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Application of Neural Networks for Avalanche Forecasting

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ABSTRACT

Application of neural networks is investigated for the prediction of avalanches on Chowkibal-Tangdhar road axis in Jammu and Kashmir. The networks are developed and trained monthwise using the past snow and weather parameters recorded at the Stage-II Observatory on the axis to generate an assessment of avalanche and non-avalanche activities. Two approaches have been considered for training the network. In the first approach, only avalanche activities observed in the axis were taken for training, and in the second approach, along with the observed activities, the opinion of expert forecasters were also considered. The performance of the networks varies from 67 to 82 per cent for correct predictions. Winter data for 2001-2002 has been used to validate the network performance.

Keywords: Neural networks, artificial intelligence, avalanche prediction, avalanche forecasting

1. INTRODUCTION

Various forecasting methods such as statistical, deterministic, and artificial intelligence are being used worldwide to assess avalanche hazard[1-4]. In the whole world, widely used conventional forecasting, forecasters use their knowledge and experience with snow stability situations to perform avalanche forecasting. In early nineties, attempts were made to use artificial intelligence for avalanche forecasting, Schweizer[4], *et al.* developed a hybrid system, ALUDES, which clubs neural network and rules extracted from the database. Schweizer[5], *et al.* experimented with commercially available judgement processor COGENSIS™ MEPRA, a French expert system, analyses snowcover data for avalanche risk forecasting[1]. In Snow and Avalanche Study Establishment, Manali, attempts have also been made to use artificial intelligence techniques for avalanche forecasting[6-9].

The present study investigates the application of neural networks for prediction of avalanches on Chowkibal-Tangdhar road axis in Jammu and Kashmir, which falls in the lower Himalayan zone (Fig. 1). It negotiates and crosses the Pir Panjal range[10] at Nastachun pass. A stretch of 36.18 km is characterised by 26 registered avalanche sites. It is on account of heavy pedestrian traffic (approx. 3000 personnel per month) and their unavoidable interaction with the avalanches, this axis is considered for the study.

2. METHODOLOGY

A neural network is a network of many simple units called processing elements or nodes linked by unidirectional communication channels, which feed the signal forward in response to the input. Neural network utilises mathematical expression and the nodes are valued with numerical weights[11-13].

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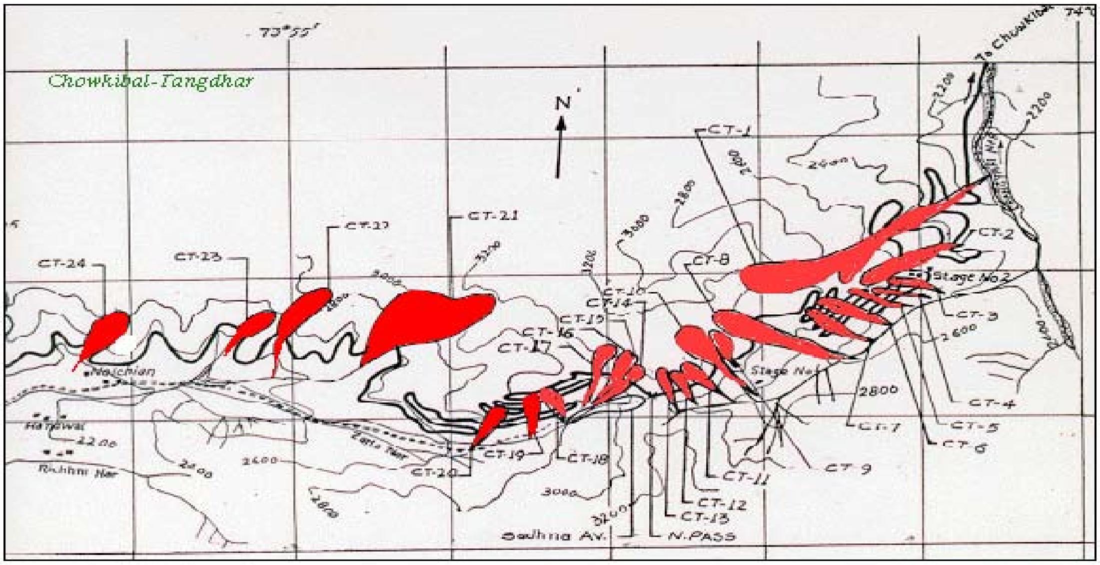

Figure 1. Avalanche sites of Chowkibal-Tangdhar axis.

Input values in the first layer are weighted and passed to the second (hidden) layer; the nodes in the hidden layer produce output that are based on the sum of the weighted values passed to these. The hidden layer passes value to the output layer in the same fashion, and the output layer produces the results. Neural network works on parallel processing, through several input, perform a series of operations on these, and produce one or more output. A typical network has one input, one output, and few hidden layers (Fig. 2).

For monitoring any avalanche-prone road axis, snow and weather parameters are recorded daily at 0830 h and 1730 h at a representative observatory in the axis. For the present study, a total of 751 records of seven relevent[14] snow and weather parameters recorded at 1730 h for the past eight years winter, from 1991-1992 to 2000-2001 at the Stage-II observatory in Chowkibal-Tangdhar axis have been considered. These parameters are directly observed and the derived variables, viz, maximum temperature, 24 h

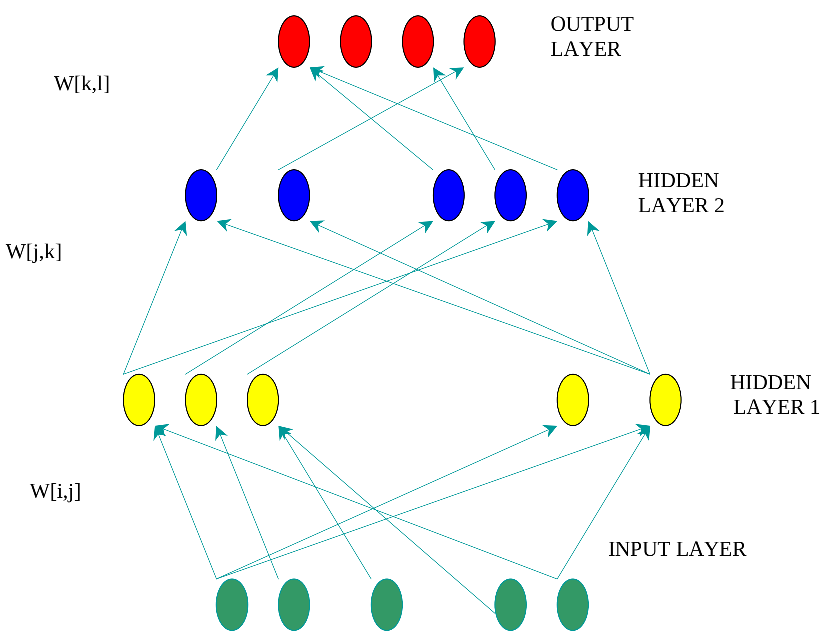

Figure 2. Schematic diagram of multi-layered neural network.

departure of ambient temperature, fresh snowfall, 24-h fresh snowfall, 72-h fresh snowfall, standing snow, and 24 h departure of snow surface temperature. Each parameter is scaled prior to the implementation of the neural network using linear scaling (Table 1). Since the output is the subjective information regarding avalanche activity, this information is implemented by assigning the numeric equivalence index. It is assumed as 0.9 for avalanche activity and 0.1 for non-avalanche activity. Randomly selected 80 per cent of the data set is used for training of the network and remaining 20 per cent data set is used for testing it.

The backpropagation algorithm is used to reduce the error between the predicted and the desired output in a gradient-descent manner[15]. The output (O_k) is calculated by the relation

$$O_k = \sigma\left(\sum_{i=1}^{i=n} W_{ki} X_i\right) \tag{1}$$

where σ is the activation function, X_i and W_{ki} are the i^{th} input and weight associated with it and k^{th} output. The calculated values of the output are compared with the desired output, the difference constitutes the error.

During the learning process, the error is reduced using least square error minimisation scheme. The process then modifies weights through an iterative training procedure. The weight-modification mechanism, which reduces the total error, E, to a tolerance limit is given by:

$$\Delta W_{ki} = -\eta \frac{\partial E}{\partial W_{ki}} \tag{2}$$

Table1. Input parameters used in neural networks

Input parameter	Scaling scheme
Tx (Maximum temperature) (°C)	(Tx+7.5)/30
Dta (24-h departure of ambient temperature) (°C)	(Dta+7.5)/20
Hn (Fresh snow) (cm)	Hn/60
Hnf (24-h fersh snow) (cm)	Hnf/150
Hns (72-h fresh snow) (cm)	Hns/250
Hs (Standing snow) (cm)	Hs/350
Dts (24-h departure of snow surface temperature) (°C)	(Dts+8.5)/17

where

$$E = \frac{1}{2}\sum_{k=1}^{m} (T_k - O_k)^2 \tag{3}$$

In Eqn (2), ΔW_{ki} is change in weight, η is the learning rate, which controls the rate of change of weight, and in Eqn (3), E is the error, T_k is the target output, and O_k is the predicted output.

3. RESULTS AND DISCUSSION

Networks are trained monthwise for afternoon data set of winter months using various network sizes. It was found that for December and January months, three-layered network with 7, 3, and 1 nodes and for the other months, four-layered network with 7, 4, 2, and 1 nodes give optimal solutions. During training, the weights were updated to reduce the error in each cycle. Total 4000 to 6000 cycles were considered for training the networks. Figure 3 depicts the change in error during the training of the network.

The output index is calculated on the basis of the weights settled during training the networks. Most of the predicted indexes are close to 0.1 and 0.9 while a wide floating numerical range in between is also obtained; therefore, the values closer to 0.9 are considered as accurate avalanche prediction, values closer to 0.1 are considered as accurate non-avalanche prediction, whereas values other than these are considered as mis-matched prediction. For training the networks, two strategies were adopted. In the first approach, only the avalanche occurrences observed in the axis were used, while in the other approach, along with the avalanche occurrences, the opinion of expert forecasters on avalanche hazard in the form of avalanche warnings on that axis were also considered. The test results obtained in both the strategies have been compared in Table 2. The validation of the network performance is done for both the methods and presented subsequently.

3.1 Test Performance when Only Avalanche Occurrence Used

The overall test performance of the networks is 67.7 per cent. The network trained for December predicts avalanche days with 40 per cent and non-

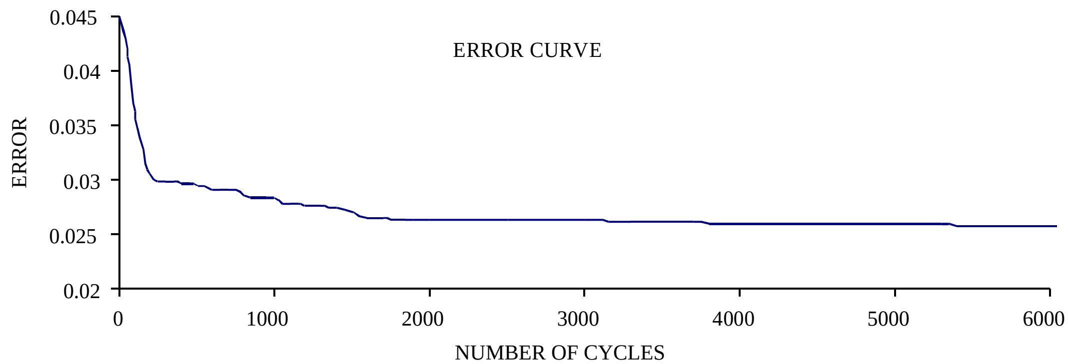

Figure 3. Error wrt number of cycles.

avalanche days with 84.6 per cent accuracy. Network trained for January predicts 42.8 per cent avalanche days and 87.5 per cent non-avalanche days correctly. Network trained for February could not predict avalanche days but predicted non-avalanche days with 81 per cent accuracy. Further investigation of the network structure and training methodology is required for better predictions of the avalanche days. Network trained for March predicts avalanche days with 66.7 per cent and non-avalanche days with 55.5 per cent accuracy. Trained network for April gives cent per cent correct prediction on avalanche days and 80 per cent correct prediction on non-avalanche days. Figure 4 shows the comparison between prediction and observed index values for the test data of December.

The performance of the networks on validation data is summarised in Table 3. The trained networks tested for winter 2001-2002 for validation gave overall 76.8 per cent correct predictions, 74 per cent correct predictions for December with 33 per cent correct predictions for avalanche days and 78.6 per cent for non-avalanche days. For January, it gave 87 per cent correct predictions, avalanche days with 33 per cent and non-avalanche days with 93 per cent accuracy. Network trained for February could not predict avalanche days but predicted non-avalanche days with 87 per cent accuracy.

Validation results for March gave 67.7 per cent correct predictions with 33 per cent for avalanche days and 71 per cent for non-avalanche days. In April there were only non-avalanche days and were predicted with 83 per cent accuracy. Fig. 5 shows the comparison between the predicted and the observed index values for December.

Table 2. Monthwise test performance of the trained networks

Month	Cases	Network trained with only observations			Network trained with observations along with expert opinion		
		Observed	Predicted	Mis-match	Observed / Assessed	Predicted	Mis-match
December	Avalanche days	05	02	03	06	05	01
	Non-avalanche days	13	11	02	12	09	03
January	Avalanche days	07	03	04	08	05	03
	Non-avalanche days	16	14	02	15	14	01
February	Avalanche days	08	-	08	08	06	02
	Non-avalanche days	16	13	03	16	14	02
March	Avalanche days	06	04	02	07	05	02
	Non-avalanche days	09	05	04	08	06	02
April	Avalanche days	03	03	-	03	03	-
	Non-avalanche days	10	08	02	10	09	01

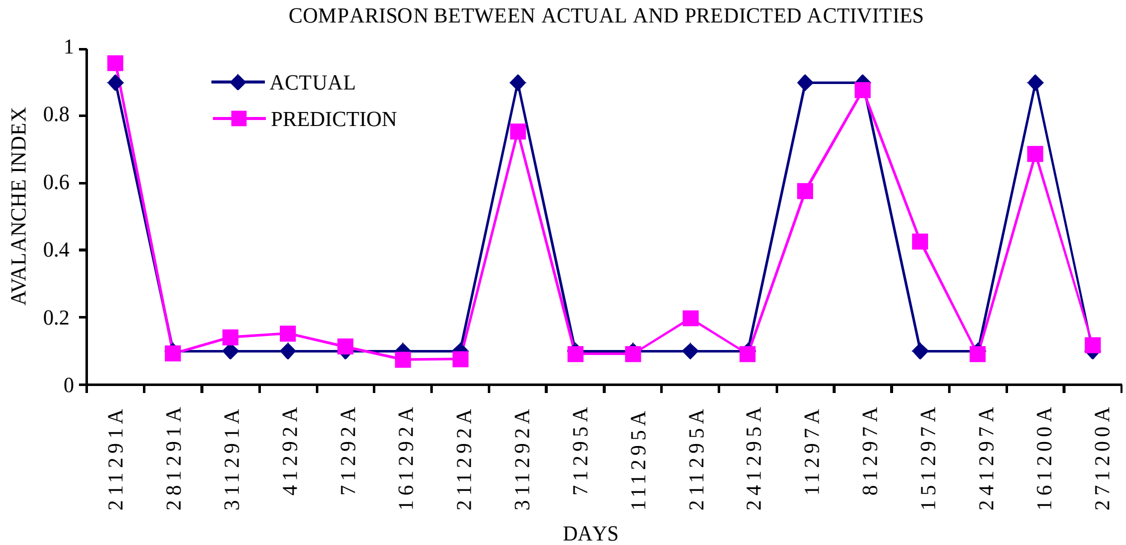

Figure 4. Test results for December.

3.2 Test Performance: Avalanche Occurrence with Expert Opinion

The overall test performance of the networks was increased to 81.7 per cent using the information regarding the expert opinion for avalanche activity, ie, the warning issued for avalanches in the axis. The network trained for December predicted avalanche days with 83 per cent and non-avalanche days with 75 per cent accuracy. Network trained for January predicted 62.5 per cent avalanche days and 93 percent non-avalanche days correctly. Network trained for February could predict 75 per cent avalanche days and 87.5 per cent non-avalanche days accurately. Network trained for March predicted avalanche days with 71.4 per cent and non-avalanche days with 75 per cent accuracy. Trained network for April gave cent per cent correct prediction on avalanche days and 90 per cent correct prediction on non-avalanche days. Figure 6 shows the comparison between the prediction and the observed index values for test data of December.

The performance of the networks on validation data is summarised in Table 4. The trained networks tested again on winter 2001-2002 for validation, which gave overall 82.7 per cent correct predictions. For December, 87 per cent correct predictions, with 60 per cent for avalanche days and 92 per cent for non-avalanche days was observed. For January, it gave 87 per cent correct predictions, avalanche days predicted with 67 per cent accuracy and non-avalanche days with 89 per cent accuracy. For February, network performance was improved

Table 3. Validation results for winter 2001-2002

Month	Cases	Observed	Predicted	Mis-matched
December	Avalanche days	03	01	02
	Non-avalanche days	28	22	06
January	Avalanche days	03	01	02
	Non-avalanche days	28	26	02
February	Avalanche days	05	-	05
	Non-avalanche days	23	20	03
March	Avalanche days	03	01	02
	Non-avalanche days	28	20	08
April	Avalanche days	-	-	-
	Non-avalanche days	30	25	05

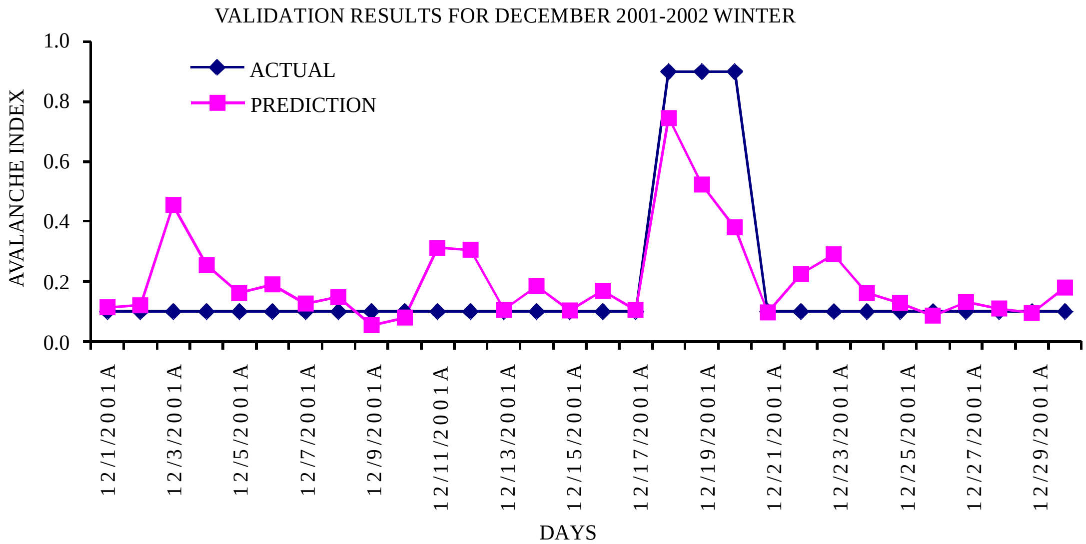

Figure 5. Validation results for December 2001-2002.

and the predictions were 85 per cent accurate, avalanche days with 60 per cent and non-avalanche days with 91 per cent accuracy. Results for March gaves 67.7 per cent correct predictions, 60 per cent correct predictions for avalanche days and 69 per cent correct predictions for non-avalanche days. In April, there were only non-avalanche days and which were predicted with 86 per cent accuracy. Figure 7 shows the comparison between the predicted and the observed index value for December.

4. CONCLUSION

The monthwise networks were developed using snow and weather data recorded at Stage II observatory of the axis in the afternoon. The networks were predicting the avalanche and the non-avalanches days with reasonable accuracy. Test results showed an average of 41 per cent and 80 per cent correct prediction on avalanche and non-avalanche activities, respectively on the axis, when only avalanche occurrence reports were considered for training the networks, while it had improved when expert opinion in terms of the avalanche warnings was also considered for training the network and it gave 61 per cent correct predictions for avalanche days and 84 per cent correct predictions for non-avalanche days. The validation results are also in good agreements and the performance was increased when tested with the trained network in which expert opinion was also considered.

Though the performance of networks improved by incorporating the expert opinion, but it might

Table 4. Validation results for winter 2001-2002

Month	Cases	Observed/ assessed	Predicted	Mis-matched
December	Avalanche days	05	03	02
	Non-avalanche days	26	24	02
January	Avalanche days	03	02	01
	Non-avalanche days	28	25	03
February	Avalanche days	05	03	02
	Non-avalanche days	23	21	02
March	Avalanche days	05	03	02
	Non-avalanche days	26	18	08
April	Avalanche days	-	-	-
	Non-avalanche days	30	26	04

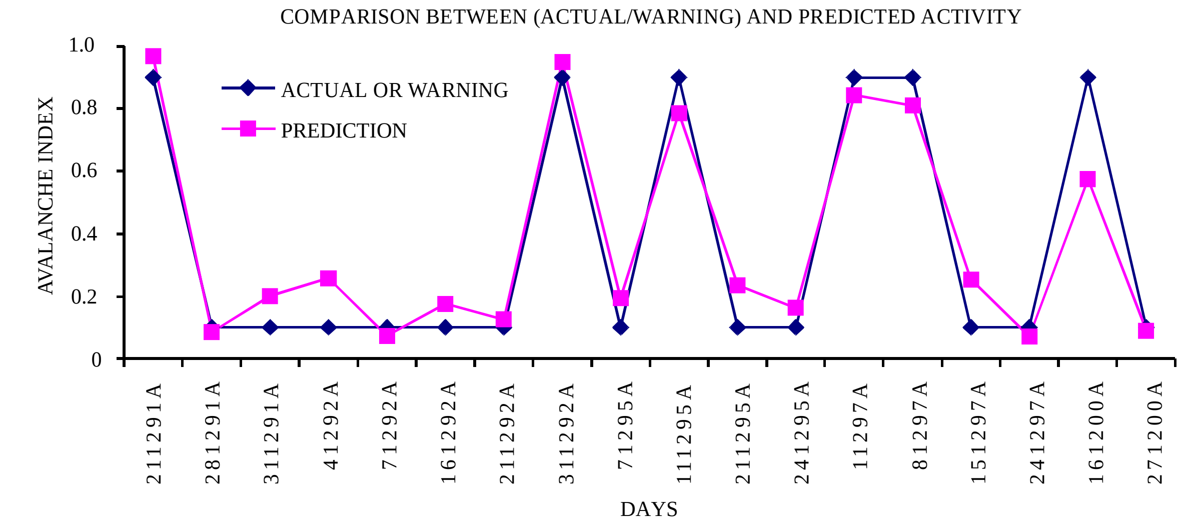

Figure 6. Test results for December (when predicted activity and actual warnings are used).

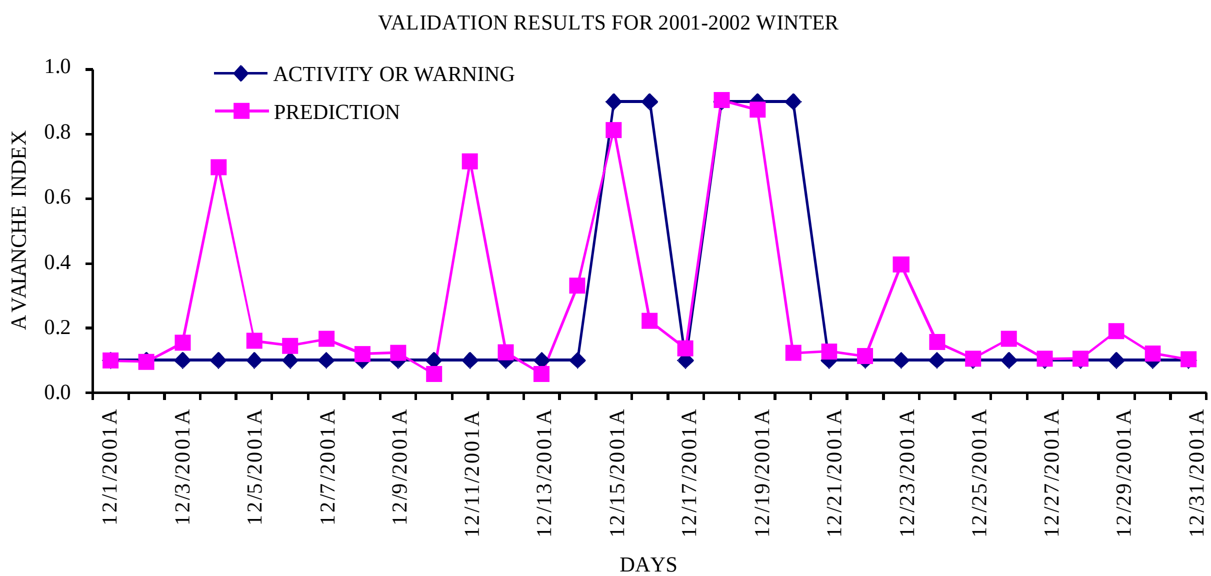

Figure 7. Validation results for December 2001-2002 (when predicted activity and actual warnings are used).

have been improved to a far greater extent if a large data set was used for the training of the network. In the present study, it was only possible in the case of non-avalanche activities but for avalanche activities, networks encountered very few cases, this might be one of the reasons that the correct prediction of avalanche days are less. Though there are many factors and parameters responsible for the avalanche initiation, but only the most relevant snow and meteorology parameters were considered for the present study, while an in-depth analysis is required to incorporate other parameters in the process for better performance of the network.

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Mr Ashwagosha Ganju obtained his MSc (Geology) from the Punjab University, Chandigarh. He joined SASE as Scientist B in 1985. He carried out the reconnaissance of entire Siachen and its tributary glaciers and prepared an avalanche atlas of the area. Helping local commanders in troop movement, he made first ever-successful attempt of artificial triggering of avalanches on the glacier. He was deputated to Switzerland for on-job training in avalanche forecasting in March 1995. While working there, he developed nearest-neighbour model for the prediction of avalanches in Siachen glacier. In Avalanche Forecasting-2000 project, as Principal Investigator, he and his team developed different types of avalanche forecast models for the entire western Himalayan region. He has carried out detailed avalanche reconnaissance of Kargil-Dras-Batalik area during *Operation Vijay*. He has published 25 papers in various national/international journals. He guided three MTech students in their dissertation work. Presently, he is the Joint Director, SASE.