A Neural Network Approach for Forestal Fire Risk Estimation

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Abstract. This paper describes an intelligent system for the prediction of forest fire risk in Galicia, a region in north-west Spain. The system has been designed to calculate a risk fire index for each of the 360 squares of 10x10 kms into which the area map has been divided digitally. In our research, the problem was approached using a feedforward neural network. The information used to train the network was gathered at five meteorological stations on a daily basis from 1985 to 1999, and consisted of basically meteorological data, namely temperature, humidity and rainfall, in conjunction with previous fire records for the areas represented by squares. Network topologies were tested using 125,156 training data and validated over 13,906 test samples, and that achieving the best performance was the 6-9-1 topology. Finally, our results indicate that the system performs satisfactorily, with a sensitivity of 0.857 and a specificity of 0.768.

1 INTRODUCTION

The forest fire season of the year 2000 in southern Europe was characterised by a loss of human life and substantial environmental damage. Over the last two decades, a total of more than ten million hectares of wooded areas in the European Union have been affected by fire. Similarly, forest fires in Spain represent important costs, namely in terms of

- Loss of life, the major consideration.
- Environmental damage resulting from a reduction in wooded areas. The concentration of CO_2 in the atmosphere are also affected. For each ton of vegetable material burnt the atmosphere receives 30 to 40 kgs of carbon dioxide, which would normally be absorbed by forests [8]. Other losses are more difficult to evaluate, such as soil degradation, erosion, destruction of animal and plant life, damages to the water cycle, etc.
- Financial costs are another consideration, particularly the millions of euros allocated to preventative measures and fire-fighting campaigns, not to mention the costs borne by the wood industry.

During the 1990s Galicia alone, representing a mere 5.8% of the surface area of Spain, accounted for half the forest fires in Spain. Over the last ten years, moreover, and despite the human and financial resources allocated to fire-fighting, the number of fires has increased. Nearly half of the Spanish timber and lumber industry, valued at around 811 million euros per year and employing 15,000 is located in Galicia [2, 16]. In terms of forest fire prediction in Europe, therefore, Galicia is considered to be a particular challenge.

This paper describes our research into an intelligent forest fire risk prediction system. Our approach was based on neural networks, given their capacity for modelling non-linear functions. This subsystem is part of a larger project funded by the European Regional Development Fund (ERDF), in which Galicia's three universities (the University of A Coruña, the University of Santiago de Compostela and the University of Vigo) and several industries are involved. The project has as its aim the prediction of forest fires and the management of available fire-fighting resources.

2 BACKGROUND

Artificial Intelligence techniques have for some time been recognised as appropriate tools for forestry management [14]. The first intelligent systems with forest fire applications appearing in the literature date from the late 1980s. One of these is the Phoenix project [5], a real-time adaptive planner that manages forest fires in a simulated environment (Yellowstone National Park, USA). This system consists of an autonomous agent architecture integrating multiple planning methods, with the agents organised hierarchically so as to improve fire-fighting performance by adapting to the environment.

Other intelligent systems with forest fire applications have been developed [14], but to our knowledge, none of these predict forest fire risk. In more recent years, other projects have been developed for specific European regions. One of these, FOMFIS (Forest Fire Management and Fire Prevention System), is an international project, partly funded by the European Union. This is designed to obtain the most cost-effective strategy for both preventing and fighting forest fires. Operating offline, it provides information on the likely outcome in terms of fire-fighting costs and damage. It also provides a measure of apparent fire risk in a given area on the basis of weather conditions. A prototype of this system is currently been tested in three southern European areas, namely, Galicia, Aquitaine (France) and Evia Island (Greece). Another system is currently being developed by the Joint Research Centre of the European Commission under its Natural Hazards Project [17]. Its forest fire programme consists of three areas: fire risk evaluation, fire detection, and mapping of burnt areas and damage assessment. Fire risk indexes based on linear regression models are used to predict the fire hazard for an entire province [18].

Finally, other forest fire hazard indexes have been developed and applied [4], but their preventative capacity is reduced when they are used to predict fires outside the area for which they have been developed, as was demonstrated in [6]. For this reason, a new fire forest

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index applicable to Galicia has been developed, which we describe below.

3 PROBLEM DESCRIPTION

Our forest fire index has been developed for Galicia, a region in the north-west of Spain similar in size to Belgium or Massachusetts. Its surface area of 29,575 km^2 was divided into 360 fire location squares, each measuring 10 x 10 km (see Figure 1). For each new fire, therefore, the UTM (Universal Transverse Mercator) coordinates for the square in which it occurs are known but not its exact location.

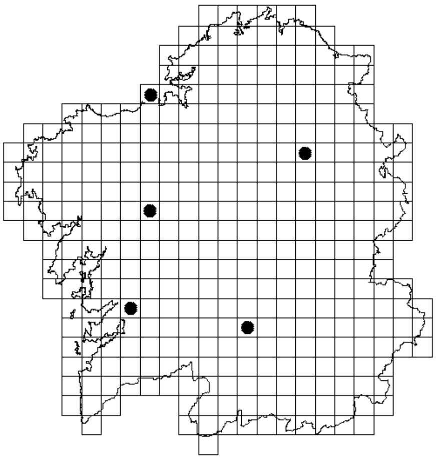

Figure 1. Galicia divided into 360 squares. The dots represent meteorological stations

The purpose of the system is to calculate a risk fire index for each square, which will subsequently be classified in terms of one of four symbolic categories (low, medium, high and extreme risk) in order to facilitate interpretation by the user. These categories will be graphically represented on the map of Galicia using a colour code to represent the categories. Since forest fire outbreaks and subsequent development depend to a large degree on meteorological and climatic factors [19], meteorological data is always included in forest fire prediction methods. In our particular case, these data were obtained from five Galician meteorological stations (represented as dots in Figure 1) and corresponded to the square where the station is located. The meteorological data for the remaining squares were extrapolated from the nearest station, taking into account features such as altitude or distance from the station.

4 DESCRIPTION OF THE TRAINING/TEST DATA

In order to build the train/test data set, available meteorological data for the years 1988 to 1999 were used. Specifically, for each square i and each day j, the following variables were selected, based on multiple correlation analysis [7]:

- Maximum Temperature for the day in question measured in centigrade degrees ($T_{max}(i,j)$).
- Humidity percentage for the day in question ($H(i,j)$).
- Number of days with rainfall of less than 3 mm up to the present day ($R(i,j)$).
- Number of fires in this square ($F(i,j)$).

The train/test data set was built on the basis of these variables using $T_{max}(i,j)$, $T_{max}(i,j-1)$, $T_{max}(i,j-2)$, $H(i,j)$, $R(i,j)$ as well as the mean number of fires in the previous three years $m(i,j)$ calculated using $F(i,j)$. The data set available was composed of 1,577,880 instances. However, only around 5% of the samples represented positives cases, i.e., a square with a detected fire. Therefore, to ensure a balanced train/test data set, all the positive cases were selected for each year and an equal number of negative examples were chosen uniformly from among all the squares and randomly from within each square. The final train and test sets consisted, respectively, of 125,156 and 13,906 samples.

5 NEURAL NETWORK MODELS

For this research, the selected approach to resolving the fire risk prediction problem was based on neural networks. The non-parametric ability of neural networks to model any non-linear function [13] and to establish non-linear boundaries among decision regions is well documented. Neural networks also represent a practical method for dealing with highly complex classification problems [3, 11]. Furthermore, neural networks have been demonstrated to be tolerant of input noise, a particularly important criteria for this research, where both, real and extrapolated data will be used. Moreover, data precision will vary depending on the period in which these were recorded on the database. The model used for this research was a multilayer perceptron [3] (see Figure 2). In this kind of network, neurons are organised in M sequential layers and each neuron in the m^{th} layer is connected to all the neurons in the $m+1^{th}$ layer. The strength of

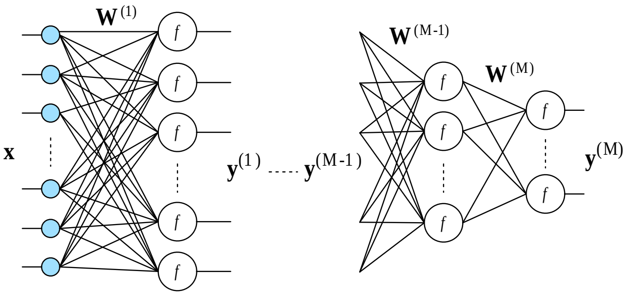

Figure 2. Multilayer perpectron

these connections is determined by a set of parameters called weights ($\mathbf{W}^{(m)};\ m = 1,\ldots,M$). The output of each neuron i at layer m is calculated as $y_i^{(m)} = f_i^{(m)}(\sum_{j=0}^{N_{m-1}} w_{ij}^{(m)} y_j^{(m-1)})$, where N_{m-1} is the number of neurons in layer $m-1$ and $f_i^{(m)}$ is the non-linear transfer function of the neuron. In this case, a sigmoidal transfer function for the neurons was used, defined as $f(x) = 1/(1-\exp^{-x}) \in [0,1]$. In order to resolve a problem, the network parameters (i.e., the weights) are adapted by means of a supervised training process, where for each input $\mathbf{x}$ a desired output $\mathbf{d}$ is supplied. For this research, the system was trained using the Levenberg-Marquardt algorithm [10] and the mean squared error (MSE) as the minimising cost function, where MSE is defined as $E[(\mathbf{d}-\mathbf{y})^T(\mathbf{d}-\mathbf{y})]$. This algorithm was chosen because it is one of the most efficient methods for training moderate-sized neural networks. The weights are updated using the following equation: $\mathbf{W}(n+1) = \mathbf{W}(n) + (\mathbf{H}+\mu\mathbf{I})^{-1}\mathbf{g}$, where $\mathbf{H}$ is the Gauss-Newton approximation of the Hessian weights matrix, μ is the step size and $\mathbf{g}$ is the error function gradient. Furthermore, in order to improve the learning process performance the desired output was offset by $\varepsilon = 0.05$ from the limits of the transfer function in the output layer [11]. Several topologies were trained using the Network Growing strategy [11], which begins with a very simple network to which new elements, hidden neurons and layers are added to the point where performance is improved no further. The results described in [9, 12, 15] were employed, which state the minimum (H_{min}) and maximum (H_{max}) number of hidden units needed in the network as $H_{min} > n$ and $H_{max} <= 2n + 1$, where n is the number of inputs. Therefore, several network topologies with 7 to 13 hidden units were trained. Each network was trained several times, using a different set of initial weights, in order to increase the probability of obtaining an optimal solution. Once the error was stable the training process terminated.

6 RESULTS

In order to characterise the performance of the system the following measures [20] were used:

- Accuracy (A) = (TP+TN)/(TP+FN+FP+TN)
- Sensitivity (S) = TP/(TP+FN)
- Specificity (Sp) = TN/(FP+TN)
- Positive Predicted Value (PPV) = TP/(TP+FP)
- Negative Predicted Value (NPV) = TN/(FN+TN)
- False Positive Ratio (FPR) = FP/(FP+TN)
- False Negative Ratio (FNR) = FN/(TP+FN)

where TP, TN, FP, FN represent the number of true positives, true negatives, false positives and false negatives, respectively. All the topologies described in the previous section were trained using the 125,156 training data and validated using the 13,906 test samples. Of these, the 6-9-1 topology (6 input, 9 hidden and 1 output neurons) achieved the best performance.

Figure 3 contains the ROC (Receiver Operating Characteristic) curve [1] for the test data. This curve was constructed by varying the detection threshold from 0.05 to 0.95. Using this curve, and follow-

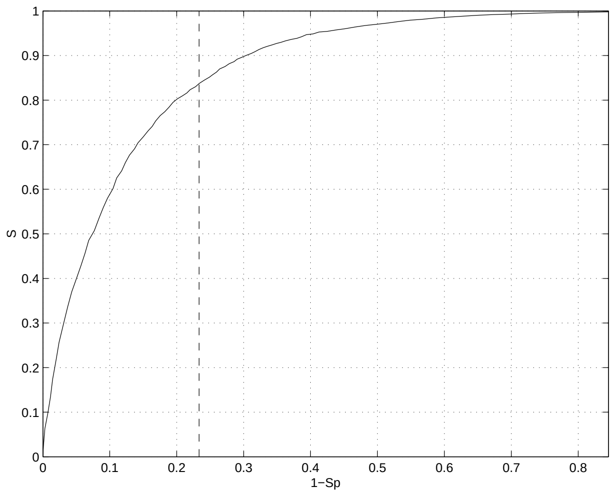

Figure 3. ROC curve for the test data

ing the recommendations of experts in the field regarding the maximum false positive rate allowed (around 23.3% and represented by the broken line in Figure 3), the final detection threshold was fixed as 0.5. The network was also applied to all the available data (the years 1988 to 1999). Figure 4 depicts the ROC curve for these data. Similarly to the test data, this curve was constructed by varying the

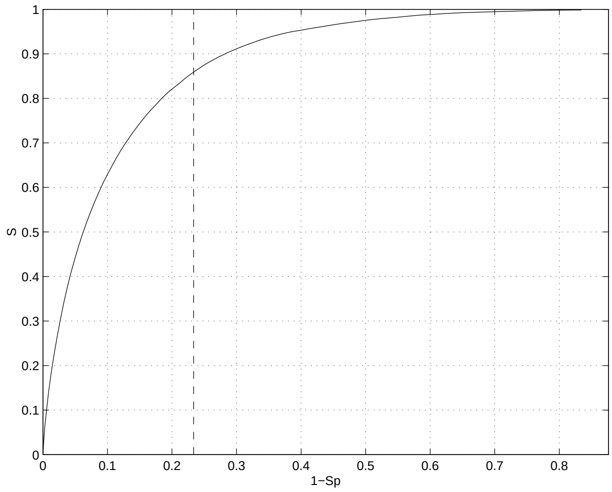

Figure 4. ROC curve for the data for 1988-1999

detection threshold from 0.05 to 0.95.

Table 1 shows the contingency matrix obtained for these data. The values of the performance measures are *Sensitivity* = 0.857, *Specificity* = 0.768, *PPV* = 0.146, *NPV* = 0.991, *FPR* = 0.232, *FNR* = 0.143 and *Accuracy* = 0.772.

		Real classification	
		Fire	¬Fire
System classification	Fire	59588	349184
	¬Fire	9943	1159165

Table 1. Contingency matrix

Subsequently, in order to check the variability of the system's performance this study was carried on a year-by-year basis. Figure 5 shows the ROC curves for each of the years in question. As can be observed, the sensitivity obtained for the fixed threshold (broken line) varies from 0.757 (years 1989 and 1992) to 0.915 (years 1996 and 1997).

As was previously mentioned, the threshold used to determine fire detection was $\gamma = 0.5$; in other words, if the network output is less than γ then the corresponding square is categorised as being a low risk area. If an area is rated as constituting a serious fire hazard, the risk level (medium, high and extreme) is fixed using a further two thresholds that proportionally divide the interval $[0.5, 1]$ into three sub-intervals. On the basis of these thresholds, the set of positive cases detected by the system in Table 1 was broken down as is shown in Table 2.

7 DISCUSSION

As was illustrated in the previous section the highest performance indexes achieved by the neural network were the sensitivity and the

		Real classification	
		Fire	¬Fire
System classification	Extreme	28496	65902
	High	21887	145324
	Medium	9205	137958
	Low	9943	1159165

Table 2. Contingency matrix considering the four risk levels

NPV measurements. This means that overall the system's capacity for detecting a fire was quite satisfactory, and that it almost invariably predicted a negative classification for cases when no fire was recorded. On the other hand, the specificity value - and particularly the PPV - indicate that the false positive rate is high (evident also in Table 1). This is partly explained by the following:

- The detection threshold was fixed on the basis of expert criteria so as to minimise the risk of failing to predict a fire which in fact occurs, for the simple reason that the cost of this error is higher than that incurred by a false prediction of a fire.
- The system was designed to evaluate whether meteorological conditions favour an outbreak of fire. However, the fact that meteorological conditions are favourable is no guarantee of a fire.

It is interesting to note, in Table 2, the correlation between the risk level for each positive category (medium, high and extreme) and the number of true positives classified for that category.

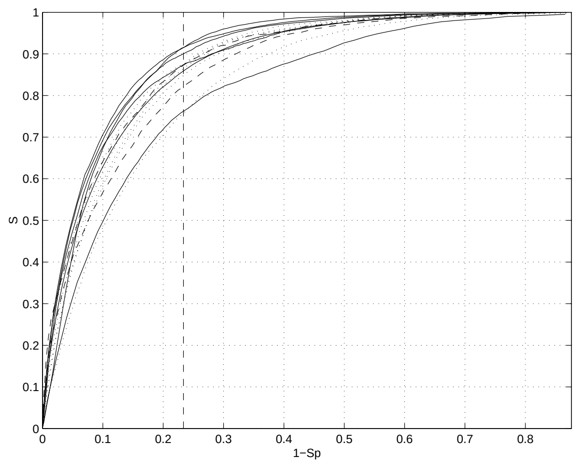

Figure 5. ROC curves for each year (1988-1999)

In reference to the ROC curves, the test curve and the curve for the years 1988 to 1999 are similar. As was to be expected, this indicates that the train and test data sets were adequately designed to take advantage of the generalisation capacity of the neural network. In addition, the ROC curves in Figure 5 are useful in identifying those years when performance was significantly better or poorer. This information will be useful for a future analysis that will focus on improving our system by identifying new relevant input variables.

In order to verify whether there were meaningful differences between systems developed using extrapolated and real data, the selected network topology was also trained using only the latter, i.e., the information obtained from the five meteorological stations. The results obtained were similar to those obtained when employing extrapolate data.

A further experiment was carried out which consisted of training five different networks, one for each meteorological station. The aim was to determine whether this approach would produce a better performance than our global network, and in fact, there was no improvement in results.

Also interesting would have been a comparison with other fire risk prediction systems, such as those described in Background above, but this was not possible since comparable results are not available.

The neural model described in this paper is included within a larger system for real-time prediction and management of fires. The latter includes a geographical information system, an expert system for the management of fire-fighting and post-fire terrain recovery resources, and a module for the automatic acquisition of meteorological data. One of the features of this system is that it graphically illustrates the fire risk predictions of the described neural network (Figure 6). Each square is assigned a colour code representing the risk level and is also marked with the number of fires that genuinely occurred in the area represented by that square. By clicking on a square, moreover, the user can call up detailed maps of the area and other information such as type of vegetation or the population of villages and towns.

The costs and complications involved in fire-fighting during the worst periods of the year make it impractical to maintain active fire-fighting units in all areas of the country. A spatial analysis of fire risk is, therefore, an extremely useful tool since it permits fire-fighting units to focus on those areas where there is a higher probability of damage.

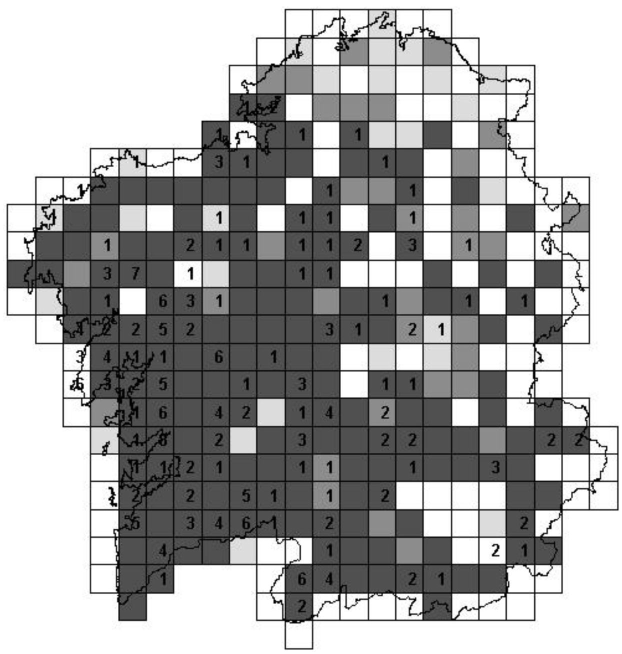

Figure 6. System prediction for Galicia, 20 August 1998. The level of risk is indicated by a colour code and the number in each square represents the number of recorded fires

8 CONCLUSIONS AND FUTURE WORK

Our paper describes an intelligent system for forest fire risk prediction. The proposed system is based on a neural network and uses meteorological data to assess fire risk probabilities. Our system obtained acceptable results over real data, bearing in mind that a significant number of fires are deliberately provoked, representing an intrinsic level of error that cannot be reduced. In addition, the meteorological data provided to the network, are not sufficient in order to be able to make an accurate prediction. Other information which would be relevant to this problem includes socio-economic and terrain factors (e.g., existence of a road, type of vegetation, etc). These factors, which play an important role in fire outbreaks, are more appropriately managed using symbolic techniques, and an expert system is currently been developed to take account of this additional knowledge. This expert system will eventually be integrated within the neural network described above, and will modify the calculation of the risk index so as to improve the performance of the system.

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