Proceedings of the Second International Conference on Smart Electronics and Communication (ICOSEC).
DVD Part Number: CFP21V90-DVD; ISBN: 978-1-6654-3367-9

Leveraging Machine Learning to Predict Wild Fires

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Abstract - A raging wildfire is a catastrophic event which damages forests, which has a serious effect on people, fauna and flora that are dependent on the forest ecosystem. A study of the size of wildfires in a Canadian Province in USA i.e. Alberta is seen in this article. A variation of the duration of the fire and the area it burns defines the scale of a fire. Our predictive algorithm helps wildfire rescue workers to use their foreseen level in the initial phases in order to mitigate destruction inflicted by a forest fire. Modeling information has been gathered from Natural Resources Canada's real-time dataset, including forest fire and weather information for Alberta, Canada. To evaluate the severity of flames, the dimensions of the region affected with fire and the timeframe of the flames have been used. The information was split into training and evaluation environments after multi-linearity validation and function normalization. In addition, the climatic variables were used to create predictive model by using inputs, a Neural Network for Back Propagation (BPNN), a type of artificial neural network i.e. Recurrent Neural Network (RNN) and a type of RNN i.e. Long Short-Term memory (LSTM). LSTM showed the greatest precision, 95.9 percent, of these classification models. The findings suggest that the scope of a wildfire can be forecast using climatic knowledge at the outset of the event.

Index Terms - *Multi-scale forest fire prediction, Prediction of Forest Wildfires, Environmental Integrity, Machine Learning (ML).*

I. Introduction

Forestry, one of the most important and needed tools for conserving the environmental integrity of the Planet, is a safe refuge for human livelihoods. However, disasters like forest fires can cause significant damage to forest, and many other assets such as infrastructure, human life and wildlife are overabundant. Forest fires flame fields of farmland and in just seconds kill anything in their directions. Forest fire is destroying houses, livestock, forests, plants, habitats and foliage. There are various and far-reaching consequences of fires. The effect on the economy, climate, history and social fabric of remote regions is enormously important. The parameters [1-2], such as weather, precipitation, moisture levels, pressure, and so forth, will, of course, prevent wildfire.

Forests are completely a living and non-living ecosystem, with cattle, birds, plants etc., and water, stones and atmosphere in the forest environment. Forest fires are one of the worst naturally occurring hazards in the planet. During the warmer months there is a fire each year. Global warming is responsible for those disasters in forests. A huge wildfire started in Australia in July 2019. At last year, Australia has burned at minimum 27 thousands of acres, lost 29 human lives and lost 2 500 houses. In Australian forest fires it is claimed that 1.25 billion livestock were killed [3]. Study suggests that the origins of Australian forest fires are global warming and thunders. In January 2019, some other destructive wildfire occurred in the Amazon rainforest. The burning lasted until October 2019. In the 2019 Amazon jungle fires, 906,000 hectares of land have been burned [4]. The number of fire4 in the Amazon of Brazil is high, though noticeably smaller, until July-2020 than the July-2019 period (Fig.1).

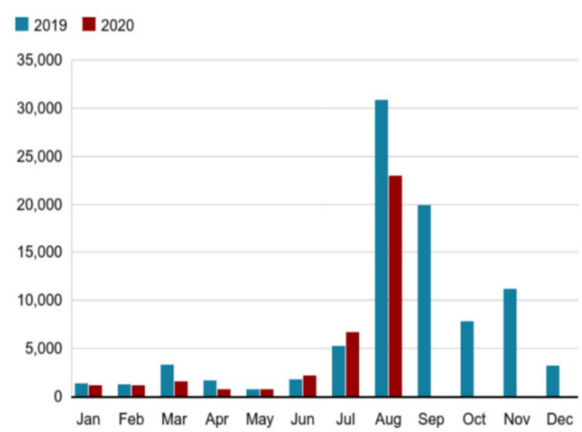

Fig 1: Wild fires in Brazil's Amazon 2019-2020. (2020 data up to 23 August).

According to a research carried out by many organizations, an aggregate of 67,000 forest fires have been burning each year over the last 10 years, and an aggregate of 7.0 thousand hectares each year. The main reasons for forest fires are flashes, violent eruption of volcanic material, shaking of earth, hot temperatures and droughty vegetation. Fires harm biodiversity and have prolonged environmental effects. Wildfires have little to do with the fatalities, crops and trees, land degradation, impotence and unproductiveness of soil, pollution levels of air and water and release of toxic gases. The main impact of wildfires is climate change. The flames can be punishable, exceptional and very hard to deal with when they are endangered. Trying to predict the frequency of this dramatic situation could perhaps be useful and helpful and plays a crucial role in taking preventative and safety steps to deal with the incident and to plan and even to stop forest fires in the future. Extreme wildfires ravaged many areas worldwide in the past few years and threaten to devastate them. Consequently, prevention of wildfires needs more focus and consistent procedures. Wildfires have become more complex than most fires. By expanding into adjacent fire-prone zones, they can also cause serious effects and produce a chain reaction in which the main wildfire extends to suburban, commercial and industrial neighbourhoods. The dynamics of wood, forest composition, topography, combustion and weather patterns at any region lead to wild lands fires. Fires in wild lands are a major concern worldwide. Wild land fires are a vital factor of preserving the ecological balance, but under such climate conditions, such as extreme temps and drought, they can be a significant danger to the community and wildlife. Forest fires are disastrous. Not only the natural habitats, but also the whole wildlife species regime, are fatally threatened, which seriously perturb the ecosystem. Fig. 2 depicts the intensity, magnitude and severity of wildfires in Alberta.

Fig.2: Wildfires in Alberta

Due to climate change, there's really an increase in the intensity of wildfires. A robust, multidimensional strategy is therefore important, which allows forest land to be monitored and responded quickly in real time. Therefore, the objective is to create an ML model which will be:

1. Assessing historical evidence on wildfire.
2. Forecasting the possible use of real-time data feeding into the structure of wildfires.

II. RELATED WORKS

Zope etal., (2020). [5] In this study, the forecasting of wildfires is encouraged by employing ML techniques, organizational surveillance of a zone, and environmental issues by various sensors. The Wildfire Prediction System (WiPreSy) tracks and documents environmental issues and predicted wildfires severity based on the available information, thus preventing huge losses due to wildfires. The model trained by them forecasted the risk of wildfires as cloud data are supplied to the model in real time. The estimate is calculated by a measure of confidence. Their Deep Neural Network classification performance is 91 percent, while the loss caused by binary cross-entropy is 1.12. The ranges are mild, moderate, large, very large and the intensity levels are reflected. Their study involved assessing historical evidence on wildfire, forecasting the possible use of real-time data feeding into the structure of wildfires and Identification of a pattern based on valuable and differentiated metrics including position, height, and weather in order to forecast the potential for wildfire as inputs are provided in real time.

H. Liang et al., (2019). [6] Studied three prediction models and concluded that LSTM model showed highest ability to forecast the levels of wildfire with a total predictive precision of 90.9 per cent of the three neural network models tested. In the forests of Alberta, Canada they explored the link between meteorological and forest fire causes. M. Naderpour et al, (2020). [7] Used probability prediction methods to predict bush fires in New South Wales, Australia. In order to calculate the likelihood and adjust the probabilities attributable to any expected or unscheduled improvements in New South Wales region, the model incorporated data from a Geographic Information System (GIS) for a given location at the micro-level. Their Bayesian Network (BN) based method also contributed to potential global and multi decisions in areas susceptible to forest fire.

K. Hyeong-su et al, (2019). [8] Proposed an efficient digital- twin system for predicting forest fires by employing bilateral spread simulator. H. Kaur et al., (2020). [9] Deployed Internet of Things (IoT), Fog Computing and Cloud technology to predict wildfires in four forest divisions in Punjab. They collected the wildfire related datasets from Punjab forest department. They also deployed IoT sensors to check and collect timely data and employed Principal Component analysis (PCA) for reducing the parameters that affect forest fires. The region of the charred forest is also estimated with the Support Vector Regression (SVR). The extent of vulnerability of forest area to fires is estimated using the classification of Naïve Bayes (NB) and Seasonal Auto Regressive Integrated Moving Average model (SARIMA).

M. T. Rashid et al., (2020). [10] Deployed a surveillance system for wildfires that takes advantage of combined forces from computer simulation for wildfires and drone sensing framework to reliably monitor wildfires. Drone sensing approach is a modern sensory model that identifies early signals of forested fires from online social media feeds and pushes drones towards reliable sensing. In the context of major fires, drone sensing solutions frequently fail due to the lack of data from social media in distant regions and short flight times of drones. Two inherent problems which have not been overcome with current operations are mitigated under their framework: (i) reduced the problem of social network data availability of the wildfire areas; and ii) determining likely fire spots in which drones are dispatched. They achieved a classification accuracy of 65% on real-world wildfire dataset. They employed 50 drones to evaluate the system.

A. Massetti et al, (2018). [11] Employed a new post-fire indicator to track forest conditions. They had applied index based method to 2005 Perth Hills fire in Western Australia. The original flames, including most topography, were fairly well detected in their research. Their experimental outcomes led to a very strong distinction between unburned and burned forests shortly after the flame upheaval.

M. T. Rashid et al., (2020). [12] Presented a poster abstract on forest fire surveillance system by employing drone sensing paradigm. The Wildfires in the area of the Amazon between July-August 2019 using the globe's actual forest fire repository was used in their research. The repository consists of Twitter live data gathered from July-August 2019 via the GetOldTweets information gathering app. Furthermore, daily quality of air, climatic readings were also taken from Brazil test sites. The mark of the underlying data showed the real fire spread is produced from ancient world laboratories aerial photographs.

A. Jayakumar et al., (2020). [13] They employed a mixture of foggy logic and neural network to forecast massive fires in Kerala's Idukki and Wayanad forestry hotspot. The clustered response is generated by a variation of the fuzzy logic system and the neural network by cluster analysis. Data were collected from the meteorological department of India for 2007-2018 and the metrics involved are humidity, dryness, initial spread index etc. Two algorithms were used. One is the Fuzzy C-mean algorithm and one is the rule-based classification algorithm. The result is 193 nodes with 0.364703 as root mean square error (RMSE). S. Dian et al., (2019). [14] In order to avoid disruption to electricity plants and distribution network by forest fires, they developed an advanced early warning system architecture, which included forest fire predictions and the advance detection about a possible outage. They demonstrate the wildfire danger, the most fragile poles can be predicted and the fire protection facilities can be distributed as far as they can. The machine will predict the propagation of flames and their future threats to the power line in time for weeks and the automation infrastructure allows the system to efficiently process the troubling processes in an efficient manner.

R. Rodriguez et al., (2008). [15] They suggested combining two methods of the Adaptive Data Oriented Application System to prevent the spread of wildfires. They have created a system which responds dynamically when a risk arises and in strict real-time periods to permanent environmental changes. To this end, they developed a concurrent wildfire prediction approach to interpret data to be inserted at the execution time into the prediction model.

N. Alamgir et al, (2015). [16] They suggested an integrative framework for the latest rural-metropolitan interface fire monitoring and fire forecasting strategies. The model forecasted fire danger as a result of the climate and the initial signal of fire was to sense haze using video surveillance systems. Moreover it will be used to increase the security of fire detection and decrease error levels by using the fire hazard indicator given by the base classifier. Test results revealed that the method forecast fires with an mean accuracy of 94.92 per cent and haze is more accurate compared to other techniques with mean accuracy of 97 per cent.

R. Rodriguez et al., (2010). [17] Genetic algorithms and statistical integrating have been used to illustrate the advantages of concurrent implementation in forecasting forest fire, especially when the atmosphere is very complex and abrupt shifts in the wind and wind direction are apparent. They found that data injection could dramatically increase the outcomes of the forecast in real time. However, trials in a wider infrastructure were not planned and the consequences of delay in the transmission of distributed and geographical data that would have been inserted. They can boost the forecast results if circumstances improve unexpectedly during a wildfire with real time data injection.

S. Gao (2019). [18] Amazon rainforests are being drawn through a devastating, unsustainable period of collapse by wildfires and act of cutting down the trees. In the interest of saving these rainforests, the speed of deforestation must be estimated using modern technology. Two AI strategies were suggested to prevent possible degradation of Amazonian rainforests, including, the Time Series and LSTM. The model predicts that intervention was urgently needed to avoid further degradation. The support of improved AI methods is expected to effectively reduce deforestation enhancing environmental conditions in the near future. L. Ju Hyoung (2021). [19] Studied prediction of large scale forest fires in Gang-won Province, South Korea. They explored a stress index to improve the wildfire prediction capacity of soil moisture. Two major and recent wild fires in kang-won province showed the close association between stress index and fire intensity. Their research revealed that the stress index can accurately estimate the gravity of massive forest fires, and differentiates dry soils from wild fire dangers a week before fire incidents. In the region of Kang-won, two new wildfires are marking extremely harmful yet low-frequency occurrences. A new stress index is proposed in this analysis to help fire rescue crew over large-scale fire disasters.

S. Trilles et al., (2013). [20] They provided a model focused upon space-point processes for multi-scale forestry fires prediction and developed a standard distributed framework to publish this feature for the sharing of these models and their performance. L. L. Bourgeau-Chavez et al, (2008). [21] They measured fuel moisture in satellite C-band imagery detector and enhanced forecasting of wildfires risk for boreal alaska. In order to enhance fire safety and fuel humidity control, they have developed two methods. They found that a generic algorithm for back dispersion can be used to combine the data from different years and burnt regions.

S. Jazebi etal., (2020). [22] They reviewed and classified works in various scientific disciplines and technological initiatives that discuss problems relating to wildfires. They investigated means of estimation and avoidance, mechanisms for identification, techniques for tracking and monitoring, strategies of removal, allocation and visualisation, and summaries of the research and education efforts. They have addressed the threats and the losses caused to the power grid by wildfires and the disruptions in their continual use. Ultimately, the different scenarios of defective power networks that lead to wildfires were evaluated and classified.

S. Lall et al., (2016). [23] For forest fires risk analysis in City of Cape Town, they created a new data based intelligence model which uses artificial neural networks. The model used landscape, temperature and place characteristics to estimate the probability of forest fire inflammation for two types of vegetation. The method is educated and validated on historical fire incident figures from 2009-2015 and delivers medium, mild, strong and severe categorical outcomes. All round, with an efficiency of 0.97 and a precision of 0.87 the machine is capable of doing predictions correctly.

D. Chaparro et al, (2016). [24] They utilized dynamically detected soil moisture data as a key element in the connection between environment and forest fires. The research is concentrated on the wildfires recorded during 2010-2014 on the Iberian Peninsula. Tests also showed that wildfires have been reduced in temperature and humidity conditions, and that the possible optimum burning region was achieved by pairing humidity model parameters (R-squared value is 0.43). The precision of model estimates was 83.3% with a cumulative error of 40.5. Divya T.L et al., (2015). [25] They proposed a method that processes the satellite images to determine the fire affected area according to their size of hot spots. The clustering algorithm is employed to find hot spots and the fire propagation area is traced. When implemented on wild fire images, the performance of the algorithm is comparatively high. They proved that it is possible to identify flames and fire behaviour from the picture of forest fire and wind patterns by using their model. It also seeks to track affordable fires through satellite images and then forecast the direction of fire propagation. In their future work, thermal imaging can be improved for the identification and development of forest fire control systems.

N. Hamadeh et al., (2015). [26] They examined seven of the world's most popular fire forecasting indicators. A comparative analysis is presented with the mathematical models, attributes, features, and efficiency and implementation area of each system. The various models that have been created have been tailored for local research locations. The topic of adequacy and conformity with indicators is also being addressed in other areas under various circumstances. M. L. Tardivo et al., (2016). [27] Their dissertation offered a study of three approaches used in the estimation of fire comportment to minimise variance in input parameter values. The three approaches are used to direct the search using concurrent Evolutionary models, statistics in order to modulate the outcome, concurrency in order to improve time and space.

K. D. Julian et al., (2020). [28] They suggested two methods to estimate the wildfires pictures from noisy on-board cameras. A basic Kalman filter reduces interference and updates an overview map of the region you are looking at is the first solution. A particulate filter is used for prediction of wildfire growth in the second method, and experiments are used to quantify uncertainty about wildfire spread. W. Zhou et al., (2020). [29] The data mining methods were used like Support Vector Machine (SVM), BPNN and Random Decision Forest (RDF) to forecast the activities of the wildfire-inducing trips. They claimed that RDF with an Area Under receiver operating characteristic Curve (AUC) of 0.97 is the most accurate, retrieval and accurate, and all 91.7%. J. Zhang et al., (2021). [30] They have created a successful SqueezeNet framework which primarily works as a separator and forest fire classifier. This model focuses on valuable functionality and removes redundant components. Finally, they used an embedding segment to identify true fire. Findings clearly demonstrated that accurate forest fire identification can be achieved with a comparative precision of 0.93 and a best classification time of 0.89 seconds per picture.

III. CASE STUDY LOCATION

Fig. 3 illustrates the case-study of Alberta, a sunny state in Western Canada. The moist continental weather of Alberta is warmer in hot season and frigid wintertime. Average local climate ranges from 15°C in summer time, and average yearly climate levels ranges from 2.5°C in cold season to 24.5° C in hot season. The seasonally average moisture in winter is 200 to 325 mm and in hot season between 150 and 275 mm and yearly moisture between 300 and 600 mm. The gross estimated natural light ranges from 1,900 to 2,600 annually. Boreal forest forms the majority of the northern portion of the state and mountain range is mostly wooded along their southern boundary.

Fig. 3: Case study region, Alberta, Canada.

IV. METHODOLOGY

The methodology followed to predict the wildfires is illustrated in fig. 4.

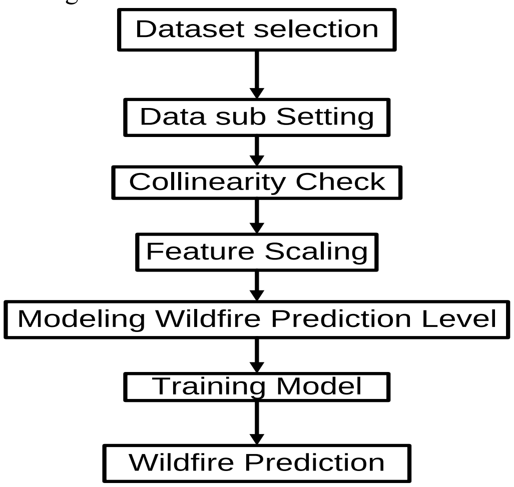

Fig.4 Wildfire Prediction Methodology

A. Dataset Selection

The wildfire statistics for the research area have been gathered from the National Fire Database in Canada (CNFDB). This dataset comprises geographic coordinates and combustion timings for all flames that happened between 1990 and 2018 in the Alberta area, including. The dataset also tracks essential data about wildfires, particularly exact location, combustion day, extermination period, amount burnt and reason.

B. Sub Setting data

There were a maximum of 266,828 entries of wildfire information recorded. All Eleven environmental factors were not included in the information stored, so we deleted the entries without any information unique to the forest fire. In addition, wildfires like firefighting or smoking have been removed by means of the wildfire type. There were 35,785 entries available for modeling for the residual wildfire information.

C. Collinearity Check

Multicollinearity results in a sharp connection between underlying factors in the regression model that distorts the estimates generated by the model and can lead to differences in the reality of the base. We estimated the inflation factor of variances to assess the relationship among variables in order to prevent features with strong multi-collinearity affecting the precision of our forest fire prediction model. A variable with a multi-collinearity severity higher than 10 is typically thought to be deleted since such values show that considerable multi-collinearity across predictor factors.

D. Feature Scaling

To minimize the intricacy of the data and to improve the prognosis accuracy of the ML models, all occurrences were scaled by min-max scaling. In Equation 1, the Min-Max Scaling formula is specified.

$$N_p = \frac{M_p - \min(M)}{\max(M) - \min(M)} \quad (1)$$

Scaled value is denoted by N_p, data point is given by M_p, lowest and highest values are given by min(M) and max(M) for the respective features.

E. Modeling the Prediction of Wildfire Level

(1) Back Propagation Neural Network (BPNN)

A BPNN is a multilayered, backpacking-based neural feed network. Conventional BPNNs are one layer of input, one or several hidden layers and one layer of output. There are numerous nodes in each level. Each neuron's input value, transfer function and threshold determine its output value.

(2) Recurrent Neural Network (RNN)

An RNN is neural network model generally applied to time series data. The unusual network topology of RNN allows the neuron's output to operate forthrightly as an entry to itself at the next stage. The outcome of the actual input and the output of the previous hidden layer determine the consequence of each hidden layer in the network, that is to say, the conclusion of the preceding computing is recorded by RNN. Moreover, the RNN can quickly lead to issues of disappearing gradient or detonation.

(3) Long Short-Term Memory network (LSTM)

LSTM is a RNN architecture which is utilized in deep learning (DL). In contrast to traditional neural feed forward networks, LSTM has feedback links. It can handle not only individual data points (for example images), but also whole data streams like speech or video. LSTM is involved in the construction of our network, which Hochreiter and Schmidhuber suggested in 1997. Different components consist of LSTM (including input, output, and forget gate). These components attempt to store critical data and to neglect redundant input data. Fig.5 illustrates the connection between LSTM components. The LSTM is somewhat different, and the form of the conventional LSTM model is seen in Fig.5.

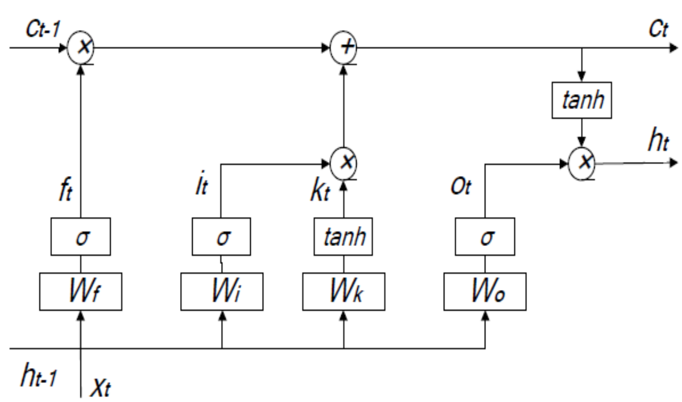

Fig 5: LSTM Components at time 't'

With the calculations within every phase the outcome is determined using mathematical equations *(2)-(7)*. Due to the series of input (x_1, x_2, … x_t), the state in which the layer is hidden (h_1, h_2,… h_t), the cells in LSTM are up-dated at times t as displayed in Eqs. *(2)-(7)*.

$$f_t = \sigma(W_f \cdot x_t + Z_f \cdot h_{t-1} + v_f) \quad (2)$$
$$i_t = \sigma(W_i \cdot x_t + Z_i \cdot h_{t-1} + v_i) \quad (3)$$
$$k_t = tanh(W_k \cdot x_t + Z_k \cdot h_{t-1} + v_k) \quad (4)$$
$$o_t = \sigma(W_0 \cdot x_t + Z_0 \cdot h_{t-1} + v_0) \quad (5)$$
$$c_t = f_t \times c_{t-1} + i_t \times k_t \quad (6)$$
$$h_t = o_t \times tanh(c_t) \quad (7)$$

The input, output and cell state vectors at time t are described using x_t, h_t and c_t. k_t represents the present input unit state. Transfer function (σ) is given in (8). Input gate i serves in taking fresh data and forget gate f determines how much of the network's input is preserved to the cell state at the final stage. The output gate checks the outcome or end value of the unit state for the LSTM. Weight matrices and bias or deviation vectors are represented using W, Z and v respectively.

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (8)$$

LSTM is an RNN subtype; it can learn knowledge about long-term dependence and prevent the loss of gradient. By enhancing input, output and forget gates in neural cells, LSTM increases long-term dependence. Input, output and forget gates regulate the status of the cell in every LSTM neuron.

F. *Training the Models*

In this work, the target function for the modeling of forest fire forecasting was to measure RMSE, which will be reduced as follows mathematical equations *(9)-(11)*:

$$r = d - s \quad (9)$$
$$RMSE = \sqrt{mean(r^2)} \quad (10)$$
$$Target\ Function = min(RMSE) \quad (11)$$

Where d is the output data, s is the source data function and designs with optimized values and r is the fault rate that should be minimized.

V. RESULTS AND DISCUSSION

Post normalization, we utilized the average N_p of the normalized fire time and the normalized burnt region to determine the magnitude of the forest fires. Five evaluations as per their N_p values were divided between the wild-fires. No fire, no small, medium, big and extremely large-scale fire at levels 0, 1, 2, 3, 4. The research implemented BPNN, RNN, and LSTM algorithms to assess the association between climatic data and wildfire level to determine the 8 environmental data as input data and forest fire level as result. Table 1 shows a comparative analysis of the three methods' predictive accuracy on the validation data set. The strongest classification power for the LSTM model has been achieved by the three approaches with 95.9% of the greatest accuracy level; 20,821 of the 21,697 test entries in the validation data set were properly forecasted. Fig. 6 shows the accuracy levels of three approaches used to predict wild fire.

Table 1: Outcome comparison of RNN, LSTM, BPNN prediction models

Model	Accuracy (%)					
	Level-4	Level-3	Level-2	Level-1	Level-0	Final
LSTM	95.9%	95.8%	96.7%	95.2%	96.2%	95.9
RNN	83.7%	81.3%	82.8%	84.6%	82.1%	82.9
BPNN	75.6%	73.9%	72.7%	75.6%	74.6%	74.4

The findings of the research showed that LSTM can forecast the extent of Forest fires through the use of environmental factors that give a basis in science for the forecasting of forest fires in Alberta.

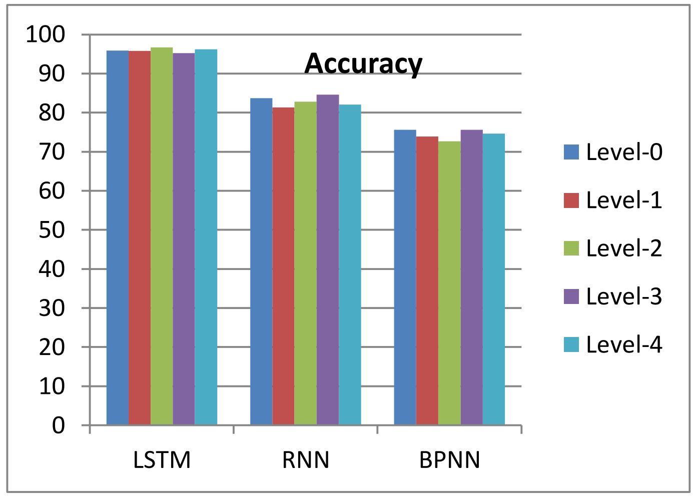

Fig. 6: Accuracy rate achieved by BPNN, LSTM and RNN to predict wildfire

VI. CONCLUSION

In the forests of Alberta, Canada we explored the link between meteorological and forest fire causes. The LSTM model showed highest ability to forecast the levels of wildfire with a total predictive precision of 95.9 per cent of the three neural network models tested. The experimental outcome of this research showed that forest fires with climatic parameters can be predicted on the scale, which is beneficial to deter and save wildfires, particularly forest fires. In line with the fire scale expected at the beginning phases, fire rescue crews can take decisive action, minimizing the casualties of the forest fires.

Although the data employed for the modeling were from a specific location, types of forests and weather patterns were identical in the dataset, and there are some shortcomings in the classification algorithm. This research therefore represents a significant path towards forecasting of forest fire, taking into consideration other parameters namely landscape topography, height, type of forest, size of population and human firefighting activity which can affect the size of wildfires along with environmental parameters. The sizes of a wider variety of wildfires can be predicted in the model, with more considerations.

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