Very unfavourable condition. Numerous large avalanches are likely from all possible avalanche slopes, even on moderately steep terrain. Suspend all movements. Airborne avalanche likely.

Table 3. Prediction of avalanche danger with the help of the expert system for test winter period

Forecast		Observation							
		Actual avalanche occurrence reports				Actual avalanche reports available combined with the expert forecaster's assessment of the situation			
Avalanche danger scale	Total days	AV days	NAV days	Accuracy (%)		Total days	AV days	NAV days	Accuracy (%)
Low avalanche danger	65	26	39	40.00		65	31	34	47.69
Medium avalanche danger	32	16	16	50.00		32	19	13	59.38
High avalanche danger	20	9	11	45.00		20	12	8	60.00
All around avalanche danger	22	17	5	77.28		22	19	3	86.37
No avalanche danger	411	17	394	95.86		411	18	393	95.62

AV days, Avalanche days; NAV days, Non-avalanche days.

Table 4. Various accuracy measures of the expert system (AV days/ NAV days)

Statistical accuracy measure	Actual avalanche occurrence reports available	Actual avalanche occurrence reports combined with the expert forecaster's assessment of the situation
Probability of detection	0.80	0.82
False alarm rate	0.48	0.42
Miss rate	0.20	0.19
Correct non-occurrence	0.85	0.87
Critical success index	0.44	0.52
Bias	1.63	1.41
Per cent correct	84.0%	86.2%

avalanche day) for suspicious days was also considered, in addition to the actual avalanche occurrence reports available. Model performance under each avalanche danger scale has been verified considering the proportion of avalanche days, although it may not be adequate to consider the proportion of avalanche days for verifying the model forecast under different avalanche danger scales. Due to lack of accurate avalanche occurrence information (i.e. suspicious day), we consider only proportion of avalanche days.

For evaluating the performance of the expert system, a 2×2 contingency table was prepared for both types of avalanche occurrence information. To verify any forecast system under categorical forecast, various accuracy measures have been suggested[8] and reported in the literature[9]. Probability of detection (POD), false alarm rate (FAR), miss rate (MR), correct non-occurrence (C-NON), critical success index (CSI) and per cent (PC) correct were taken as the various accuracy measures and bias was taken as the measure of tendency of model prediction (i.e. overforecast/underforecast).

Comparing model predictions with the actual observations on a day-to-day basis, the expert system predicts more than 80% days correctly with both types of avalanche occurrence information (Table 4). However, this appears to be a high score achieved. In view of the rarity of the avalanche days (i.e. 15% days in test data), overall performance cannot be taken as the measure of the performance[10]. Particularly, when the event to be forecast (i.e. avalanche day) occurs substantially less frequently than its non-occurrence (i.e. as no avalanche day). The various accuracy measures of the model performance are shown in Table 4. The POD of the expert system was found to be 0.80 and 0.82 respectively, for the actual avalanche occurrence reports available and the actual avalanche occurrence reports combined with the expert forecaster's assessment of the situation. The MR of model was 0.20 and 0.19 for both types of avalanche occurrence information. This indicates that the model prediction for avalanche days is fairly good. The FAR of expert system was above 0.40 with both types of avalanche occurrence reports. The expert system over-predicts with both types of avalanche occurrence information. However, overforecast tendency of the expert system is found to be less with the actual avalanche occurrence reports available combined with the expert forecaster's assessment of the situation compared to the actual avalanche occurrence reports available (Table 4).

The performance of the expert system under different avalanche danger scales is given in Table 3. Under each avalanche danger scale, the performance of the expert system is expressed as percentage of avalanche days. Model performance is poor with actual avalanche occurrence reports and it improves for all the danger scales with the inclusion of expert forecaster's assessment of the situation (Table 3). This indicates that the model is in good agreement with the assessment of the expert forecasters. Significant improvement in model performance under high avalanche danger scale with the inclusion of the expert forecaster's assessment of the situation (Table 3) indicates that there is definite loss of avalanche occurrence information.

The expert system developed correctly predicts more than 80% days with both types of avalanche occurrence information. The performance of the expert system is fairly good for the prediction of avalanche days along the road axis with the available information. It performs poorly for identification of avalanche danger with the actual avalanche occurrence reports. However, it improves with the inclusion of the expert forecaster's assessment of the situation. This is mainly due to the lack of complete avalanche occurrence reports.

The situation-based rules can be developed according to time of winter and the expert system can be calibrated accordingly to propose decision. Further, it is necessary to integrate the latest avalanche occurrence reports in any avalanche prediction model for better assessment of the avalanche danger situation, which has not been included yet. The developed expert system needs to be tested on a large dataset with accurate avalanche occurrence information. This may help largely to improve the expert system.

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Discovery of trilobite trace fossils from the Nagaur Sandstone, the Marwar Supergroup, Dulmera area, Bikaner District, Rajasthan

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Well-preserved trace fossils produced by trilobites are reported from the upper part of the Nagaur Sandstone of the Nagaur Group, the youngest group of the Marwar Supergroup (Trans-Aravalli Vindhyans). The trace fossils are preserved as epirelief on the sole of the silty shale beds. The trace fossils are *Cruziana* isp., *Dimorphichnus* isp., *Rusophycus* isp. and *Aulichnites* isp. Except *Aulichnites*, the trace fossils are known to have been produced by trilobites. Indication of the presence of trilobites in the Nagaur Sandstone gives the trace fossil-bearing horizon a Lower Cambrian age. Thus the present finding supports a Lower Cambrian age to the upper part of the Marwar Supergroup.

Keywords: Marwar Supergroup, Nagaur Sandstone, trace fossils, trilobites.

THE Marwar Supergroup occupies a large area in north-western Rajasthan and attains a thickness of more than 1000 m that unconformably overlies ca. 779–681 Ma old Malani Igneous suite[1]. As such the sediments of the Marwar Supergroup are considered younger than 680 Ma. No radiometric dates are available for the Marwar Super-

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