Forest Fire Prediction Using Multi-Source Deep Learning

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Abstract. Forest fire prediction is an important aspect of combating forest fires. This research focuses on the effectiveness of multi-source data (lightning, hydrometric and weather) in the probability prediction of forest fires using deep learning. The results showed that the weather model had the best predictive power (average $F1Score = 0.955$). The lightning model had an average $F1Score = 0.924$, while the hydrometric model had an average $F1Score = 0.690$. The single-source models were then merged to see the impact of the multi-source data. The multi-source model had an average $F1Score = 0.929$, whereas the average $F1Score$ for the previous three single-source model was 0.856. The results showed that the multi-source model performed similarly to the best-performing single-source model (weather) with a 60% reduction in training data. The multi-source model had a negligible impact from the poor-performing single-source model (hydrometric).

Keywords: Deep Learning · Multi-Modal · Multi-Source Data · Big Data · Big Data Analysis · Binary Classification · Forest Fires

1 Introduction

Forestry contributed 2.3 billion dollars in revenue to the Canadian economy in 2022 and accounted for 205,365 direct jobs [2]. So, it is essential to protect forests. Deforestation is governed and controlled by governing bodies, but forest fires cannot be governed and are difficult to control. They can only be mitigated. For this reason, it is important to have tools that can predict their occurrence. Forest Fires can be broadly classified as anthropogenic and natural. Anthropogenic factors are quickly detected and reported as they are caused by humans. Hence,

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they can be more easily controlled and subdued. On the other hand, naturally occurring forest fires are hard to combat as they can go unnoticed for long periods causing greater destruction. For this reason, the research focuses only on naturally occurring forest fires.

Naturally occurring forest fires are often ignited by lightning [5]. Although lightning might be the cause of ignition, other factors can also impact the occurrence of forest fires [6] such as drought, weather, wind, etc. For this reason, it is essential to have multiple sources of data. A single source of data may not be effective in correctly predicting forest fires, hence multi-source approach was investigated in this research. In multi-modal learning, multiple sources and/or types of data are used, but only one model exists which makes the prediction. The terms multi-source and multi-modal learning are used interchangeably in this paper.

This paper is an extension of the research on the applicability of the Spatio-Temporal Agnostic Sampling (STAS) framework [10]. In this research, the applicability of multi-source data in forest fire prediction is studied. In the initial research, it was found that the historical feature data had an impact on the models' performance for the single-source weather data. With the introduction of multi-source data in this research, it was found that the models' performance was not impacted by the historical feature data. This research aims to investigate a multi-modal approach to predicting forest fires. A single source or type of data is not sufficient to build general models on forest fires, as they are impacted by multiple factors. It was noticed that the models could predict the probability of forest fires by taking in time series information from different sources of data. The models learned the variation in time series information to predict the severity and probability of forest fires. From the proposed research presented in this paper, it is clear that a multi-source approach using lightning, weather, and hydrometric features was successful in making predictions about forest fires.

The rest of the paper is divided as follows: in Sect. 2, we take up a Literature Review in related areas. In Sect. 3, Datasets used in the research are presented while Sect. 4 discusses the Methodology applied. Section 5 deals with Experimentation and Results followed by the Conclusion in Sect. 6.

2 Literature Review

A review of related literature shows extensive research on forest fires and lightning. There is also sizable work separately on water level, fires, and deep learning. However, there is hardly any research on multi-modal deep learning for forest fire prediction. This paper is an attempt to address this research gap. Due to space limitations, this paper does not address some points in detail. These points are discussed in the previous work [10].

Holle [4] reviewed global lightning impacts and suggested that people living closer to lightning-prone areas are increasingly affected by forest fires caused by lightning. Kochtubajda and Burrows [7] discussed such lightning-caused fires. Data for their study period (1998 to 2018) were obtained from Canadian Lightning Detection Network (CLDN). These provide a good source of background information on lightning detection and lightning-caused forest fires.

The Canadian Forest Fire Weather Index system is the main source of data for hydroponics. Hydrometric sensors facilitate real-time monitoring of groundwater levels. Research on water level and forest fires, duff moisture code, hydroponics and hydrometrics was carried out by [9,13] among others. In [13], the authors stated that the vulnerability of the study area was based on the hydrological condition. They found that when the groundwater level was less, there was more probability of fire. It was found that the highest risk of fire was in the month of March. Earlier research on hydroponics [18] also presented the increased risk of fire with decreased groundwater levels.

In [17], the authors proposed that the outputs from their study could be used for calibrating and validating the hydrological and climate models. Sanjaya et al. [12] proposed the use of satellite data or weather data in place of the Fire Danger Rating System (FDRS) which is implemented in Canada. They proposed Advanced-FDRS as a new algorithm to develop a fire warning system. In their study, Sun et al. [15] stated that forest fire spread behaviour depends on both dynamic factors and static factors. The dynamic factors include moisture content in vegetation and air. The static factors are the vegetation type in a particular region and the terrain slope. Research on water level and fire is limited. Though research on hydroponics and hydrometrics is vast, it is mainly focused on irrigation and drought. A consideration of drought as a possible factor of forest fire and the role of water both as fuel moisture content and groundwater level in forest fire research is limited.

In a recent study, Akkus et al. [1] defined multi-modal deep learning as the method of combining different channels of information simultaneously. They presented an overview of the different methods used in multi-modal deep learning to overcome the challenges of unstructured data and combining inputs of individual modals. Gao et al. [3] stated that multi-modal data consist of several modalities containing descriptions of things of interest with each modality-independent distribution. Correlations between modalities may also be understood through multi-modal approaches. In [11,14], the authors also presented a review and survey of multi-modal deep learning.

The authors in [8] described Random Multi-modal Deep Learning (RMDL) and showed how it could improve classification by including a variety of data as input. In their proposed RMDL approach, they used Deep Neural Network (DNN), CNN and RNN DL architectures. In a recent research, Vikram and Sinha [16] proposed a multi-modal framework for the detection of forest fires. They used two types of sensors, i.e., one for sensing the temperature, relative humidity, and drought condition of the forest zone. The other sensor was used to simultaneously capture images of the forest zone. However, this is not a very effective method, because the forest has to be divided into many small zones to capture images. Further, a large number of sensors would need to be installed. Their proposed framework is not suitable for large forests.

3 Datasets

This section describes the data used in the research. Four sources of data were used: 1) Fire, 2) Hydrometrics, 3) Lightning, and 4) Weather. Hydrometrics, lightning, and weather are the three single-source datasets used in this research, while the fire data is used to classify this data between fire and non-fire events. All the sources of data contain information for only Canada. The fire and weather datasets are discussed in detail in [10].

The hydrometrics dataset is used because drought plays a major role in forest fires [5]. It was acquired from Environment Canada (EC). It is a collection of different tables, of which, daily flow and daily level are of importance to this research. Spatio-Temporal Agnostic Sampling (STAS) [10] was applied to both features in the hydrometric dataset, as was done for weather data in [10].

The lightning dataset is a proprietary dataset and was obtained from EC. It is not publicly available. The dataset contains a number of features, of which, only two features, event strength and multiplicity are of importance. The event strength gives the strength of a lightning strike, while the multiplicity specifies how many flashes occurred for a single event of lightning. Spatial and temporal information was also recorded to perform aggregation on the data. The lightning data were aggregated to smaller regions, as there are no stations associated with this dataset. Minimum, maximum, and average values were extracted for both event strength and multiplicity. Additionally, the sum of multiplicity was also considered. The final dataset for lightning had 7 features. The aggregated values for the lightning dataset then underwent STAS preprocessing [10] where spatial and temporal information is discarded.

Hydrometric, lightning, and weather datasets are recorded in different timeframes. Hydrometric information was available between the years 1860 to 2022, while lightning information was available only between 2011 to 2022 and weather information was available between 1998 to 2017. When training the single-source models, the entire timeframe of each source was considered for training. While training the multi-source model (multi-modal model) the timeframe between 2011 to 2018 was considered as it intersected all three datasets. A summary of the above-mentioned dataset is provided in Table 1.

Table 1. Datasets Summary

Source	Data Available Timeframe		No. of Features
	Start Year	End Year	
Fire	1917	2020	-NA-
Hydrometric	1860	2022	2
Lightning	2011	2022	7
Weather	1998	2018	31

4 Methodology

As stated earlier, this research is an extension of the previous research conducted in [10]. The preprocessing for data from all three sources of data followed the STAS instructions. Since it was known from previous research [10] that the number of nearest stations (K) hyperparameter did not play an impact on the models' performance, K was not considered in this research. The other two hyperparameters for STAS, the number of past days (N) and the number of past months for non-fire events (M) are considered in this research. N determines the amount of historical information that will exist in the dataset for both fire and non-fire events. M specifies how many months in the past we are looking at since the time of a fire event to extract the non-fire points. For example, consider $N = 7$ (one week of historical information) and $M = 3$ (looking back 3 months to extract non-fire points). If a fire event occurred on February 28, 2023, then the fire event for the dataset will consider features from February 28, 2023, backward up until February 21, 2023, since we are looking at a week of historical information. Similarly, the non-fire event for the dataset is extracted from November 28, 2022, backward up until November 21, 2022, since M was chosen to be 3 months in the past for non-fire events.

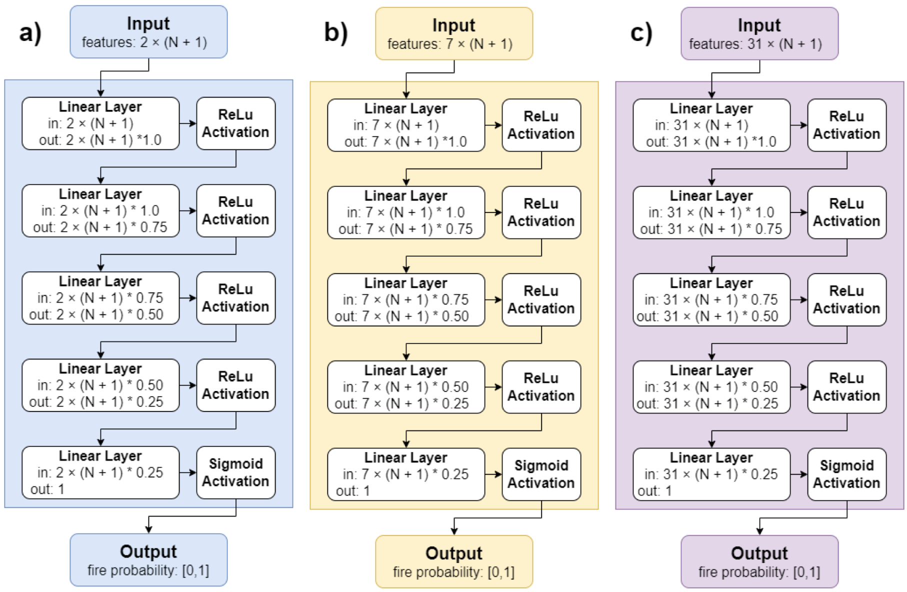

Fig. 1. Single-Source Deep Learning Binary Classification Model Architectures: a) Hydrometrics Model, b) Lightning Model, and c) Weather Model

The models need to output the probability of fire, given a set of features. A binary classification model was chosen for this task. Since the aim was to study the effects of multi-source data on the performance of the models, deep learning models were chosen as they provide the flexibility of merging different single-sourced models. The single-source deep learning models for hydrometrics, lightning, and weather were built similarly to the weather models as described in [10]. A pictorial representation of the three single-source deep learning binary classification models is shown in Fig. 1. All three single-source models output values are in the range [0–1]. 0 indicates fire will not occur while 1 indicates fire will occur. The final activation in these models is Sigmoid to ensure the values are in the range [0–1]. The three different single-source models are colored differently throughout this paper to distinguish them. The hydrometrics model is colored blue, the lightning model is colored yellow, and finally, the weather model is colored purple.

The multi-source deep learning models are built by fusing the single-source models. When fusing the single-source models, a weighted average approach is not used. The output layer in all the single-source models is dropped and is then joined to a fully connected network with a final activation of Sigmoid. During the training, the fully connected network determines the weights associated with the input provided by each of the single-source models. Since the final layer is dropped in the single-source models, they will be referred to as networks instead of models in the case of multi-source models. A high-level overview of the architecture for multi-modal learning is shown in Fig. 2. It can be seen that the single-source data is provided to their respective networks. The output values of these single-source networks are then fed into the fully connected network. This fully connected network for a multi-source model will, hereafter, be referred to as the fire network. Finally, the fire network will provide the probability of fire as output.

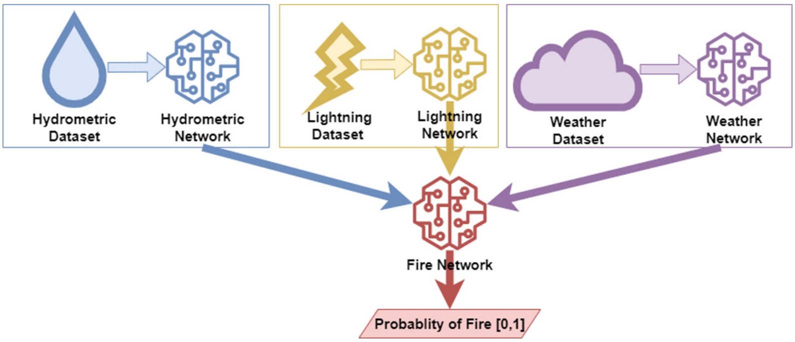

Fig. 2. Multi-Modal Learning Architecture

A deeper representation of the multi-source models can be seen in Fig. 3. It can be seen that the final layer for all the single-source models shown in Fig. 1 is discarded for the multi-source network in Fig. 3. The output of the final hidden layer in all the single-source networks is then passed on to the fire network as input. The fire model then outputs the probability of fire between [0–1]. The number of inputs for all single-source networks is different. It can be calculated using Eq. 1 with the following description:

$$NIF = SFC \times (N + 1) \tag{1}$$

NIF represents the number of input features for the network, while SFC represents the feature count of the source. SFC is multiplied by $(N + 1)$ because the day the fire occurs is also considered a part of the historical information. The input is then fed to their respective source networks. The hidden layer size in each network drops by 25% and there are a total of 3 hidden layers and 1 input layer [10]. The final hidden layer neurons (FLC) can be calculated using Eq. 2 with the following description:

$$FLC = SFC \times (N + 1) \times 0.25 \tag{2}$$

The value of FLC is rounded up to the nearest integer. Then the number of input features for the fire network (NIF_f) can be calculated using Eq. 3, derived as follows:

$$NIF_f = \sum_{single-source} FLC$$

$$NIF_f = (\sum_{single-source} SFC) \times (N + 1) \times 0.25 \tag{3}$$

The sum of SFC for the proposed approach in this research is 40 $(2 + 7 + 31)$, therefore, $NIF_f = 40 \times (N+1) \times 0.25$. The layer size in the fire network also drops incrementally by 25% for each layer. The final output layer has an activation of Sigmoid to have an output value between [0–1].

For this research, $F1Score$ was used as a metric to evaluate the models. $F1Score$ provides the harmonic mean of precision and recall, therefore, the impact of both precision and recall can be seen in the model. Ideally, an $F1Score \geq 0.9$ is considered to be excellent. If the score is between 0.8 and 0.9, it is considered to be good. A score between 0.7 and 0.8 is considered to be acceptable. Scores less than 0.7 are considered to be bad.

5 Experimentation and Results

The single-source models shown in Fig. 1 were first trained on their respective datasets for the entire timeframe. The hyperparameters were the same as the ones used in the previous research [10]. The $F1Score$ was recorded for all the single-source models for the varying values of the hyperparameters N and M. Table 2 shows the model metrics of both the single-source models and multi-source models. The first two columns are the hyperparameters N and M, respectively. The remaining columns are for different model types (single-source and multi-source). Two columns are grouped for each model type. The first column in the group specifies the number of input features for the model and the second specifies the $F1Score$ for the model. It can be seen that the weather models are the best-performing single-source models followed by the lightning models. The hydrometrics models are the worst-performing models.

For the multi-source, first, the dataset needed to be built. Since all single-source data are in different timeframes, a timeframe that was common to all three was chosen. It can be seen from Table 1 that the common years are 2011 and 2018. Therefore, a timeframe from 2011 to 2018 was chosen. This reduced the dataset size significantly. Then the data from all three single-sources were collected for the timeframe 2011 to 2018. The data from all the single-sources were merged by location and time to form the multi-source dataset. This dataset was then randomly split into test (20%) and train (80%).

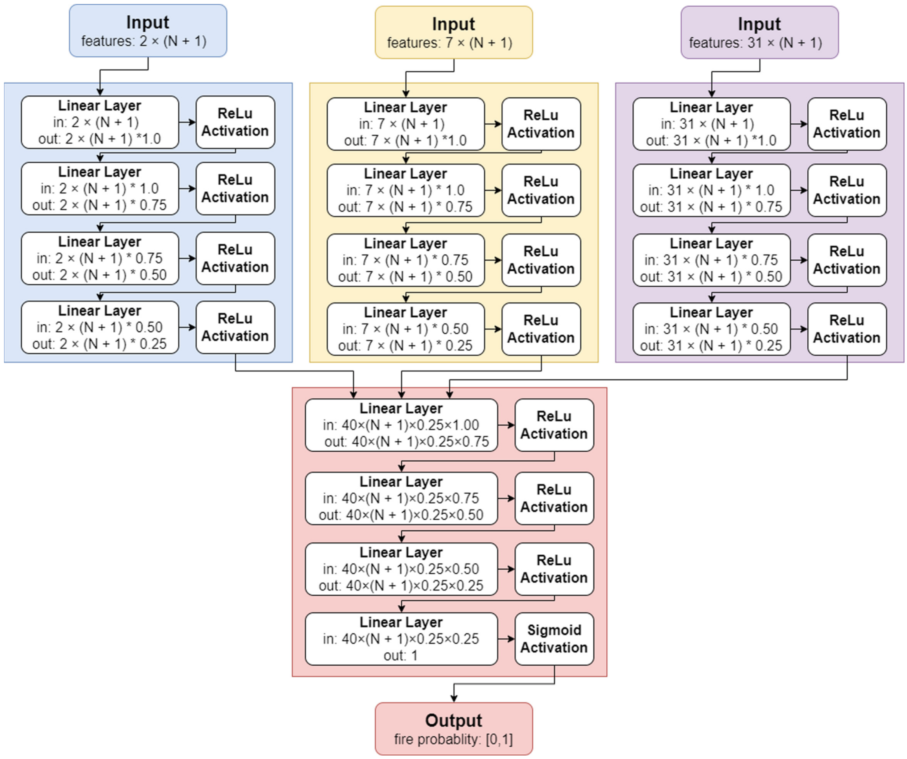

Fig. 3. Multi-Source Deep Learning Binary Classification Model Architectures

The multi-source model was built for each combination of hyperparameters (N and M) described in the previous research [10]. For all the pre-trained single-source models, for a given combination of hyperparameters, their output layer was discarded. The resulting models are called single-source networks (as seen in Fig. 2). The final hidden layers from all single-source networks were then connected to a fully connected fire network as shown in Fig. 3. This formed the multi-source model. The weights for the single-source network were frozen in the multi-source model. The only trainable weights were the weights from the fully connected fire network. The multi-source model then underwent training similar to the single-source models for all the combinations of hyperparameters defined in [10]. The results of the multi-source models for different hyperparameter combinations are presented in Table 2. A description of how to read the table was provided earlier. A comparison of multi-source model performance with N and M is shown using the box plot in Fig. 5. It can be seen that in the multi-source models, N has an insignificant impact on model performance, whereas M has a major impact on the models' performance.

Table 2. Model Metrics Preprocessed using STAS

N	M	Single-Source Model						Multi-Source Model	
		Hydrometrics Model		Lightning Model		Weather Model			
		No. of Input Features	F1 Score	No. of Input Features	F1 Score	No. of Input Features	F1 Score	No. of Input Features	F1 Score
7	3	16	0.687	56	0.913	248	0.962	320	0.958
14	3	30	0.647	105	0.932	468	0.975	600	0.951
30	3	62	0.674	217	0.949	961	0.986	1240	0.962
7	5	16	0.692	56	0.977	248	0.991	320	0.993
14	5	30	0.691	105	0.984	468	0.994	600	0.988
30	5	62	0.674	217	0.988	961	0.995	1240	0.988
7	6	16	0.685	56	0.977	248	0.995	320	0.996
14	6	30	0.683	105	0.986	468	0.997	600	0.995
30	6	62	0.684	217	0.989	961	0.998	1240	0.994
7	7	16	0.681	56	0.976	248	0.994	320	0.989
14	7	30	0.764	105	0.979	468	0.997	600	0.989
30	7	62	0.742	217	0.985	961	0.997	1240	0.989
7	9	16	0.683	56	0.906	248	0.976	320	0.964
14	9	30	0.636	105	0.927	468	0.983	600	0.965
30	9	62	0.809	217	0.940	961	0.991	1240	0.973
7	12	16	0.662	56	0.709	248	0.760	320	0.682
14	12	30	0.663	105	0.732	468	0.801	500	0.666
30	12	62	0.664	217	0.788	961	0.813	1240	0.659

A comparison of the single-source models with the multi-source model is shown in Fig. 5. The comparison is presented with box plots for the multi-source model with all three of the single-source models. One key thing to note for this comparison is that the dataset size for the multi-source model was 0.4 times the single-source weather data, 0.72 times the single-source lightning dataset,

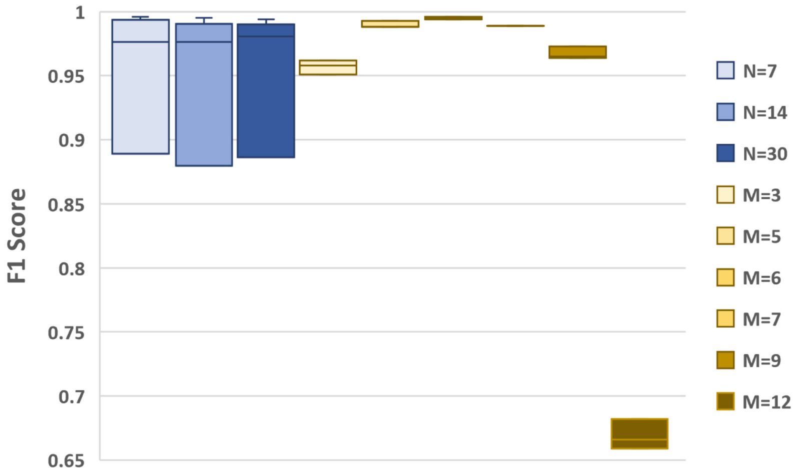

Fig. 4. Impact of N and M on Multi-Source Models' Performance

and 0.08 times the hydrometric dataset. It can be seen that the multi-source model shown in red in Fig. 5 was not impacted by having poorly performing networks exist in it (hydrometric). The multi-source model did as well as the best-performing single-source model (weather) shown in purple in Fig. 5. On average the $F1Score$ for the multi-source models was less than 1% lower when compared with the best single-source weather model, while the sizes of the training data for the multi-source model was 72% of the size of training data for single-source weather models.

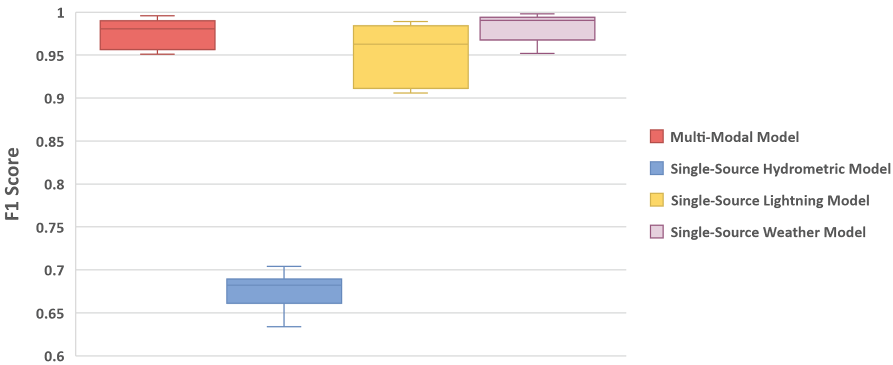

Fig. 5. $F1Score$ Comparison of Multi-Source Model and Single-Source Models

6 Conclusion

This paper proposed a multi-source deep learning approach to forest fire predictions. To the best of our knowledge, there is no research on forest fire prediction using multi-source data. Three different data sources (hydrometric, lightning, and weather) were used to investigate and predict the probability of forest fires. The single-source models in this research were trained on a larger timeframe (hydrometric over 103 years, lightning over 10 years, and weather over 20 years). The proposed multi-source model was trained on a shorter timeframe of 8 years to ensure that all the sources of data are in the same timeframe. Based on the experimental results, the proposed approach seemed viable for forest fire predictions. Even with less training data, the $F1Score$ of the multi-source model was high. It was also seen that the multi-source model was not impacted by the low-performing single-source networks in the model. On average the $F1Scores$ of the multi-source model were only 1% lower than the $F1Scores$ of the best-performing single-source model (weather). It was also seen that the multi-source model's performance is independent of N. In future, it is proposed to compare this research with an increased timeframe of data and study the impact of federated learning. It is also proposed to compare the impact of multi-source data on severity (area burned) shown in our previous research [10].

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