The Application of Artificial Neural Networks for Wildfire Risk Prediction

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***Abstract*—The City of Cape Town is declared the most fire-prone city in South Africa. This is attributed to its unique topographical, vegetative and climatic features. A novel data-driven intelligent system utilising artificial neural networks is proposed and developed for wildfire risk assessment for the City of Cape Town. The model uses vegetation, climate and location features to predict a rating corresponding to the risk of wildfire ignition for two different vegetation types. The system is trained and tested on historical fire incidence data from 2009-2015 and produces categorical outputs of low, moderate, high and extreme. Overall, the system is able to perform with an accuracy of up to 0.97 with a precision of 0.87 and a recall of 0.88.**

***Index Terms*—artificial neural networks, wildfire risk, fire risk assessment**

I. Introduction

Cape Town is a city with a unique and dynamic ecosystem, in that the vegetation is both fire-prone and fire dependent, making it a complex system to manage. Coupled with the prevalent strong winds that are characteristic of Cape Town, wildfires are inevitable, causing damage to homes, infrastructure, farmland and forests. Cape Town has a population of more than 3 million people that is rapidly on the rise. In line with this, is the ever increasing trend of urban development which results in urban environments having to encroach on the natural environment. These zones are found on the slopes of the mountain ranges and hills bordering the city. Land uses on the edges of the city range from high-density urban development and informal settlements to rural residential development, agriculture, institutional uses and conservation. Cape Town is currently declared as the most fire-prone city in South Africa. The fires are also a contributing factor in the degradation of air quality. The combined climatic, topographical and seasonal features specific to Cape Town, makes the assessment of wildfires one of particular interest.

With more than 200 informal settlements in Cape Town, residents live in abject poverty and are potentially vulnerable to a range of environmental hazards, of which fire is one of the most common. Approximately 69% of all fires that the fire services in Cape Town attend to, are vegetation based fires. Not only are these wildfires capable of causing severe damage to animals, biodiversity, and human dwellings; but substantial resources are utilised by the fire rescue services in controlling these fires. Fire also poses a major logistical problem for managers, as they are expected to deal with the threats of wildfires to property owners on the boundaries of national parks such as the Cape Peninsula National Park or the Table Mountain National Park. Fig. 1 depicts the magnitude and severity of wildfires in Cape Town.

Fig. 1. Wildfires in Cape Town

It is an obvious inference that this prevailing problem should be addressed appropriately in effort to minimise the devastation caused to crops, pastures, forestry plantations, livestock, human habitation and human life. The first step for fire prevention is through a fire risk assessment. The authors develop an intelligent system that takes a computational data-driven approach using artificial neural networks, for the determination of the risk associated with wildfire ignition based on various climatic and vegetative features.

II. Prior work

A. Fire risk modelling

Wildfires are imperative for maintaining balance in the ecosystems and is essential for the regulation of vegetation growth. However, if the fires are not properly managed, the result thereof can be disastrous, and can pose a great risk to life, the natural environment and property. Fire risk modelling is a critical part of fire prevention, since pre-fire planning resources require objective tools to monitor when and where a fire is more prone to occur, or when will it have more negative effects [2].

A fire risk model can be viewed as a fire danger rating system that ultimately produces indices for rating the danger of fire. It also normally ranks these into discrete classes for the purpose of conveying public warnings, implementing mitigation measures and for setting an appropriate level of readiness for suppression resources. Fire risk (or potential) cannot be measured directly but can only be inferred by measuring the components of which the index consists, such as temperature, relative humidity, rainfall and wind speed [3]. There are numerous fire danger rating models that have been developed and applied, however their preventative capacity is reduced when they are used to predict fires outside the area for which they have been developed [4]. Some popular fire

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risk models as well as the areas for which they have been devised, are discussed in table I.

TABLE I
POPULAR FIRE RISK RATING SYSTEMS ACROSS THE WORLD

Fire risk model	Area	Inputs
Angstrom Index [5]	Scandinavia	Temperature, relative humidity
Nesterov Index [6]	Widely used in Russia	Dry-bulb temperature, dew-point, precipitation
Canadian Forest Fire Weather Index [7]	National index in Canada and has been adapted for a number of countries (e.g. New Zealand, Portugal, Indonesia)	Temperature, rainfall, wind-speed, relative humidity
United States Fire Danger Rating System [8]	United States of America	Weather, fuel types, live and dead fuel moisture
McArthur Forest Fire Danger Rating System [9]	Used for open forests in Australia	Air temperature, relative humidity, wind speed, rainfall, time since last rainfall
McArthur Grassland Fire Danger Rating System [10]	Used for grassland areas in Australia	Air temperature, relative humidity, wind speed, rainfall, time since last rainfall, curing factor

B. Fire danger rating system for South Africa

The Lowveld model was approved as the official wildfire danger rating system for South Africa [11]. This is an adaptation of the fire hazard index developed for Zimbabwe [12]. The model uses the same inputs as the McArthur models, which are scaled to produce a simple model that can calculate index values easily without needing any complex calculations. A burning index (BI) is first obtained as shown in eq. 1, where T is the dry-bulb temperature (°C) and RH is the relative humidity (%). This is then adjusted by wind speed, while the availability of excess moisture (above the plant fibre saturation point) provided by recent rainfall, is taken into account through a rainfall correction factor. The BI, corrected for wind and rainfall, is known as the fire danger index (FDI) and is shown in eq. 2, where BI is the burning index, WCF is the wind correction factor and RCF is the rain correction factor. It is important to note that the rain correction factor is only taken into account if the temperature exceeds 23°C, the relative humidity is less than 50% and the wind speed is greater than 20 km/h. The wind and rain correction factors are given in tables that can be found in Notice 1099 of 2013 which is in accordance with the National Veld and Forest Fire Act for South Africa [11].

$$BI = \left((T-35)-\left(\frac{35-T}{30}\right)\right)+((100-RH)\times 0.37)+30 \tag{1}$$

$$FDI = (BI+WCF)\times RCF \tag{2}$$

C. Artificial neural networks

An artificial neural network (ANN) can be seen as an information processing paradigm that seeks to imitate the way a biological nervous system, such as the brain, processes information. It consists of a large number of interconnected neurons that work in parallel towards a specific solution [13]. A fundamental result of such a learning procedure is its ability to generalise and associate data. After successfully training a neural network, it is able to find reasonable solutions to similar problems that it was not explicitly trained for.

There are numerous applications of neural networks due to its ability to derive meaning from complicated and coarse-grained data. An added benefit of neural networks, is its high tolerance for noisy data which is seldom found in computationally based algorithms and heuristics [13]. This makes it well suited for application to real-world data-intensive problems such as stock market prediction, economic indicator forecasts, industrial based applications for process and quality control, real inventories optimisation, biological system analysis and even for medical diagnosis [14]-[17].

A neural network consists of neurons, which are basic processing units, and weighted connections between them. Data is transferred between neurons via connections with the connecting weight being either excitatory or inhibitory. There are two primary functions associated with the neural network, namely, a propagation function and an activation or transfer function. The propagation function is used to transform the data for input to neurons within the network. A weighted sum function is most often used. The activation function on the other hand, determines the activation of a neuron dependent on the neuron input and the threshold value. A particular neuron gets activated if the input value is above a certain threshold value. In summary, each neuron takes a weighted sum of its inputs and applies the activation function which determines what value the neuron passes on to the next neuron. This acts as a simple emulation of biological neurons which selectively pass on data to other neurons depending on whether it is fired or not.

D. City of Cape Town

Cape Town is a port city on South Africa's South-west coast and is approximately 2455 km^2. It has a varied and rugged topography with large mountainous regions and is home to the famous Table Mountain. The city is also notorious for its strong and prevailing wind gusts which can reach up to 120 km/h. According to the Beaufort wind scale, wind is only felt by humans when it exceeds 1.5 m/s [18]. Cape Town experiences winds of more than 1.6 m/s or more, on 96% of the days of the year.

The dominant vegetation in Cape Town is a mixture of evergreen shrublands and heathlands, with an understorey dominated by varying proportions of low, small-leaved shrubs, fine, reed-like restios, herbaceous plants and sedges. The three main vegetation types in Cape Town include various species of fynbos, renosterveld and strandveld. Approximately 57.82% of the area in Cape Town is covered by different species of the fynbos vegetation type, 23.98% is covered by various renosterveld species and approximately 16.93% is strandveld. The remaining 1% include wetlands, lagoons and forests [19]. The fynbos's low average moisture content makes this a suitable fuel for wildfires.

Van Wilgen *et al.* [20] studied the behaviour of wildfires for the fynbos biome. The authors compared the behaviour of experimental fires to predictions from the Rothermel's fire behaviour and spread model. The Rothermel model uses fuel characteristics and environmental conditions in its prediction. It was found that rates of fire spread and fire intensity are greater in fynbos than in similar shrublands despite similarities in biomass. Fynbos is a heterogeneous fuel type, and fire behaviour in heterogeneous fuels, especially on mountain slopes, is difficult to predict using empirically derived fire risk models [20]. Additionally, with the added variability of winds that are inevitable in Cape Town, it was further stated that fire models are unlikely to be successful in accurately predicting fire behaviour in fynbos biome [20].

III. Contributions

The authors develop a novel method for wildfire risk assessment using ANNs. It seeks to address the problems of utilising traditional empirical models that are not suited for the prevalent fynbos biome in Cape Town. It aims to provide a more accurate prediction of fire danger risk than the Lowveld FDI, taking into account the unique climatic, wind, vegetation and topographical features of Cape Town. The Lowveld model does not take into account the difference in fire behaviour as a result of the vegetation type that is unique to Cape Town. The proposed system is able to accommodate both the fynbos and strandveld vegetation types, which combined accounts for approximately 75% of the vegetation in Cape Town, by providing an appropriate rating based on the climatic conditions on that day. The system achieves this through the application of ANNs that takes into account the climatic and vegetative features of Cape Town. The neural networks are able to effectively capture the unique non-trivial behaviour of wildfires as a result of its structure and operation. To the best of our knowledge, there has been no work on the use of artificial intelligence techniques for wildfire risk prediction for the city of Cape Town.

IV. Method

A. Neural network approach

The fire risk prediction system will have the primary purpose of preventing and controlling wildfires. This prevention should come about through the ability to identify the conditions that would lead to dangerous fires, and then through the effective prevention of activities that would lead to the ignition of fires under such conditions. ANNs will be used in attempting to determine the wildfire ignition risk, based on daily historic fire records for the years 2009 to 2015. The number of fires that occurred on each day is recorded per vegetation type. An appropriate rating of the risk of wildfire occurrence is then assigned for that particular day based on the number of fires. Wildfires occur on a daily basis in the city of Cape Town and therefore assigning a fire occurrence risk rating based on the number of fires was found to be a suitable method.

There are three main vegetation types that cover approximately 99% of Cape Town's landscape. These are the fynbos, renosterveld and strandveld vegetations. As part of the data preparation process, a daily rating based on the mean number of wildfires per day and their corresponding standard deviation over the 7 years, was assigned. This rating was obtained as follows: the number of fires less than the mean number of fires was given a rating of 1 or *low*, the number of fires lying between the mean and 1 standard deviation above the mean was given a rating of 2 or *moderate*, the number of fires lying between 1 and 2 standard deviations above the mean was given a rating of 3 or *high*, and finally, if the number of fires for a particular day was over 2 standard deviations above the mean, then a rating of 4 or *extreme* was given for that day. There were on average 10 wildfires per day with a standard deviation of 10. This then translates to the following rating system:

- 0-10 fires: Low
- 10-20 fires: Moderate
- 20-30 fires: High
- More than 30 fires: Extreme

It is important to mention that the distribution of the dataset itself has little relevance in assigning the fire danger rating for that particular day. There are significantly more days with a lower number of fires than days with a large number of fires, as expected. The number of actual fire ratings for years 2009 to 2015 for the three different vegetation types is shown in table II.

TABLE II
Number of fire ratings for different vegetation types

	Fynbos	Strandveld	Renosterveld
Low	1566	1874	2533
Moderate	545	556	23
High	343	119	0
Extreme	102	7	0

As can be seen from the table, there are no fire danger ratings exceeding the moderate level for wildfires occurring in the renosterveld vegetation type. In fact, they are predominately assigned a low rating. This implies that a neural network for classifying the fire danger rating for the renosterveld would be futile; therefore neural networks for the fynbos and strandveld vegetation types are developed. Having two different neural networks seeks to take into account the different effects on wildfire behaviour that the climatic conditions will have for that particular vegetation type.

The data that was used for the training and validation of the ANNs include 2556 daily fire ratings for the years 2009 to 2015. There are 7 features that the ANNs take into account for each vegetation type:

- Maximum temperature ($^{\circ}C$)
- Minimum temperature ($^{\circ}C$)
- Maximum relative humidity ($\%$)
- Minimum relative humidity ($\%$)
- Maximum wind speed (km/h)
- Mean wind speed (km/h)
- Precipitation (mm)

The mean number of wildfires per day are used as a metric for the rating system as our model considers the risk of fire occurrence, which in turn is related to the frequency of fires.

B. Training of the ANNs

The type of ANN used for the model is a feed-forward network. The neurons in such a network are grouped into three types of layers namely, an input layer, a hidden layer, and a single output layer. Each neuron in such a network only has a direct connection to neurons in the proceeding layer. A validation set used for determining the architecture of the neural network consisted of 10% of randomly selected days for each vegetation type. The optimal architecture obtained in terms of time taken for training for a 5% error rate is shown in table III.

TABLE III
ANN DESIGN PARAMETERS FOR WILDFIRE RISK PREDICTION

Parameter	Value
Input neurons	7
Hidden neurons	213
Output neurons	3
Normalisation method	Equilateral
Propagation Function	Weighted sum
Activation Function	Tanh
Target Error	5%

The popular weighted sum propagation function was found to be suitable for the network. There were three activation functions that were considered for the ANN, namely, the sigmoid function, the basic straight line linear function and the hyperbolic tan (tanh) function. The performance of the neural network in terms of the error rate was significantly better when using the tanh function. A reason for this can be attributed to the fact that neural networks tend to converge faster with this function and tanh has a wider range than the sigmoid function [21].

Before the data can be used as input to the neural network, it first needs to be balanced and normalised. The data is balanced using an oversampling approach which involves duplicating instances of under-represented classes until a balanced dataset is created [22]. Normalisation makes the training faster and reduces the chances of getting stuck in a local optima. The input data is normalised to a value between 0 and 1. As seen from table III, the normalisation method used is the equilateral method. This is for the output neurons. The aim of this method is to reduce the errors from misclassification as a result of the normalisation process. In this normalisation strategy, the number of output neurons is one less than the total number of classes. The equilateral normalisation can be seen as an encoding process which maintains that the euclidean distance between classes remain equidistant. There are only N-1 dimensions needed to place N points equidistantly, thus there are 3 output neurons for the four classes (low, moderate, high and extreme). This normalisation technique is an alternate to one-of-N normalisation which only activates the output neuron that corresponds to a particular class [13]. With one-of-N normalisation, the distance between different output vectors for each class, are varied. Equilateral normalisation, on the other hand, seeks to determine a unique set of values for each class such that each set of unique values has an equal euclidean distance from the others. For more details on this scheme, refer to [23].

The learning algorithm used for the adjustment of the weights in the neural network is the resilient backpropagation algorithm. This is a variant of the popular backpropagation algorithm which has been one of the most studied and used algorithms for neural networks [24]. Essentially, the learning algorithm seeks to obtain the combination of weights that minimises the error between the output of the ANN and the desired output. Please refer to [25] for details on the resilient backpropagation algorithm.

V. Results and Discussion

A. Performance metrics

After the ANNs were constructed and appropriately trained using 75% of the total data set, the test set, which consisted of the remaining 25% of the data, was used to evaluate the performance of the networks. There were 639 days worth of fire danger ratings that was used for the testing process. Several metrics were calculated comparing the predicted output with the desired output.

The accuracy of a neural network is a measure of how often a classifier makes the correct prediction. The equation governing the accuracy is shown in eq. 3. The accuracy includes how well the classifier is able to classify a particular data point as being a part of a certain class and how well it is able to classify it not being a part of that class.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{3}$$

The precision metric measures the ability of the classifier to not falsely classify an output. The equation that governs this is given in eq. 4. The *true positives* refers to outputs that are correctly classified for a particular class, whereas *false positives* refers to outputs that were wrongly classified as belonging to that particular class.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{4}$$

The recall or sensitivity metric can be thought of as a measure of the classifiers completeness. This is shown in eq. 5. The total number of correctly classified data points for a particular class (the true positives) is divided by the total number of data points that the classifier classified as belonging to that particular class.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{5}$$

From the above determined precision and recall values, an F-score can be calculated. The F-score can be interpreted as a weighted average of the precision and recall values where it reaches its best value at 1 and worst score at 0. This equation is shown in eq. 6

$$F\text{–}score = 2 \times \frac{precision \times recall}{precision + recall} \tag{6}$$

Tables IV and V summarise the performance metrics for the two neural networks used for classifying the level for wildfire risk ignition. In calculation of the metrics for each class, each class (low, moderate, high or extreme) can be thought as a binary classifier, in a one-vs-all formation. This gives a categorical performance.

TABLE IV
PERFORMANCE METRICS FOR FYNBOS NEURAL NETWORK

	Low	**Moderate**	**High**	**Extreme**
Accuracy	0.929	0.899	0.966	0.969
Precision	0.925	0.726	0.897	0.876
Recall	0.943	0.747	0.813	0.833
F-score	0.934	0.736	0.853	0.854

TABLE V
PERFORMANCE METRICS FOR STRANDVELD NEURAL NETWORK

	Low	**Moderate**	**High**	**Extreme**
Accuracy	0.923	0.929	0.986	0.999
Precision	0.932	0.804	0.863	0.963
Recall	0.959	0.871	0.836	1
F-score	0.945	0.836	0.849	0.981

In general, the performance of the neural networks across the different ratings is acceptable. The most important of which, is the classifier's performance for the *extreme* class. The overall F-score rating is excellent for the extreme rating for the strandveld vegetation type at 0.981. The accuracy is also very high. For the fynbos vegetation type, the accuracy and F-score is slightly lower in comparison. This can be as a result of the larger number of data points with an extreme rating for the fynbos vegetation type which covers a significantly larger area. There is thus a greater probability of deliberately generated fires for the fynbos vegetation type which cannot be captured efficiently by the neural network.

B. Confusion Matrices

A confusion matrix serves as means of summarising the performance of the classifier. 25% of the total dataset was randomly selected to validate the network's performance, this equates to 639 randomly selected days for which the neural network's predicted rating is compared to the actual rating for that day. The confusion matrix for the fynbos vegetation is shown below.

Actual Values \ **Predicted Values**	Low	Moderate	High	Extreme
Low	341	15	4	2
Moderate	19	94	11	2
High	3	5	65	6
Extreme	2	7	3	60

As can be seen, the classifier is able to successfully classify the ratings for the different types barring a few exceptions. This can be attributed to other factors that are responsible for the fire ignition other than just climatic conditions. A similar confusion matrix is shown below for the strandveld vegetation type. As can be seen, this neural network is also able to successfully classify the ratings. In fact, it able to perfectly classify all extreme ratings for this particular vegetation type.

Actual Values \ **Predicted Values**	Low	Moderate	High	Extreme
Low	437	17	1	0
Moderate	15	118	16	1
High	0	1	26	3
Extreme	0	0	0	18

C. Overall analysis and discussion

Table VI shows the overall performance for each of the vegetation types as well as the combined performance.

TABLE VI
OVERALL SYSTEM PERFORMANCE

	Fynbos	**Strandveld**	**Overall**
Accuracy	0.941	0.996	0.969
Precision	0.856	0.891	0.874
Recall	0.834	0.917	0.876
F-score	0.844	0.903	0.874

The overall performance is satisfactory across all the 4 different classes of ratings for each of the vegetation types. It is important to note that there are inherent errors that will be present as a result of fires that are caused deliberately and are not solely dependent on the environmental conditions.

D. Comparison to Lowveld FDI

The use of neural networks as a method for measuring the risk of fire occurrences is not a new one. Yang *et al.* [26] used feed-forward neural networks for predicting the number of dwelling fires. Goldrag *et al.* [27] implemented a similar neural network model for forest fire assessment in Iran. The features considered include humidity, precipitation, air temperature, wind speeds, duration of sunshine, and topography. The output of the neural network was a dichotomous variable where 1 indicated a fire, and 0 indicated no fire. There was no associated level of risk computed as has been performed in this paper. Goldrag *et al.* reported an accuracy of 0.93, which is slightly lower than the accuracy of the neural network model obtained in this paper [27].

The results are compared to the Lowveld model which is currently the only model used for determining wildfire risk in

South Africa. A comparison of the ratings that are determined from application of the Lowveld FDI (as stipulated in eq. 2) is shown in table VII. These ratings are compared to the ratings determined as a result of the actual number of fires that occurred that day (observed rating), as well as the rating determined from the output of the neural network (ANN prediction). As the Lowveld FDI has a 5-category rating scheme as opposed to the 4-category rating scheme described in section IV(A), the FDI values corresponding to ratings of *very dangerous* and *extreme* is considered to be comparable to the *extreme* rating in the 4-category rating scheme. The *safe*, *moderate* and *dangerous* ratings from the Lowveld FDI will be respectively viewed as equivalent to the *low*, *moderate* and *high* ratings from the proposed system.

TABLE VII
COMPARISON OF ANN RISK RATING WITH LOWVELD RISK RATING

	Observed rating	**ANN prediction**	**Lowveld FDI**
Low	1566	1477	121
Moderate	545	462	2029
High	343	362	393
Extreme	102	255	13

As can be seen from the table, the Lowveld FDI substantially underestimates the number of days where more than 30 vegetation fires occurred. Even though the ANN predicts more number of days with an extreme rating, it is important to note that vegetation fires are not guaranteed even if the environmental conditions are conducive to such, however fire management need to be aware of such conditions. As the ANN is trained on past occurrence of fires, it is able to better identify the environmental conditions that increase the risk of wildfires for the City of Cape Town, bearing in mind the vegetation type. Furthermore, for this application, false detections are preferred over missed detections.

VI. CONCLUSION

A novel data-driven intelligent wildfire risk system was developed for the City of Cape Town. The system makes use of data from historic fire records for the years 2009 to 2015. As a result of the unique topographical, wind, vegetation and climatic conditions of Cape Town, experimentally determined fire danger models do not prove to be accurate in predicting the risk of fire ignition. The developed system based on the application of artificial neural networks is able to successfully classify the risk of fire ignition for various environmental conditions. The fire risk index is classified into one of four symbolic categories (low, moderate, high and extreme). The entire system delivers a satisfactory accuracy and precision of 0.97 and 0.87.

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