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Baseline Study About Forest Fires in Indonesia Using VIIRS Nightfire Data

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Abstract. Indonesia is sensitive to the environmental crisis. When the authorities have minimum control over land conversion and the illegal burning of peatland for agriculture, it sometimes spreads to the natural forest, causes enormous forest fires, and burns the area more than was intended. Visible Infrared Imaging Radiometer Suite (VIIRS) Nightfire (VNF) uniquely records near-infrared and short-wave infrared data at night. VIIRS provided the data in KMZ format containing geographical location, ambient temperature, radiant heat, and source footprint. This detects not only heat from fires but also from light emissions, mining, and gas flares. This study conducts to analyze the characteristic of fires in Indonesia. Machine learning was applied to analyze the VNF data to predict fire spots when the gas flares appear from the fires. Forest fires in Indonesia mainly spread with temperatures of 500 0K – 1000 0K, with the temperature of the peak of fire can be more than 2500 0K. The high fire risk is during the dry season between June to November. The fire cases decreased from 2019-2023. This indicates that the authorities are taking strategic steps to control forest fires in Indonesia.

Keywords: *VIIRS nightfire; forest fires; machine learning; ANN; linear regression; Indonesia.*

1 Introduction

Forest fires in Indonesia have been going on for a long time, namely since 1998 [1]. These fires are caused by many factors, including the weather, especially humidity and hot temperatures. In several countries in the sub-tropics, the problem of forest fires is also pretty complicated, as happened in Australia and America, where forest fires occur almost every year, one of the triggers being lightning and hot temperatures, and low humidity. From January 2019 to August 2019 there are 328,724 hectares area of forest experienced forest fires [2] The forest fires impacted severe environmental damage such as degradation, carbon emission, human life, health problems like breathing and vision [3] and transportation, sea, and air. In addition, the most significant impact if there is a forest fire is the occurrence of respiratory disease [4] and natural habitats.

One of the fundamental problems of forest fires is the impact they have on the surrounding environment, even if these impacts are exposed far from the location of the forest fire incident. One way to measure this impact is by using the Air Quality Index (AQI) method [5]. This AQI has become one of the references where if the figure reaches more than 300 in an area, this indicates a high level of danger, especially for health. Monitoring carried out by various agencies in the world including NASA (National Agency and Space Administration), NOAA (National Oceanic and Atmospheric Administration) Until the European Union, through one of its programs, namely Copernicus, has produced data related to forest fires and the impact of forest fires on the world .

The Fire Information for Resource Management System (FIRMS) was developed with the use of MODIS (Moderate Resolution Imaging Spectroradiometer), and the Visible Infrared Imaging Radiometer Suite (VIIRS) distributes Near Real-Time (NRT) active fire data aboard S-NPP and NOAA 20 (formally known as JPSS-1) [6]. Globally these data are available within 3 hours of satellite observation [7]. NOAA has developed observations through VIIRS satellites, one of which is the Suomi PP Nuclear Power Plant (National Polar-Orbiting Partnership using satellites).

VIIRS features daily imaging capabilities across multiple electromagnetic spectrum bands to collect high-resolution atmospheric imagery and other instrument products, including visible and infrared images of hurricanes and detection of fires, smoke and particles in the atmosphere, such as dust [8]. Machine learning is used to analyze this study, such as linear regression, SVM, decision tree, KNN, and ANN. The test was conducted to determine the characteristics of forest fires in Indonesia and test how well VIIRS data is used for modeling. In Indonesia, VIIRS Nightfire (VNF) data has been widely used to identify and validate forest fires [9], Lu et al. combined VNF data with MODIS to increase spatial-temporal accuracy [10], and analysis the characteristics of false-positive active fire for biomass burning were explored in Indonesia [11]

2 Study Area and Data

2.1 Study Area

The study area is in Indonesia. All fire spots recorded by VNF that occurred in Indonesian territory from 2019-2022 were included in this modeling. Fire spots are spread in almost all parts of Indonesia based on VNF data with resolution 375-meter pixels [12] with a minimum detected temperature is from zero, and the marking starts from 400^0K or the equivalent of $126{,}85^0$C. Each VNF detection is given a placemark according to its temperature (Figure 2(a)) [13].

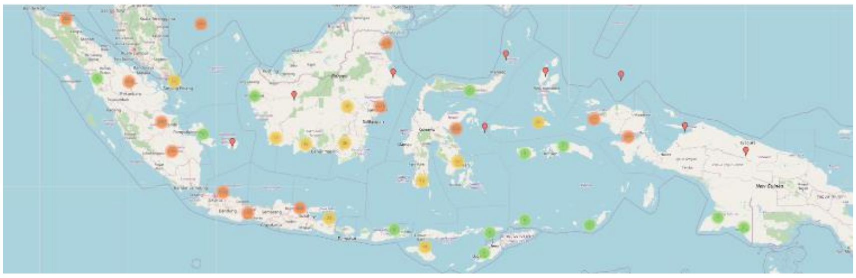

Figure 1 Fire map from VIIRS

2.2 Data

The VNF data used can be found on the Earth Observation Group website https://eogdata.mines.edu/products/vnf/ [13] as KMZ files which can be saved in CSV format. The data selected is data from 2019-2022, totaling 43218 data. VNF will record data when it detects a fire spot and then records the latitude and longitude location data, the temperature of the fire point, the radian heat intensity generated, and the area (m^2) burned at that temperature. This allows a 1 km^2 burned forest area to produce some VNF data because there are variations in the temperature of the fire in the burned area [6] following figure 2(a). Data on the radian heat intensity (figure 2(b)) generated by the fire will also be obtained from the detected flame temperature.

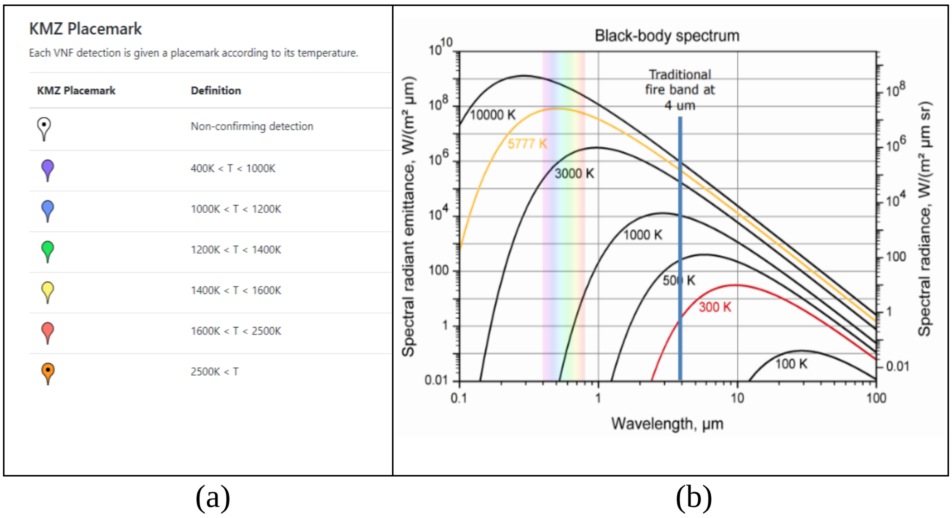

Figure 2 (a) KMZ PlacemarkEach VNF detection is given a placemark according to its temperature. (b) Radian heat wavelength from temperature.

3 Methods

The VNF data was analyzed using several machine learning methods such as Linear Regression, Ridge, Lasso, KNN, SVM, and ANN were applied to see what the criteria for forest fires in Indonesia were and to compare which method was the best to apply. VNF data is analyzed to determine the characteristics of fires that occur in forest fires in Indonesia. Machine learning is used to see predictions from flaming gas data produced by forest fires.

The flowchart for the process is presented below (Figure 3). The code first reads the inputs provided (VNF database), then the data cleans up from the incomplete data in preprocessing data. Descriptive analysis was performed to describe the characteristics of the forest fires based on the VNF data. Machine learning processes allow us to train the data and make predictions for flaming.

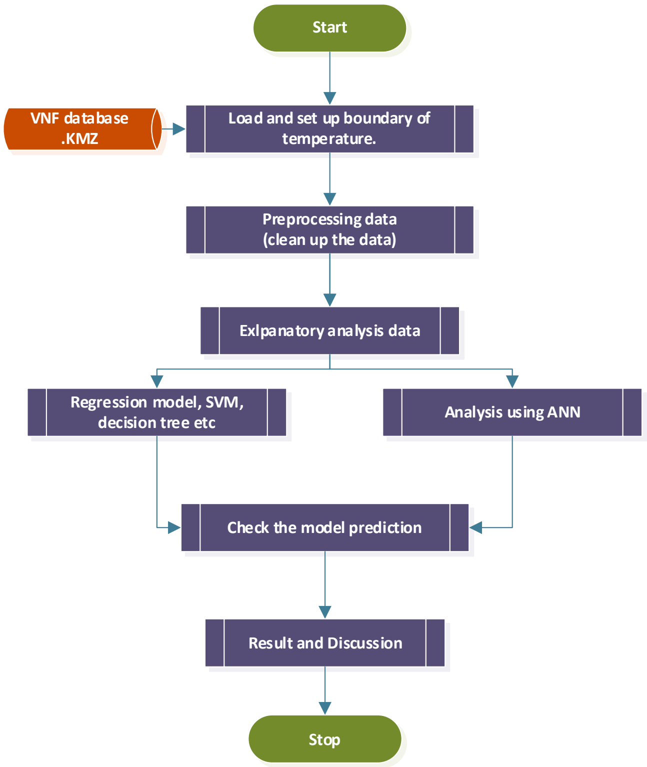

Figure 3 Research methodology flowchart.

3.1 Supervised Learning, Unsupervised Learning

In this study Supervised Learning that used were linear regression, decision tree, random forest, and support vector machines (SVM). The unsupervised learning that tried to the data was Artificial neural network (ANN).

Supervised learning is to learn patterns in the data and build a general set of rules to map input to the class or event. In this case, the classification of the fire is divided into two class, “flame” and “no flame”. No flame in this context does not mean the area has no fire, but it means that the fire’s temperatures are less than 1000^0K and not produce huge flare. Flame means the area burned in temperature more than 1000^0K and built the big flare.

The ANN applied here with five variables consist of latitude, longitude, temperature, radian heat intensity and source footprint or area burned. The model was built with two hidden layers and one output. The accuracy is the ratio of number of correct predictions to total number of predictions made (Figure 4).

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

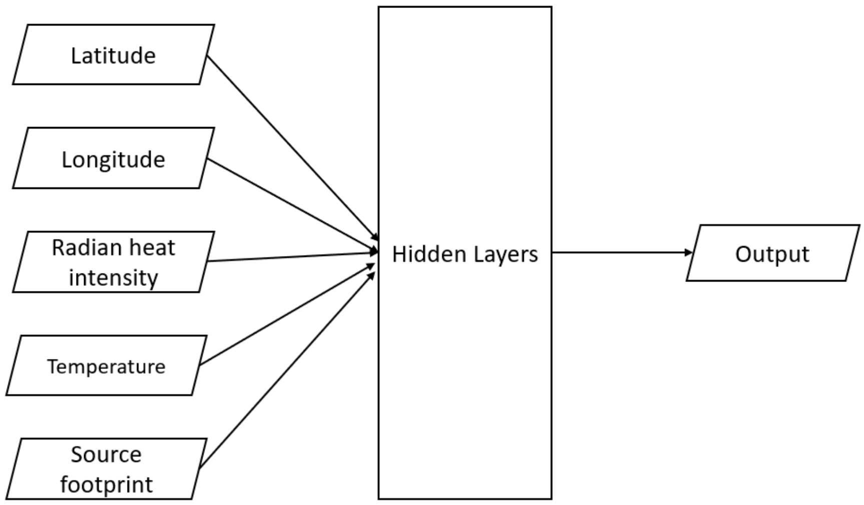

Figure 4 Model Development flow chart

4 Results and Discussion

4.1 Detect Forest Fires

Based on the analysis results, 43 thousand fire spots were recorded from 338 days in 2019-2023. Data shows that forest fires occurred very massively in 2019. From June to November, the peak of the most extensive burned area occurred in September, reaching more than 267.128 m^2 (27 ha) in one day, this number recorded at the end of the day around 06.00 PM and could be larger during the day. This data is related to what happened in the study area, wherein in 2019, the practice of burning peatlands to clear land for agriculture [14], oil palm plantation purposes increased in Indonesia. However, the implementation is often out of control, so protected forest areas are also burned [15].

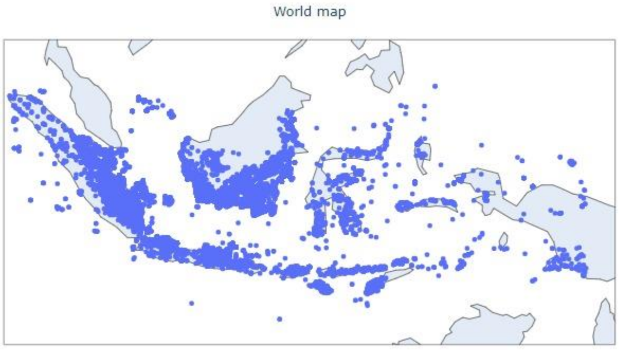

Figure 5 Fire spots in Indonesia from 2019-2023

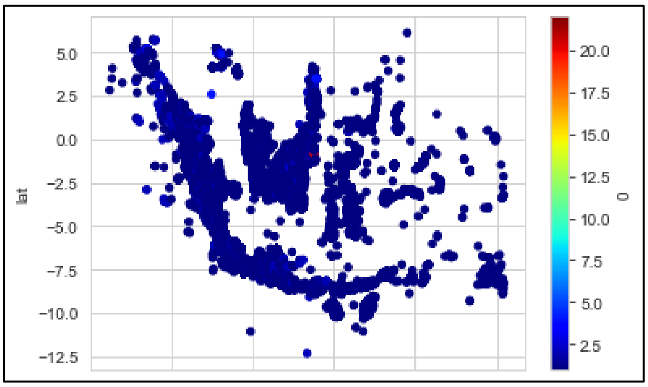

Figure 6 Burned area in 2019-2023

Figures 5, 6, and 8 show the frequency of fires based on the VNF data used. There are fire spots around Kalimantan that have experienced fires more than 17 times (red-orange color), and there are several locations with light blue fire spots indicating that these fire spots have experienced fires at least five times. The burned area has decreased since 2020 (Figure 8). This indicates that the authorities are taking strategic steps to control forest fires in Indonesia.

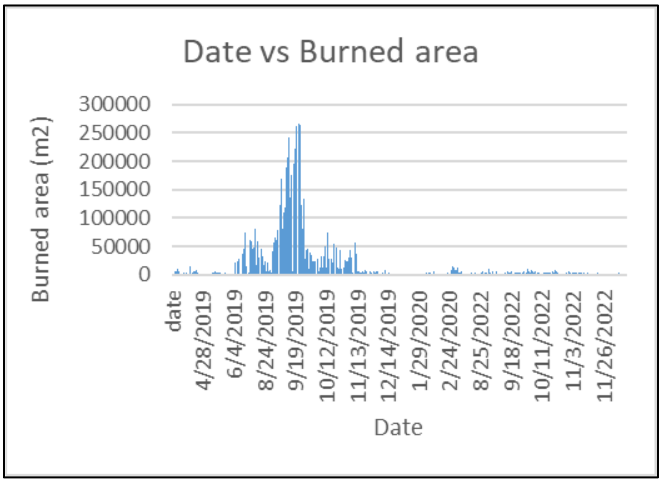

Figure 7 Date vs Burned area.

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Out[486]: 2019    25519
          2022     7974
          2020     1074
          2023        7
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Figure 8 Total fires point in 2019-2023

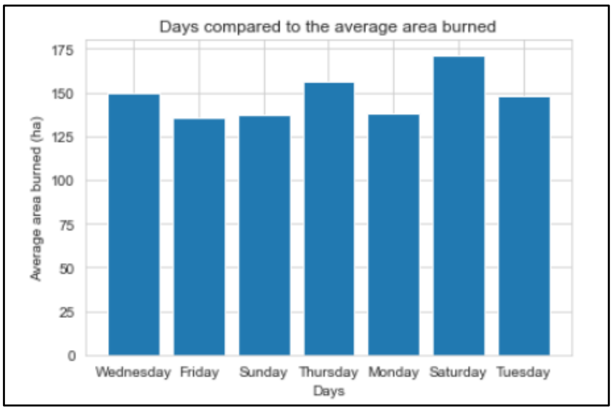


Figure 9 Days compared to the average burned area

On average, most forest fires in Indonesia occur in September and August, coinciding with the dry season in Indonesia, which is accompanied by strong winds, so that the fires will expand more quickly in these months [11], [16]. The burnt area is higher on Saturdays, which may indicate that the fire department is understaffed on weekends.

Fires in Indonesia have temperatures ranging from 500 ^{0}K – 2500 ^{0}K. The largest area has a firing temperature of around 750 ^{0}K – 1000 ^{0}K (Figure 11 (b)), and there are fire spots with very high temperatures. From this temperature, radian heat is 0.07-1000 W/m^2 (Figure 10 (a)).

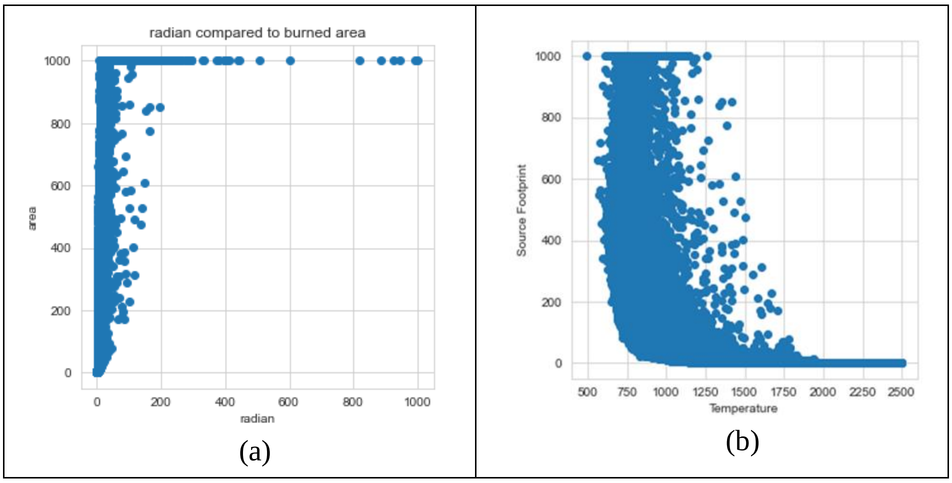


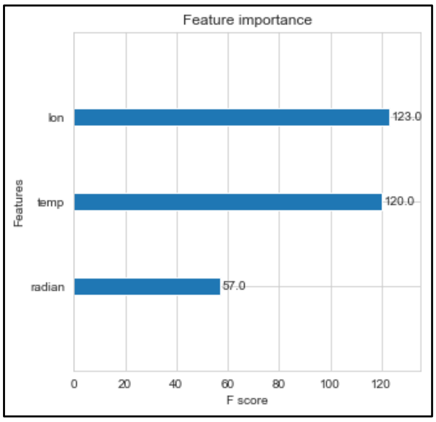
Figure 10 (a) Radian heat intensity (W/m^2) to the burned area (b) Temperature (^{0}K) to the burned area

4.2 Machine Learning

Calculations have been made to see the correlation between variables. In this study, the correlation between temperature and radian heat intensity to the variable source, which represents the footprint area of the fire, will be considered. Based on the decision tree simulation results, the essential variables from this data were longitude, temperature, and radians (Figure 11 (a)).

However, the data correlation results show that temperature negatively correlates with fire footprint (Figure 11(b)). The negative value happens because, at a location point with a very high temperature, the area of the fire footprint is small.

This might happen because areas experiencing peak temperatures are only at specific fire spots.




```
Out[484]: area_km      1.000000
          source       1.000000
          log_area     0.738011
          radian       0.521564
          month        0.069932
          lat          0.068273
          lon         -0.005080
          day         -0.034972
          Year        -0.243520
          temp        -0.532972
```

(a) (b)

Figure 11 (a) F score (b) Corelation between all variables to sourcefootprint.

```
LiR: 0.739355 (0.197806)
Ridge: 0.739355 (0.197806)
Lasso: 0.723162 (0.204417)
ElasticNet: 0.723215 (0.204575)
Bag_Re: 1.000000 (0.000000)
RandomForest: 1.000000 (0.000000)
ExtraTreesRegressor: 1.000000 (0.000000)
KNN: 0.997039 (0.001823)
CART: 1.000000 (0.000000)
SVM: 0.865074 (0.123545)
 Logistic Regression: 0.993058
```

Figure 12 Variance error in supervised learning.

Another possibility is the humidity and wind speed factors which significantly influence forest fires [16] but are not taken into account. For example, if the humidity is high, it will be difficult for the fire to spread even though the temperature is high. There may be a database, that is, the data only includes forest fires that occur within a certain period, where temperature and footprint have a negative correlation. By dividing the testing data by 0.7 and the testing data by 0.3, the results of supervised learning are in Figure 12.

Logistic Regression, Bagging Regressor, Random Forest Regressor, Extra Trees Regressor, and Decision Tree Regressor (CART) are the best estimators/models for this dataset, followed by KNN and SVM, they can be further explored and their hyperparameters tuned. The least estimator in this dataset is LinearRegression, Ridge, and Lasso. (Figure 12).

The ANN model was applied to this data with inputs: latitude, longitude, time, temperature (^{0}K), radiant heat intensity (W/m^2), and source footprint (m2). The expected output is the prediction of flame or no flame. The flame limit in this study is when the temperature is > 1000^{0}K, following the trend that occurs in Indonesia where the temperature of most of the time fire point is less than 1000K with central fire spots > 1000K. From this, it can be found the potential point where the flame appears. The use of neural networks will provide more accurate prediction results.

The Multi-layer Perceptron (MLP) classifier creates a neural network with two hidden layers. In this model, the selected layers are (12, 10, 6, 1) with a batch size 32 and epoch 50. The accuracy obtained: is 0.999, and the validation: is 1.00. The results obtained so far are still overfitting. However, the plot results still show reasonable results where there are only small fire spots where the fire will have a temperature > 1000^{0}K (Figure 13).

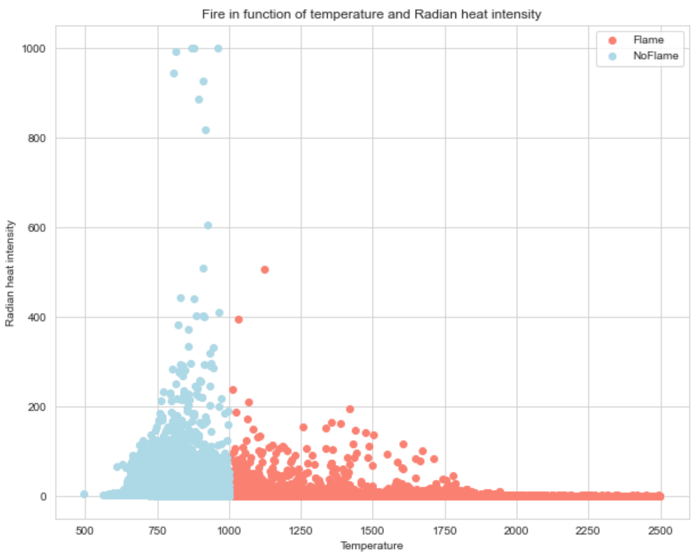


Figure 13 Temperature vs Radian heat intensity

5 Conclussion

VIIRS night fires very well detect fire spots that occur in Indonesia. However, the recording may still need to be completed because the sensor works very well at night, so there is a bias in the fire data during the day, which is incomplete. Gas flares are identified based on their high temperature and temporal persistence. In the case of Indonesia, the lowest detected hotspot temperature was 0.07 ^{0}K, and the highest was 2671 ^{0}K. Forest fires spread over a large area are 500 ^{0}K – 1000 ^{0}K, with the peak of temperatures > 1500 ^{0}K as the center fire spots.

Based on the correlation table, the temperature has a negative value for the fire spots because VIIRS has a high resolution, so the specific sensor captures the central fire area with a high temperature. It is essential to remember that correlation does not always imply causation and other factors may be at play that influence the relationship between temperature and burned area. In this case, the negative correlation between temperature and burned area makes the data look like a statistical anomaly. However, further analysis may be needed to understand the true nature of the relationship.

VIIRS night fires provide accurate data in identifying the characteristics of the fire, temperature, radian heat intensity, and source footprint of the fire. The Logistic Regression, Random Forest KNN, and SVM show the minimum error results. The ANN model also gives an accuracy of 0.99. However, despite changing testing and training specifications, the tested model shows overfitted accuracy results. All the variables included in these models were essential based on the F-scores. Building a forest fires model using the VIIRS data is highly recommended, and it will be easy to couple the data with rain data and humidity or other factors that have a more significant influence.

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