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Wildfire Risk Prediction and Detection using Machine Learning in San Diego, California

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***Abstract*—Wildfires are the most deadly and dangerous accidents across the United States, especially in California. Many lives are lost, and billions of dollars' worth of property damages occur in wildfire every year. Wildfires are fueled and accelerated by several different factors, such as weather, climate, vegetation types, land cover, and human activities. This research aims to develop a machine learning and big data-based fire risk prediction model considering the different geographical factors outlined above. We propose a systematic way to make fire risk prediction and detection models that analyzes satellite data, weather data, and historical fire data to predict fire. We got an accuracy of 100% using ensemble model and 93% using Faster R-CNN for wildfire risk prediction and fire detection, respectively, using machine learning models.**

Keywords— wildfire, machine learning, remote sensing, re-enforcement learning

I. Introduction

Wildfires are one of the most dangerous and common natural disasters that we encounter every year. As per the California fire department, around 5,715 wildfire incidents were recorded between 2013-2017 [1]. Uncontrolled wildfires not only cause damage to the environment and disrupt the ecological balance and cause significant loss to life and property [2]. If we look at statistics, over 3000 lives were lost, and more than $23billion in property damage was reported in wildfires [3]. Wildfires are both difficult to predict and fight because each wildfire is unique to the place where it occurs. A combination of various factors such as dry vegetation, gusty wind, terrain, weather, etc., further aggravates the situation. With so much impact on social and economic factors, it becomes necessary to build a near real-time solution for predicting and controlling wildfires.

A myriad of research papers has been published addressing wildfire detection and prediction by using mathematical and statistical methods. Still, these models have a lot of limitations such as limited parameters, low accuracy of risk prediction, the complexity of equations, and lack of real-time decision-making processes. According to the recent wildfire survey, most of the wildfire emergency systems still use conventional wildfire detection and prediction approaches [4][5][6]. In statistical and mathematical methods, we infer the relationship among the variables, while in the machine learning (ML) models, the focus is to make the most accurate predictions possible. Hence with the advancement in Machine Learning and Neural Networks, we can leverage the advanced algorithms to improve the lagging outcomes of wildfire risk prediction and detection systems. Many types of research are focused on investigating the probability of the burning, while others focus on the intensity and effects of the wildfires [7]. Moreover, earlier studies also show the deployment of a limited number of paraments with limited accuracy. Therefore, we aim to include different parameters such as fire history, weather, remote sensing, and satellite data to improve the accuracy of fire risk prediction and detection models.

In our research, we have employed Machine Learning and Deep Learning techniques to solve fire risk prediction and detection with cutting-edge accuracy. We have applied many machine learning (ML) models such as Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost), Random Forest (RF), Deep Learning techniques such as Convolutional Neural Networks (CNN), Long short-term memory (LSTM), and Faster R-CNN. We also divided the study area into square grids to have diligent data collection. We have used an ensemble model for fire risk prediction, and for fire detection, we have used Faster R-CNN. The ML models for both the tasks have been validated using the ROC curves, Confusion matrices, accuracy, and computation speed.

The organization of the rest of the paper is as follows.

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Section 2 reviews and summarizes the literature survey related to our work. Section 3 reports study areas and datasets. Section 4 explains the pre-processing data for weather data, fire history data, vegetation data, and remote sensing data. Section 5 and 6 report the machine learning model and its results for fire risk prediction and detection, respectively. Section 7 discusses the conclusion of our work.

II. Literature Survey

Many researchers have recently started using machine learning models for wildfire risk prediction based on parameters such as a month, day, temperature, relative humidity, wind, and rain [8]. Guruh F. S. and Khabib M. in [9] proposed a hybrid Model using clustering and classification approaches to improve the wildfire risk prediction accuracy by considering eight parameters: temperature, relative humidity, wind, and rain. They trained a Back-Propagation Neural Network (BPNN) to get the output in three categories: no burn, light burn, and heavy burn. BPNN is one of the methods of neural network in which weights of a neural network are fine-tuned based on the error rate got in the last iteration. Marcos et al. introduce a wildfire risk prediction system based on three different machine learning models to study the effect of human-caused factors in wildfires in Spain [10]. They implemented Random Forest (RF), Boosting Regression Trees (BRT), and Support Vector Machines (SVM) to detect fire risk prediction and found improvement in the accuracy in terms of the area under the curve (AUC). AUC determines the area covered by the Receiver operating characteristic (ROC) curve. For the perfect classifier, the AUC score is 1.0, while for the random classifier AUC value is 0.5. Researchers Caroline Famiglietti et al. predict fire risk in Northern California using different machine learning models, Logistic Regression (LR), Decision Trees (DT), and Multilayer Perceptron (MLP), based on remote sensing data [11]. LR, also known as logit regression, uses a logistic function to model the probability of a specific event, DT is the non-parametric approach used for regression and classification. MLP is a type of neural network that connects multiple layers of the perceptron. Wonjae et al. developed a wildfire detection system based on deep convolutional neural networks (DNN) using crewless aerial vehicles [12]. They achieved high accuracy than conventional machine learning algorithms. DNN is the part of neural networks that have at least three or four input and output layers. Mahsa Salehi et al. developed a Context-Based Fire Risk (CBFR) model for fire risk detection using ensemble learning techniques with high accuracy [13]. They used weather data to determine the temporal variation of the wildfire danger prediction in Blue Mountains, Australia. Recently Malik et al. proposed two machine learning approaches based on random forest (RF) models to predict the wildfire risk in Monticello and Winters, California [14]. They used fire history, weather, vegetation, powerline, and weather data in their study and obtained an accuracy of 92%. RF is an ensemble learning method that consists of multiple decision trees and used for classification and regression tasks.

The real challenge with wildfires is to predict wildfire spreading patterns to provide real-time location-based solutions. Many researchers are using machine learning models to address this problem. Joana G. F. and Carlos C. D. introduced wind parameters to assist fire management in simulating wildfire propagation using a cellular automaton model [15]. A cellular automaton is a computation model in which there is a collection of colored cellular spaces on a specific grid shape that evolves through discrete time steps based on the neighboring cells states. Their model helped to decide the locations to allocate the resources for firefighting. Zhong Z. et al. introduces a spread simulation model that uses the cellular automaton by considering wind parameters for predicting fire progression probability [16]. Their model achieved better results in predicting the probability of each cell. Alexandridis, A. in [17] also uses cellular automaton to study fire progression by considering different factors such as vegetation types and density, wind speed, direction, and spotting phenomenon. Radke et al. came up with a new system, FireCast that combines the Artificial Intelligence (AI) techniques with the geographic information systems (GIS) to predict the wildfire spread based on fire history, satellite, elevation, and weather data in the Rocky Mountains [18]. Firecast is based on the supervised 2D Convolutional Neural Networks (CNN) and had better accuracy, recall, and F-score. CNN is a neural network that consists of input and output layers with hidden layers. The major limitation of fire simulation approaches is their dependency on a few parameters without considering real-time factors and environmental conditions, such as terrain and vegetation conditions.

Effective measures, if taken on time, can prevent and control the extent of potential damage significantly. Unlike the other existing research that generally focuses on only one aspect, either fire detection or fire risk prediction, we aim to address the wildfire risk prediction to find the possibility of fire on any given date and to address the location-based fire detection. We have used innovative data-driven machine learning models based on various parameters and factors such as weather, fire history, vegetation, and remote sensing. For the fire risk prediction model, we implemented the Ensemble model and achieved the cutting-edge accuracy of 100%, and for fire detection, we implemented faster R-CNN and achieved an accuracy of 93%.

III. Study Area And Datasets

The frequency of large wildfires is influenced by a complex combination of natural and human factors. Temperature, soil moisture, relative humidity, wind speed, and vegetation (fuel density) are important parameters that help to establish the relation between fire frequency and ecosystems. We have considered the data consisting of satellite images, weather data, fire history data, and vegetation data to analyze the fire risk prediction, fire detection, and fire spread prediction. The study area covered San Diego and its surrounding forests because it is prominent for fire spreading, as shown in Fig. 1.

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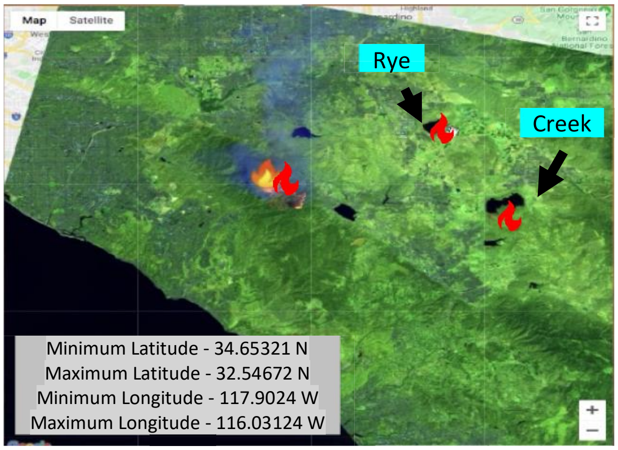

Fig. 1. Area of interest for Fire History (San Diego, California)

A. Data Sources

The data collected for various data types and their sources are given in the below table 1.

TABLE I. DATA TYPES AND THEIR SOURCES

Data	Sources
Fire History	Fire and Resource Assessment Program (FRAP), CAL Fire, United States Forest MSDA Project, Service region, Bureau of Land Management, and National park service
Weather	NCEO (National Center for Environmental Information)
Remote Sensing	Landsat 8 satellite using Google Earth Engine (GEE)
Vegetation	San Diego open GIS Data Portal

IV. DATA PRE-PROCESSING

A. Weather Data

We collected the eight years (2011-2018) of weather data to provide data analytics and insights into the relationship between weather and the possibility of wildfire in San Diego County. The weather data collected from the National Center for Environmental Information (NCEO) provides valuable information about station, date, latitude, longitude, temperature, dew point, wind speed, gust, and precipitation. The collected data was highly imbalanced as there were very few fire occurrences in a year compared to no-fire events. Hence, we used Synthetic Minority Oversampling Technique (SMOTE) to oversample and generate samples of both data classes [19]. To deal with the missing values for better performance, we filled them with the mean values.

B. Remote Sensing Data

We used Landsat 8 remote sensing images for the fire risk prediction and fire detection from 2013 to 2020. Landsat 8 images contain 11 bands ranging from Band 1 to Band 11 based on different wavelengths and resolutions. We used the rasterio library of Python to process and visualize the details of the images. In satellite imaging, each place on earth is referred to by a path and row, hence we filtered the images for San Diego that were covered by two coordinates - (path=40, row=37) and (path=39, row=37). The cloud cover value in the dataset indicates the amount of cloudiness on that day. If the cloud coverage is more, the image will not have enough features for analysis. Therefore, we have filtered the dataset for cloud cover < 10.

Study and visualize: The parameters tiled, the number of bands, size of the band image, and size of each tile were explored using the profile data of the raster image. Tiling is the process by which each scene is split into smaller windows. Landsat 8 scene covers 230.73km x 234.63km on the ground, which is significant for most of the studies. Hence, we created small windows covering the smaller area of 14km x 14km out of the entire scene. Fig. 2 shows the tiles generated for one scene of San Diego, and here, we can observe that the size of the one block in an image is 512 x 512 while the size of each image is 7691 x 7691.

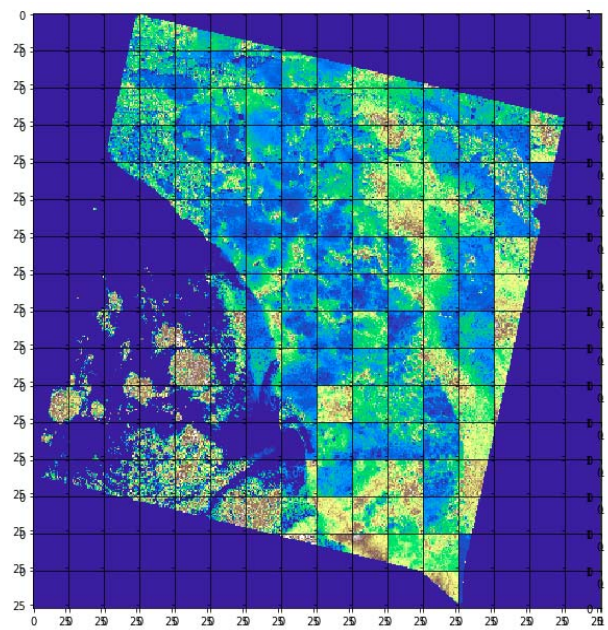

Fig. 2. Tiles generated from one scene of San Diego.

Atmospheric Correction on Red and NIR Bands: To eliminate the earth's surface reflectance and compute the vegetation indexes, we did the atmospheric correction. We used the below formula for atmospheric reflection for Landsat images.

$$band\_toa = M_P * ds + A_P$$

where band toa is the atmospherically corrected band, ds are the band file before atmospheric correction, M p and A p are scale factors obtained from the Landsat 8 metadata text file. We computed all the values on both red and nir bands.

C. Fire History Data

We used the fire history data provided by Fire and Resource Assessment Program (FRAP) for 2011-2018. The geographic locations of the past fires were divided into 1 x 1 km grids. We

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denoted the presence of fire and no fire with the binary variables.

D. Vegetation Data

The vegetation data is used to determine the exact land cover of a place and helps to calculate the Normalized Difference Vegetation Index (NDVI values). We can predict the fire risk with greater accuracy if we know the exact type of vegetation. Fig. 3 shows the vegetation layout of the San Diego area in which we generated colored labels using QGIS visualization. For example, we gave different shades of green to grasslands, scrub, and woodland. We labeled purple to our developed area of interest. NDVI is a graphical indicator to determine the live vegetation in the image. NDVI, as a value, shows the amount of chlorophyll content reflected from a place on earth. From previous studies, we found that NDVI values drop significantly during a wildfire [20]. We also combined red and nir bands to create NDVI images to be used for classification. The number of fire images in the resulting dataset was 1425.

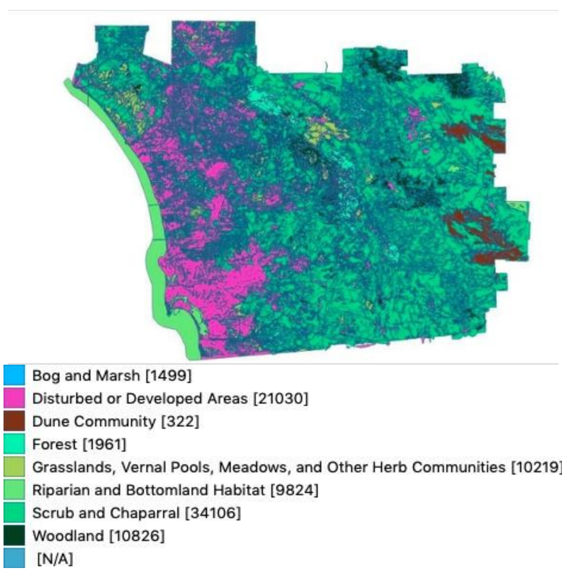

Fig. 3. Visualization of vegetation Data

We Combined different years of data from the above data sources and stratified samples for model building formulation after statistically analyzing all the samples. Then, we split the dataset randomly to 80% and 20% as training and test datasets. Further, we divided the training datasets into 4:1 ratio as training and validation datasets.

V. Fire Risk Prediction

This section talks about the fire risk prediction models and their results. The main aim of fire risk prediction is to answer the possibility of fire on a given date and a given location. This answer will help firefighters and the public to take necessary precautions at any time. The fire prediction takes three different factors to account - the weather, the land cover, and the fire history of the place. We can obtain new insights by combining all these data and have divided the datasets into weather-based data and remote sensing-based data. Then, we applied the machine learning models to these different datasets, and finally, we used an ensemble model to predict the fire risk, as shown in Fig. 4.

A. Machine Learning Models

1) Weather-based fire prediction model

For fire risk prediction, we have used three different types of machine learning algorithms to apply to our weather and fire history datasets to generate a comparative analysis and evaluation results to assess their accuracy and performance. Later we saved the results to feed into the ensemble model. We used Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost), and Random Forest (RF) algorithms on the weather and fire history datasets [21]. SVM is a linear model used for classification and regression problems. XGBoost is an ensemble machine learning algorithm that is based on decision trees and uses gradient boosting framework. Boosting is an ensemble technique in which we add new models to correct the errors of the existing models. XGBoost is one of the most powerful techniques used for classification on structured data such as table. Random Forest is a powerful technique that leverages learning from multiple decision trees for classification. These models help classify the input given weather data as either fire or no fire when combined with historical fire data for San Diego County.

2) Remote sensing-based fire prediction model

We used three algorithms – Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM) on the remote sensing datasets along with the fire history data. Later we reserved these models to be fed into the ensemble model. We have used convolutional neural networks to predict the fire risk using NDVI and fire history data. The CNN architecture has three layers: convolutional layer, pooling layer and fully connected layer. We used the seven combinations of hidden layers to predict the fire history. Layer 1 is composed of convolution layer of 3x3 with 128 filters and activation function ReLu. Layer 2 consists of a max pooling layer with 2x2 strides. Layer 3 consists of 3x3 with 64 filter and activation function ReLu, layer four consists of a max pooling layer of 2x2, layer 5 consists of convolution layer of 3x3 with 32 filters and activation function ReLu, layer 6 consists of a max pooling layer of 2x2, layer 7 consists of fully connected layer with activation function softmax. The model was compiled using the categorical cross-entropy loss function with Adam optimizer with a learning rate 0.001. We used LSTM for real-time analysis to make future predictions on the remote sensing data. LSTM is a type of recurrent neural network capable of remembering past information, and while predicting future values, it takes past information into account. We used the following configuration to build our LSTM sequential model: LSTM layer for learning the time-series sequence, Dense (Fully Connected) layer, softmax activation to transform the output to the probability values, Adam optimizer to compile the model using categorical cross-entropy loss function.

3) Ensemble model

After creating two different fire risk predictors 1) using the weather-based data and 2) using the remote sensing data, we

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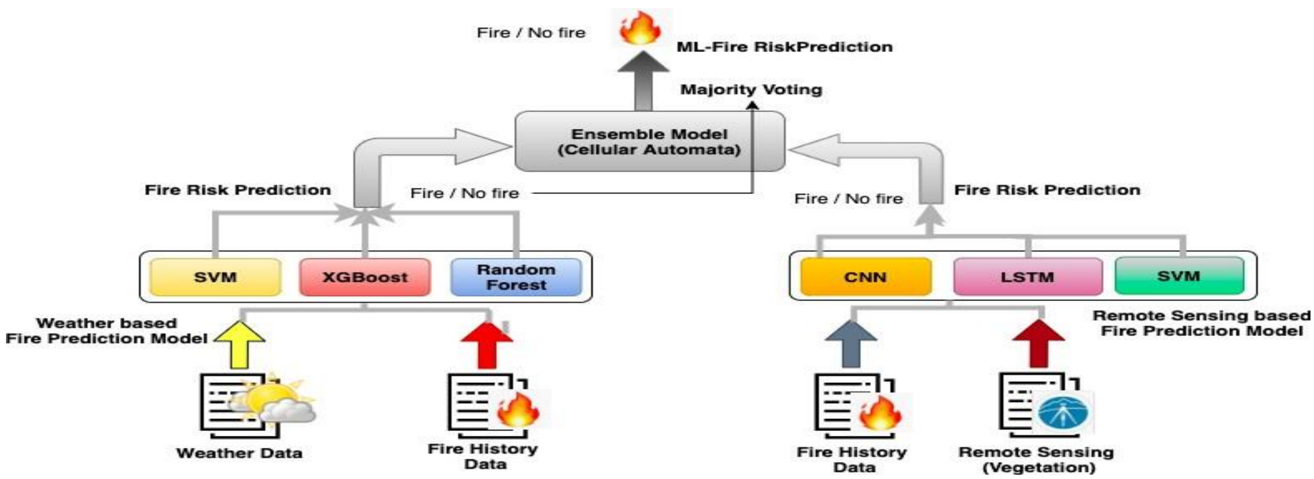

Fig. 4: Ensemble model architecture for Fire Risk Prediction (Right hand side shows the weather-based fire prediction model and Left-hand side shows remote sensing-based fire prediction model)

used an ensemble model to combine the predictions and reach a definitive result. Since there are more than two models with high accuracy, we decided that majority voting will be an excellent approach to find the ensemble result. We used cellular automata for generating the majority voting [22], which is a discrete mathematical concept. Rule 30 of the cellular automata simulates majority voting. The ensemble model will take the fire predictions from the above models as inputs and use majority voting to generate a single fire / no fire prediction as output as shown in fig. 4.

B. Results and Discussions

We have used accuracy, precision, and F1 score as our evaluation metric to compare the performance of the algorithms. Table II shows the results for weather-based fire risk prediction models. Each of the models was hyper-tuned and regularized to obtain the best evaluation metric score. From Table II, we can observe that the SVM, XGBoost, RF has the accuracies of 98.18, 98.23 and 97.54%, precision of 96, 98, 99% and F1 score of 97, 98 and 91% respectively.

TABLE II. EVALUATION METRICS RESULTS FOR FIRE RISK PREDICTION AND FIRE DETECTION MACHINE LEARNING MODELS

	Model	Recall	Precision	F1-Score
Weather based Fire Risk Prediction Model	SVM	98.18%	96%	97%
	XGBoost	98.23%	98%	98%
	RF	97.54%	99%	91%
Remote Sensing based Fire Risk Prediction Model	CNN	96%	94%	94.5%
	LSTM	97%	94%	95%
	MLP	73%	73%	73%
Ensemble Model for Fire Risk Prediction	Cellular Automata	100%	100%	100%
Fire Detection	Faster R-CNN	93%	80%	86%

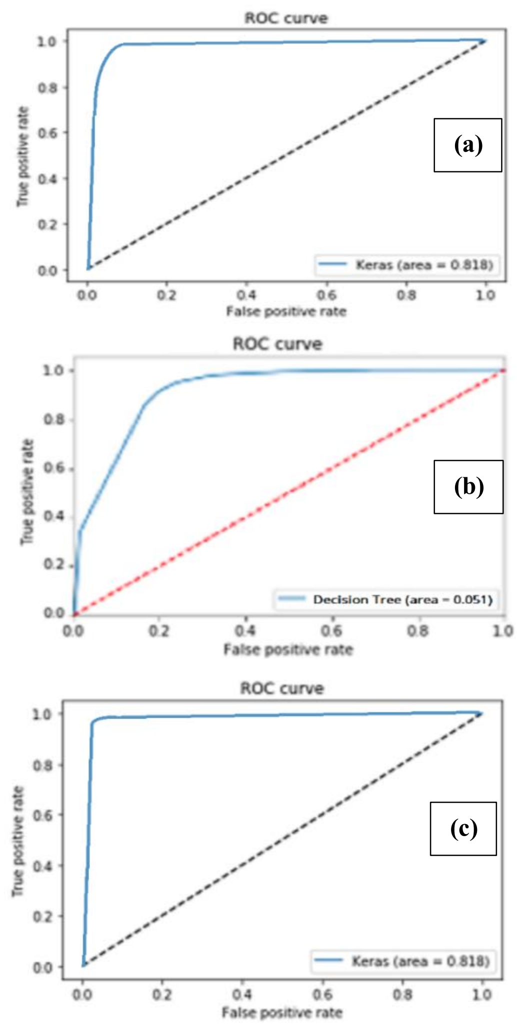

Fig. 5. ROC Curves for Weather based Fire Risk Prediction Models (a) SVM (b) XGBoost (c) RF

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The ROC curve for the weather-based model is shown in Fig. 5, which compares the true positive rate to the false positive as the threshold for predicting '1' change. The area under the ROC curve is inherently related to the accuracy. Still, the AUC-ROC is preferred because it is automatically adjusted to the baseline and gives a full picture of how the classifier performs at different threshold choices.

The ROC curve was plotted and carefully evaluated, with the best threshold of 0.499112 and a G-Means of 0.866. Similarly, for remote sensing-based fire risk prediction models, we got the highest accuracy for LSTM of 97%, followed by CNN of 96% and MLP of 73%. Here, LSTM has outperformed CNN and MLP in terms of accuracy, precision, and F1 score, as shown in table II. The same can be confirmed by analyzing the ROC curves as shown in fig. 6.

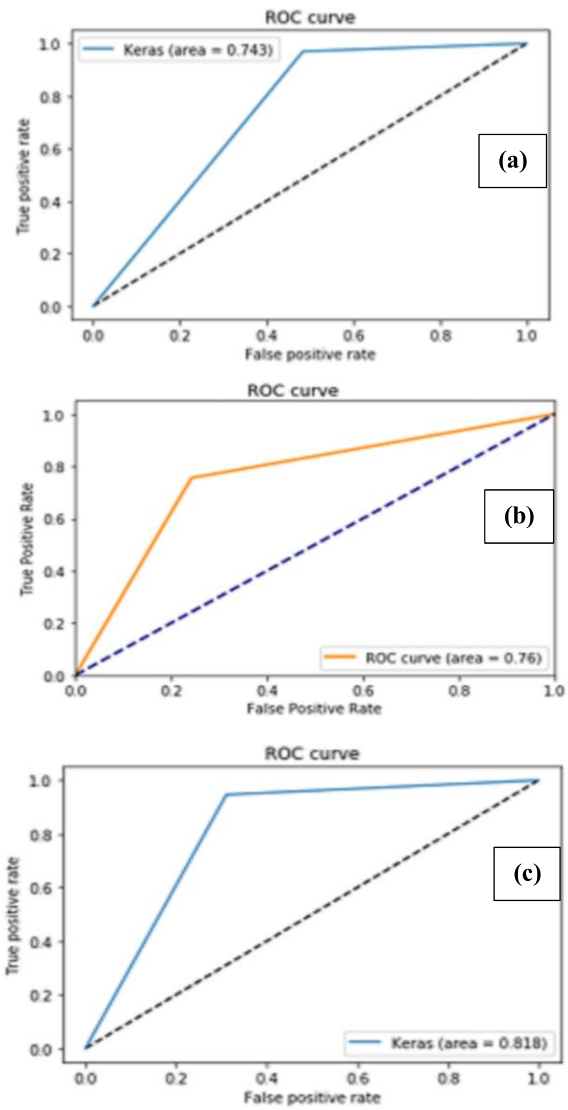

Fig. 6. ROC Curves for Remote Sensing based Fire Risk Prediction Models (a) CNN (b) MLP (c) LSTM

The ROC curve for LSTM shows an area of 0.818, followed by CNN with 0.743 and MLP with 0.76. Hence, here from our results, we can depict that LSTM is a better choice than CNN and MLP. After analyzing the results of weather-based and remote sensing-based models, we tried the Ensemble model where we used majority voting to find the result. Fig. 7(a) shows the confusion matrix, and 7(b) shows the ROC curve for the ensemble model. We observed the highest accuracy of 100%, and the ROC curve shows the value of 1 for our ensemble model. Based on the testing results, our ensemble model generates the best performance and accuracy than other models.

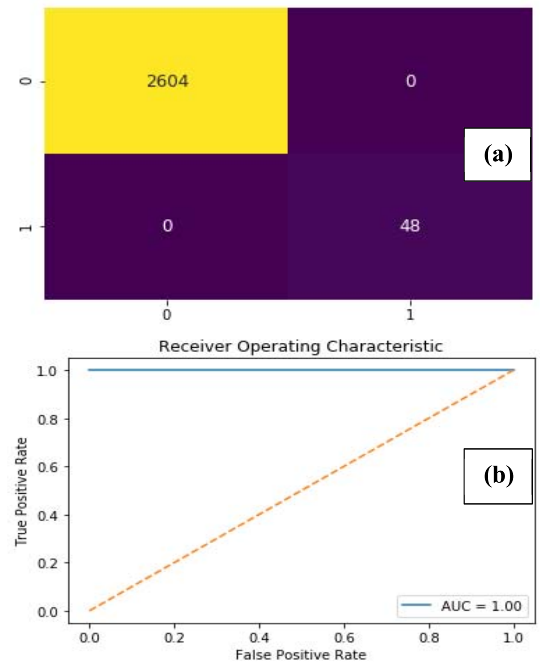

Fig. 7. Confusion Matrix (a) and ROC Curve (b) for Ensemble Model Fire Risk Prediction Model

VI. Fire Detection

Fire detection is an important aspect when it comes to validate the fire prediction results. There are a lot of intricacies involved in identifying fire occurrences in a geospatial context. Identifying fire occurrence based on satellite images requires images of good resolution to make sure that small fires are also detected. A fire can be detected by observing actual fire occurrences and identifying smoke in a specific region. We have considered both these parameters of fire and smoke detection to provide an accurate result. Once fire prediction is done, we need to validate the results using the ground truth from satellite images for the specific day. To detect fire occurrence accurately, it is necessary to have a clear satellite image with high resolution

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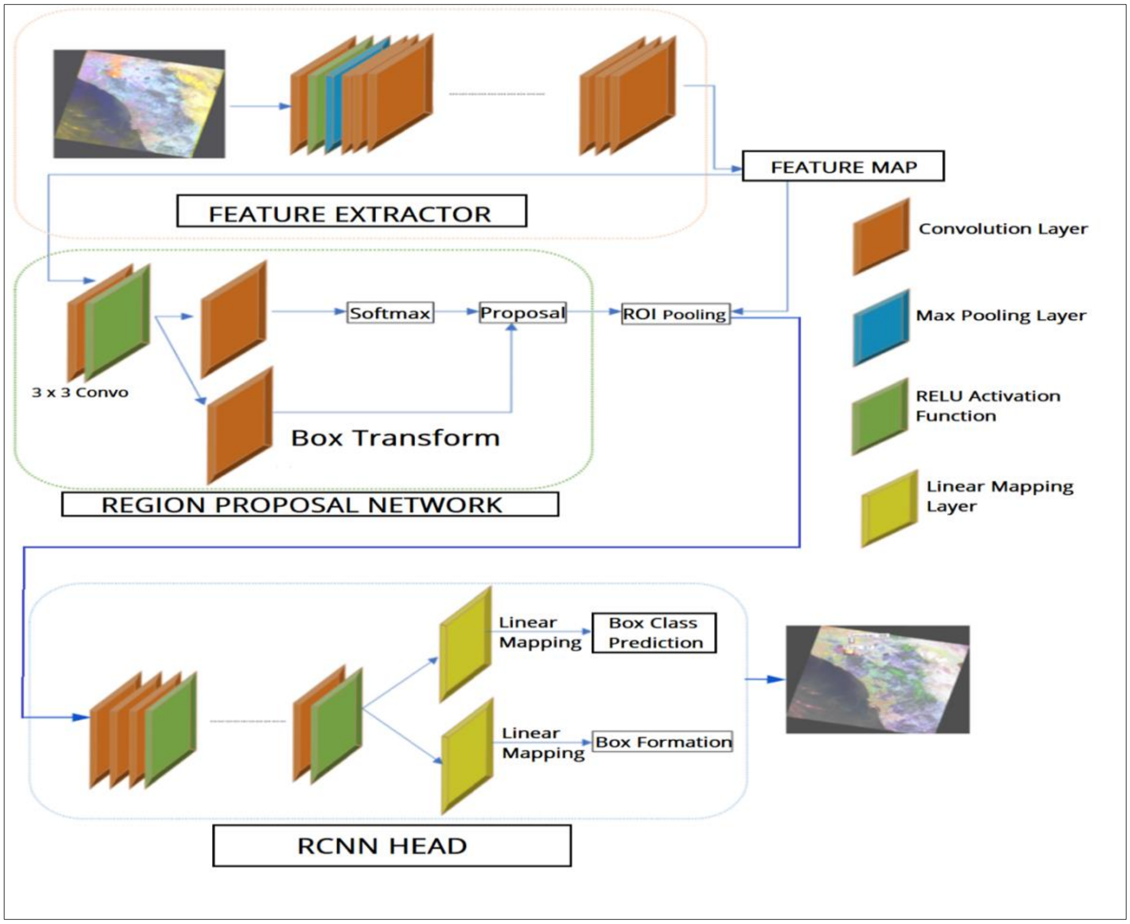

Fig. 8. Architecture of Faster R-CNN model to predict fire detection.

and no cloud cover. It is also important to convert the geotiff image into a human identifiable band spectrum to distinguish fire and smoke from other objects. Remote sensing data consists of several spectral bands which capture essential information that may not be visible to the human eye. To make the data visually valuable for fire detection from satellite images, we need to process information by overlapping different bands to form channels wherein it is easy to identify fire and smoke occurrences. We experimented with some such overlapping to distinction between fire and smoke from other geospatial features. To detect fire and smoke in the satellite image, we created distinct classes 'Fire' and 'Smoke' using the labelMe tool.

A. *Machine Learning Models*

Faster R-CNN

Object detection is used for predicting a bounding box around object instances. We used Faster R-CNN in this research for detecting fire and smoke instances in the satellite image [23]. Faster R-CNN is composed of 3 parts, as shown in fig. 8 i.e., Feature Extractor, Region Proposal Network, and RCNN Head. In Feature Extractor part of the architecture, image features are being extracted from input images by feeding them to the series of convolutional, ReLu activation, max pooling, and convolutional layers. Next, the feature map produced by feature extractor are fed to the Region Proposal Network (RPN) to generate the "proposals" for the regions with objects. RPN consists of classifier and regressor where classifier determines the probability of an object to be present in the feature map and regressor narrows down the coordinates of the classified objects. The output of the RPNs is objects proposals which later passed over to the ROI pooling layer to transform all the

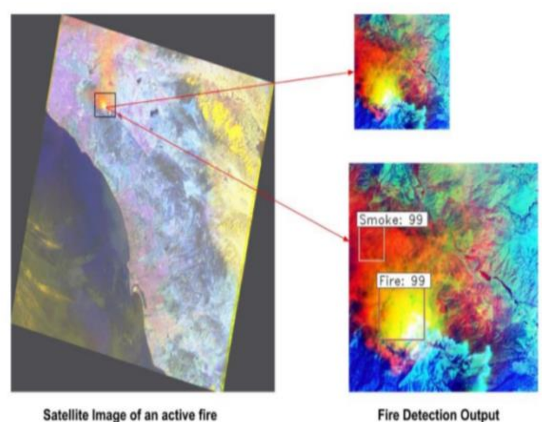

Fig. 9. Fire detection on a specific tile of 14x14 km area

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proposals to the same size. Last, RCNN Head, a fully connected Neural Network, takes the regions proposed by RPN as input and predicts object class and the bounding box for the input image.

B. Results

Fig. 9 shows the accuracy of fire detection on a specific tile of the satellite image. Faster R-CNN offers the recall of 93%, precision of 80%, and F-1 score of 86%. Fig. 10 (a) shows the model accuracy, and fig. 10 (b) shows the model loss for the fire

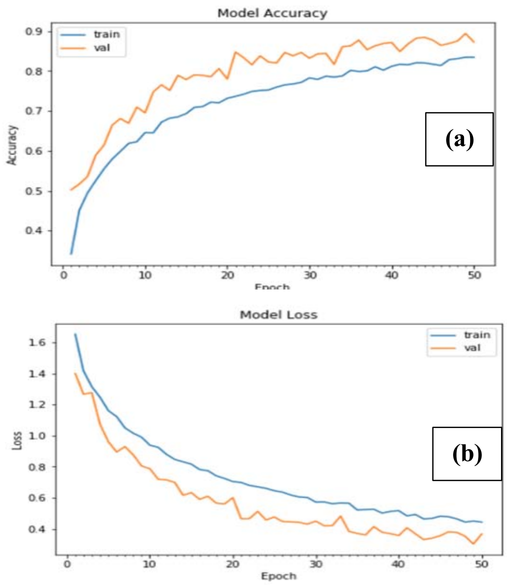

Fig. 10. (a) Model accuracy and (b) Model loss for fire detection using Faster R-CNN model

detection. Here we can observe that as the number of epochs increases, the model accuracy increases while the model loss decreases. Also, there is an increase in the validation accuracy along with training accuracy with the increase in epochs.

VII. CONCLUSION

In our research, we have explored the effect of various types of data to study fire risk prediction and detection using machine learning approaches. Unlike other research that examines either fire risk detection or fire risk prediction with limited data and parameters, our work focuses on understanding these concepts using past fire events, weather, remote sensing, and satellite data. We obtained the cut-edge accuracy of 100% with our ensemble model for fire risk prediction and 93% for fire risk detection. In the future, we plan to develop a real-time intelligent fire system that can provide information about the fire risk prediction, detection, and fire spread pattern.

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