California Wildfire Prediction using Machine Learning

Kaylee Pham, David Ward, Saulo Rubio, David Shin,
Lior Zlotikman, Sergio Ramirez, Tyler Poplawski, and Xunfei Jiang
Department of Computer Science
California State University, Northridge
Northridge, California, USA
{kaylee.pham.704, david.ward.761, saulo.rubio.491, david.shin.904}@my.csun.edu
{lior.zlotikman.183, sergio.ramirez.754, tyler.poplawski.456}@my.csun.edu, xunfei.jiang@csun.edu

***Abstract*—Wildfires in California are increasingly frequent and caused a vast range of damages to the land and society. Existing work in the field of machine learning aided fire susceptibility mapping contains promising results, however they focused on small fire prone areas or yielded less than impressive classification metrics, with even fewer groups focusing on California. In this paper, we applied five machine learning models for fire prediction using a series of remote sensing data and fire incident records of California. The fire incident records were used for labeling fire conditions, and remote sensing features (land surface temperature, normalized difference vegetation index, and thermal anomalies) were selected for model training. Two datasets were created for analysis of wildfires in California based on different sized regions: the whole state treated as one region, and California being broken into counties. For the state level dataset, fire prediction accuracies were 89% for artificial neural network (ANN), and 87% for Gaussian Naive Bayes (GaussianNB), k-nearest neighbors (KNN), and logistic regression (LR), and support vector machine (SVM). For the county level dataset, the prediction accuracies were 97% for KNN, 96% for ANN, SVM, and LR, and 94% for GuassianNB.**

***Index Terms*—Wildfire Prediction, Machine Learning, Remote Sensing Data, Spatio-temporal data**

I. Introduction

Wildfires have decimated regions around the world and are an incredibly vicious and hard to predict phenomenon. In 2020, California had record-breaking damages of over 4.25 million acres burned, 9,917 fires, 33 fatalities, and 10,488 structures destroyed [1]. Climate scientists estimate the likelihood of extreme Autumn wildfire conditions in California have doubled in the past 40 years [2]. Further data shows that the acres burned in CA has doubled from the decade of 1979-1988 to 2009-2018, from 337 thousand acres to 708 thousand acres, respectively [4]. Substantial resources have been allocated to support the fight against wildfires. For example, the U.S. Forrest Service budgeted 2.4 billion dollars in 2020 [3].

Fire prediction has drawn attention from government and academic institutions since the 1970s. Research in predictive methodologies have come a long way from origins in physics based models [14]. A researcher at the U.S. Forest Service spearheaded a tool, Farsite, to model fires and support users to input ignition points via points or polygons for tailored predictions based on initial conditions [6]. Progress has been made in fire prediction, but challenges still exist such as large scale data collection, computation-intensive analysis methods, or only being able to forecast a short time frame. In recent years, machine learning has becoming widely used for fire prediction and detection. However, there is a lack of research on using machine learning (ML) for wildfire prediction in California, which has perpetually been an area affected by evermore destructive fire seasons. This paper aims to conduct regional analysis of the state of California as well as provide means for localized analysis down to specified spatial resolution provided by the user (via GeoJSON or shape files), and support the expansion of the methods into different areas. This paper fits into the overarching field of fire safety alongside complimentary fire alert systems that broadcasts real time information about active fires (e.g., California's Cal Fire Ready for Wildfire web application).

We trained different machine learning models to predict fire occurrence on a given day in California based on environmental conditions derived from remote sensing data and past fire records. The remote sensing data are matched with the target class of Fire/No_fire from California fire record between 2019 and 2020. Two new datasets were generated, with one treats the California state as a singular region and the other subsets the state into counties for localized spatial analysis. Five machine learning models were applied to train and test these two datasets. The methodologies developed in this paper are generalized that could be easily applied to other areas in the world.

The main contributions of this paper include:

- Creation of two datasets of features correlated to fire occurrence derived from remote sensing data: one for the entire region of California and the other for counties
- Prediction of fire occurrences in California with an accuracy up to 89% at state level and 97% at county level
- Creation of streamlined process for sub-setting raw remote sensing image data into smaller regions for localized analysis

The rest of this paper is organized as follows. Section II discusses related work. Section III presents the framework of the project. Section IV presents the implementation and

978-1-6654-6283-9/22/$31.00 ©2022 IEEE
DOI 10.1109/ICMLA55696.2022.00086

experimental results, and Section V concludes the project and discusses future work.

II. Related Work

Fire prediction has been investigated to provide assistance for strategic planning of wildfires. Machine learning has been widely used as a tool in wildfire prediction. This section discusses related methods and datasets for wildfire prediction.

A. Fire Prediction

Fire research often divides prediction into two contexts: predicting fire occurrence and spread.

Liang et al. tested three different neural network models (Back Propagation Neural Network (BPNN) model, Recurrent Neural Network (RNN) model, and Long Short-Term Memory (LSTM) model) to build a prediction model in order to help firefighters and emergency personnel assess the risk and spread of a fire before it grows too large [8]. They concluded that the LSTM model had the best prediction, with an accuracy of 90.9%. Storer et al. proposed the Particle Swarm Optimization (PSO) algorithm to train a Neural Network and used Root Mean Squared Error to compare the results of the PSO algorithm with the Back-propagation algorithm [16].

There have been substantial research efforts that apply artificial intelligent to predicting fire occurrence in different regions. However, there are few studies that investigate the fire prediction in California. Rao used machine learning to predict the effects of canopy geometry on vegetation dryness using data from the western region of the United States [13]. A research group in California built a model that predicts the probability of fire for the spatial resolution of a satellite image pixel (generally 0.5-1 km grid) based on 16 years worth of data of Northern California including land cover, vegetation, and meteorological conditions with an accuracy of 73% [5]. Malik et al. applied random forest based models to predict fires in a small fire prone region of Northern California with accuracy up to 92%, in which they took into account of features such as weather, vegetation, terrain, and power line proximity [9].

B. Machine Learning Models

Machine learning models play an important role in wildfire prediction, especially when dealing with data that is extremely large and growing exponentially with time [15]. A variety of ML models have been used in fire prediction. Among these models, Neural Network models and the SVM model have produced high accuracy results in fire predictions. Lall and Mathibela used a modified BPNN, the Resilient Back-Propagation algorithm (RPROP), which resulted in an accuracy of 97%, as well as 87% precision and 88% recall [7]. Liang et al. performed a multi-collinearity test on the data to remove factors that were proven to skew the model's interpretation rather than benefit it [8]. They noted that an overall limitation of the system was due to the modeling data coming from a single area. Zhang et al. used satellite images and past fire record data along and CNNs to predict fire occurrence [18]. Naganathan et al. used a combination of meteorological data and the US forest fire database [10]. The meteorological data consists of temperature data as it pertains to weather, humidity, rain and snowfall levels among other data. The US forest fire database used includes geographical coordinates, areas affected by fires, and severity. They demonstrated differences between some of the most popular machine learning models and identified SVM as having the highest accuracy. Sayad et al. combined big data, remote sensing and data mining algorithms to process data collected from satellite images over large areas and extract insights from them to predict the occurrence of wildfires [15]. They achieved an accuracy of 98.32% with Neural Network and 97.48% with SVM.

C. Datasets

Several researches predicted fire occurrences with impressive classification metrics using past fire records, satellite data, and meteorological data [12] [15] [17]. A number of groups used combinations of the above datasets. Zhang et al. selected a conjunction of satellite images and past fire record data [18]. Storer and Green [16] and Liang et al. [8] used a combination of past fire record databases and meteorological data. Lall and Mathibela showed promising results using vegetation and environmental features to train their highly accurate ANN [7]. Perumal and Zyl focused on satellite data, specifically the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite instrument [11]. They indicated that Normalized Difference Vegetation Index (NDVI) and earth data from Moderate Resolution Imaging Spectroradiometer (MODIS) would likely improve the performance of their model.

III. Design

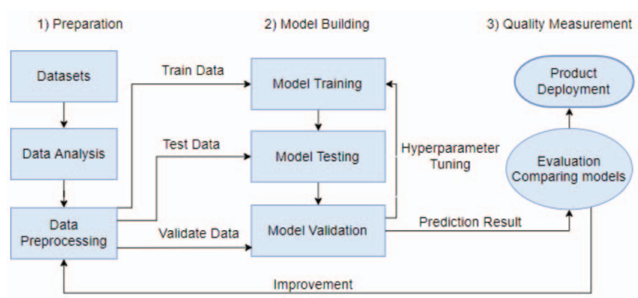

Fig. 1: Framework of the project

As shown in Fig. 1, this project is composed of three stages: (1) data preparation, where data is analyzed, preprocessed, and then split into training, testing, and validation datasets; (2) model building, where machine learning models are trained and tested for fire prediction; and (3) quality measurement, where prediction results are evaluated. If improvement is needed, data will be sent back to the training process for hyperparameter tuning until the prediction results meet expectations.

A. Data Preparation

The input datasets include a past fire record and four remote sensing datasets: normalized difference vegetation index (NDVI), land surface temperature (LST), thermal anomalies

(TA), and burned area (BA). The fire record is a CSV file with rows corresponding to fire occurrences and columns such as dates burned, county, and acres burned. It is used for labelling conditions derived from the remote sensing data as Fire/No_fire. The finest spatial resolution of the fire record is county level (with a few exceptions of cross county fires) and has daily temporally after flatting the date range of each fire. The remote sensing data is derived from GeoTIFF files, which are raster image files that contain satellite and aerial imagery data, along with geographic metadata that describes the location in space of the image. NDVI represents the plant density and health in a region. LST detects the temperature of the surface of the earth. The TA dataset contains 31 layers that take into account factors relevant to detecting fires from atmospheric conditions to the fuel type. Only the primary class and fire mask (which is used to detect fires and other TA such as volcanoes) are used as inputs for training models. Burned area (BA) maps recently burned areas by searching for rapid changes in daily surface reflectance values.

The feature datasets (NDVI, LST, and TA) are cleaned of imperfections, and then be clipped by the burned area to extract recently burned regions for analysis. After that, they will be interpolated for a consistent daily temporal frequency, and then be combined with the past fire data to match the target class of Fire/No_fire with their corresponding conditions (for training dataset). Finally, they will be merged into an output dataset (CSV file), which contains the features (NDVI, LST, TA) and a target class of Fire/No_fire. For a more localized analysis and improved tagging of the Fire/No_fire class, a second dataset is created from the output dataset by breaking down the California state into counties.

1) Data Cleaning: Data cleaning includes correcting imperfections from satellite imaging equipment which are caused by various occurrences (such as cloud cover, satellite instrument malfunctions, etc.). Satellite images have been processed for georeferencing, so data cleaning will focus on weather imperfections. The satellite image data is cleaned by masking raw images using corresponding quality assurance (QA) files with information from the quality lookup table (LUT) acquired from the Land Processes Distributed Active Archive Center (LP DAAC).

2) Data Clipping: Data clipping is performed on the state level data to extract parts of the feature datasets' GeoTIFF images that overlap with the BA dataset, which represents recently burned areas. Regions of satellite images that never catch fire are not included, because they are far less useful for model training. Data clipping is also used to subset the original raw state data into smaller regions based on CA county boundaries for localize analysis.

3) Data Interpolation: The NDVI data was collected at a temporal frequency of 16-days, while the LST and TA data products were collected daily. Time series interpolation needs to be applied to the NDVI data to standardize all the datasets to a daily temporal frequency.

4) Feature Extraction: After interpolation, feature extraction is applied to extract NDVI, LST, and TA columns from its previous datasets along with a date column. Next, a new class column is created as a target feature to be predicted. This class column has two possible values: Fire and No_fire. A fire's date column is extracted from the fire record dataset by calculating the start and end date. Then, these two dates are matched to label fire for the class column. Finally, the date column is dropped so the final dataset has four columns: NDVI, LST, TA and class.

B. Model Building

Two datasets are used for model building, both focusing on CA in the same time frame. In these two datasets, one uses values at a state level, and the other uses values at a county level which uses a subset of CA counties (44 counties that had fires). Since the class column has only two possible values (Fire and No_Fire), binary classifiers will be used to build the models.Five binary classification models are used for model building: Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Gaussian Naive Bayes (GaussianNB), and Logistic Regression (LR). All these models use the default settings from Scikit-learn as a starting point, and parameters are set based on the size and other factors of the datasets. The distribution of train/test/validation split will be tested on multiple levels until reaching the highest accuracy.

C. Quality Measurement

Prediction results are evaluated using classification metrics: accuracy, precision, recall, f1-score, and confusion matrix. As shown in Table I, True Positive (TP) indicates the model correctly predicts that there is a fire, and True Negative (TN) indicates the model correctly predicts that there is no fire. False Positive (FP) represents the model incorrectly predicts that there is a Fire (Type I error) and False Negative (FN) represents the model incorrectly predicts that there is no fire.

TABLE I: Confusion Matrix

	Predicted Negative	**Predicted Positive**
Actual Negative	True Negative (TN)	False Positive (FP)
Actual Positive	False Negative (FN)	True Positive (TP)

We define the N_p as the number of predictions that falls in the category p, which is TP, TN, FP, or FN. The accuracy of a model is defined as

$$Accuracy = \frac{N_{TP} + N_{TN}}{(N_{TP} + N_{FP} + N_{FN} + N_{TN})} \qquad (1)$$

where N_{TP} is the number of True Positive predictions, N_{TN} is the number of True Negative predictions, and N_{All} is the total number of predictions. Precision of a model is the number of True Positives divided by the number of True Positives and False Positives: $Precision = \frac{N_{TP}}{(N_{TP}+N_{FP})}$. Recall of a model is the number of True Positives divided by the number of True Positives and the number of False Negatives: $Recall = \frac{N_{TP}}{(N_{TP}+N_{FN})}$. The F1-score is used to compare the performance of two classifiers: $F1 - score = \frac{2*(Recall*Precision)}{(Recall+Precision)}$. Classification metrics are compared and the performance of models needs to be improved when the accuracy is below 95%.

Methods to improve the performance include data normalization, removing outliers, resizing the data, choosing a different subset of features, choosing another algorithm, and adjusting the parameters with hyperparameter tuning technique.

IV. Results

A. Data Preparation

Four remote sensing datasets were collected from the LP DAAC website using the data extract tool AppEEAR[1] (as shown in Table II). California fire incident records for 2019 and 2020 were collected from the California Department of Forestry and Fire Protection (Cal Fire)[2]. A shape file of California was used to extract the exact regions of the state.

TABLE II: Remote Sensing Datasets

Type	Name	Spatial Resolution	Temporal	# of images
NDVI	MOD13A1	500m	16 days	94
LST	MOD11A1	1km	daily	1462
TA	VPN14A1	1km	daily	1462
BA	MCD64A1	500m	monthly	48

Two new datasets were created: one treats the state as a singular region, and the other subsets the state into 58 counties for more localized spatial analysis. Data was analyzed at the county level because this was the largest spatial granularity of the inputs, from the fire record. The county level dataset selected 44 out of 58 counties because the other 14 had not reported forest fires in the years of 2019 and 2020.

The county level data uses the same satellite images as the state level processing, except for an extra step of separating the CA GeoTIFF images into county images in data clipping.

1) Data Cleaning: Data cleaning was performed on all of the remote sensing data to remove low-quality data or data with meteorological interference via masking. Each of the remote sensing data's GeoTIFF files comes with a corresponding QA file that states the quality of the pixels in an image. All remote sensing data was masked by their corresponding QA images in conjunction with the corresponding quality lookup table, which generated an array of good quality pixel values for feature extraction. Figure 2 shows the visualized GeoTIFF file of the NDVI state level dataset after data cleaning.

Fig. 2: California NDVI Data Visualization

[1]https://lpdaac.usgs.gov/tools/appeears/
[2]https://www.fire.ca.gov/incidents/

2) Data Clipping: For the state level dataset, data clipping isolates data from recently burned regions to ignore data from regions that never caught fire in the given month of the daily time frame. The ignored data isn't relevant for the models in identifying Fire/No_fire from a region's conditions. Data clipping was applied to the feature datasets using BA dataset's images. When masking the LST and TA datasets, we resampled the BA images because of the resolution difference. For the county level dataset, data clipping was only used to subset GeoTiff images of CA into county images using county boundaries in the form of GeoJSON geometries.

3) Data Interpolation: This step is only necessary for the NDVI dataset because it is in a 16 day temporality and the other two datasets (LST and TA) are daily. Linear interpolation from the Pandas library was applied to both the state and the county level datasets.

4) Feature Extraction: Feature extraction was applied to the NDVI, LST, and TA remote sensing data as well as the Cal Fire incident record. For the state level dataset, the clipping by BA step extracts regions from the feature dataset's GeoTIFF images, resulting in a new raster GeoTIFF image. Each pixel of the new image contains a value for an area, and it is tied to a specific date. The values of all the pixels are averaged and stored as a CSV file with their corresponding dates, which are later abstracted out when all feature datasets and target class datasets are aligned. The columns in the fire record were reduced to include only start date, end date, and incident type.

From the fire record data, only wildfires were selected and rows with NaN values were dropped. The date range of each fire was transformed into a file containing two columns: date and boolean value for fire. For the county level dataset, there was an extra column for county that was taken into account when flagging fire conditions. There were a few instances where fires crossed county lines, for which both counties were flagged. The feature datasets and the target class dataset were aligned and combined into final datasets, with 731 rows in the state level and 42,399 rows in the county level dataset. Table III shows sample data from the state level dataset.

TABLE III: Final State Level Dataset Sample.

	NDVI	LST	TA	Class
0	0.241233	280.170902	5.0	No_fire
1	0.242536	281.678667	5.0	No_fire
2	0.243840	285.865983	5.0	No_fire
3	0.245143	283.249994	5.0	No_fire
4	0.249052	286.090648	5.0	No_fire

B. Model Building

The final datasets were split with 60% for training, 20% for testing, and 20% for validation. The neural network was trained and tested using varying hidden layer and neuron amounts, and it performed the best with 8 hidden layers and 8 neurons per layer. For the SVM algorithm we chose a kernel, a map from a single dimensional space to an n-dimensional space, for efficient classification. Polynomial, Gaussian, Sigmoid, and Hyperbolic Tangent kernels were tested for the SVM model. Through a repeated process of trial and error testing amongst various kernel options, we found that the polynomial kernel was often associated with high measure accuracy in the realm of image processing. KNN, GaussianNB, and LR were all started with default parameters. After hyper-parameter tuning, parameters were changed to improve these models' performance. Table IV shows the default and new parameters for these 3 models.

TABLE IV: Parameter Changes for Models

Models	Paramters	
KNN	Default	metric='minkowski', n_neighbors=5, weights='uniform'
	New	metric= 'euclidean', n_neighbors=13, weights='uniform'
GaussianNB	Default	var_smoothing=1e-09
	New	var_smoothing= 0.12328467394420659
LR	Default	C = 1.0, penalty = 'l2', solver = 'lbfgs'
	New	C = 0.01, penalty= 'l2', solver= 'liblinear'

C. Evaluation

We evaluated five models on the two final datasets using Scikit-learn classification metrics and confusion matrix.

1) State Level Dataset: This dataset has 731 rows, with 292 Fire and 421 No_Fire values. It is small for ANN that typically requires thousands of values for effective training. The amount of false positives and false negatives are low, which is the reason for the model's high testing accuracy.

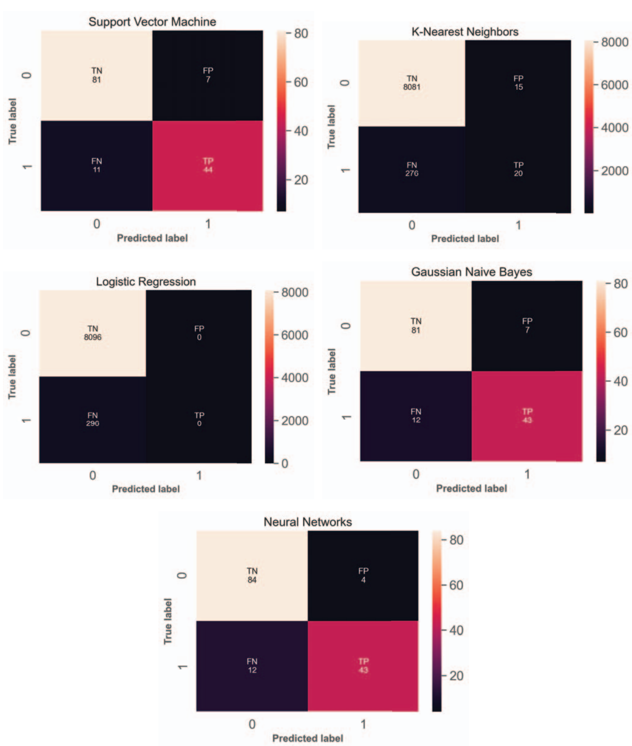

Fig. 3: Confusion matrix for all models on state level data

Table V shows the classification results of models on state level dataset. ANN has the highest accuracy of 89%, and the other 4 models have the same prediction accuracy of 87%.

TABLE V: Classification Results on State Level Dataset

ANN	Precision	Recall	F1-score	Support
0	0.88	0.95	0.91	88
1	0.91	0.78	0.84	55
Accuracy			0.89	143
SVM	Precision	Recall	F1-score	Support
0	0.88	0.92	0.90	88
1	0.86	0.80	0.83	55
Accuracy			0.87	143
KNN	Precision	Recall	F1-score	Support
0	0.88	0.91	0.89	88
1	0.85	0.80	0.82	55
Accuracy			0.87	143
GaussianNB	Precision	Recall	F1-score	Support
0	0.87	0.92	0.90	88
1	0.86	0.78	0.82	55
Accuracy			0.87	143
LR	Precision	Recall	F1-score	Support
0	0.87	0.92	0.90	88
1	0.86	0.78	0.82	55
Accuracy			0.87	143

2) County Level Dataset: Fig. 4 depicts the results on the county level dataset. The amount of false positives and false negatives are low, which results in high testing accuracy. The classification report (shown in Table VI) shows precision, recall, f1-score, and support values. The KNN model had the best prediction accuracy of 97%, while the GaussianNB model had the lowest accuracy of 94%. ANN, SVM, LR all had the same accuracy of 96%.

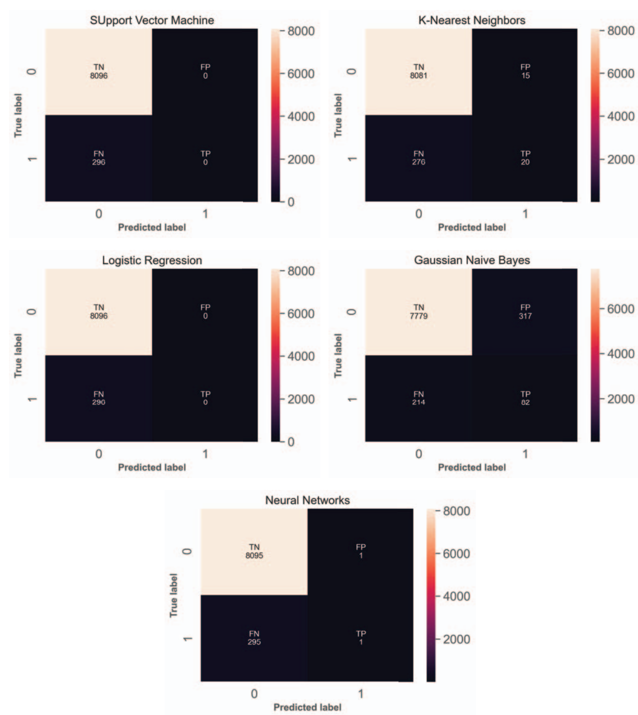

Fig. 4: Confusion matrix for all models on counties level data

A comparison of the accuracy for all models on the state and county level datasets is shown in Fig. 5. The predictions on county level had higher accuracies than on state level, however, the county level models showed signs of overfitting.

TABLE VI: Classification Results on County Level Dataset

ANN	Precision	Recall	F1-score	Support
0	0.96	1.00	0.98	8096
1	0.50	0.00	0.01	296
Accuracy			0.96	8392
SVM	Precision	Recall	F1-score	Support
0	0.96	1.00	0.98	8096
1	0.00	0.00	0.00	296
Accuracy			0.96	8392
KNN	Precision	Recall	F1-score	Support
0	0.97	1.00	0.98	8096
1	0.57	0.07	0.12	296
Accuracy			0.97	8392
GaussianNB	Precision	Recall	F1-score	Support
0	0.97	0.96	0.97	8096
1	0.21	0.28	0.24	296
Accuracy			0.94	8392
LR	Precision	Recall	F1-score	Support
0	0.96	1.00	0.98	8096
1	0.00	0.00	0.00	296
Accuracy			0.96	8392

Both datasets have the imbalance class problem on No_fire to Fire, but the county level had a much larger disparity. The state level imbalance ratio was only 1.4:1 while the county level has 29.6:1 on No_fire to fire respectively. Furthermore, the result on the state level is more valid since it was used on only burned area regions for the years of 2019 and 2020 while the county level did not clip by burn area. On the other hand, the state level dataset has only 713 rows after data preprocessing. It was further split into three subsets for training, testing, and validation. This resulted in a very small data size for some of the models, such as ANN. If more data can be added, it will help to improve the performance for models which prefer larger input data size for training.

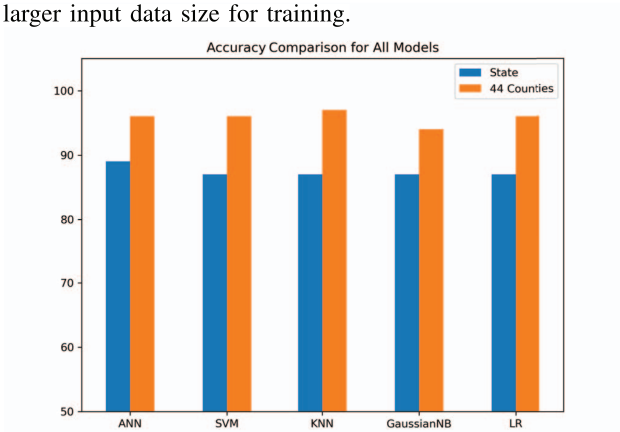

Fig. 5: Accuracy Comparison for All Models

V. Conclusion

We combined remote sensing datasets (NDVI, LST, TA, and BA) with fire incident records and trained five models to predict wildfires in California. Our models produced highly accurate predictions of regions that are likely to be on fire: 89% for ANN model and 87% for the other models at the state level; and 97% for KNN model and 96% for ANN, SVM, and LR models, along with 94% for GuassianNB model on the county level. Our fire prediction approaches provide promising results for applying machine learning to predict wildfires. The county level dataset had an imbalance of classes which led to over fitting of the model. One approach to improve the imbalance is to randomly undersample the No_fire class to create a balanced dataset. Collecting a larger dataset of at least a decade's worth of conditions and fire data would also improve the models' accuracies. BA clipping could be applied to the county level dataset to discard conditions of areas that were not recently on fire. Other meteorological conditions (wind or physical proximity to camp sites, power lines, etc.) could also be explored to improve predictions.

References

[1] California Fire Incident Archive 2020 . https://www.fire.ca.gov/incidents/2020/, 2020.

[2] Increasingly extreme autumn wildfire conditions in California due to climate change. https://weatherwest.com/archives/7550, 2020.

[3] USDA Fiscal Year 2020 Budget Justification. https://www.fs.usda.gov/sites/default/files/media$_wysiwyg/usfs - fy - 2020 - budget - justification.pdf$, 2020.

[4] Hanna Buechi, Dick Cameron, Sarah Heard, Andrew J. Plantinga, and Paige Weber. Long- term Trends in Wildfire Damages in California. *emLab and TNC Issue Brief*, pages 1–9, 2020.

[5] Natan Holtzman Caroline Famiglietti and Jake Campolo. Satellite-Based Prediction of Fire Risk in Northern California Final Report. pages 1–6, 2018.

[6] Ma Finney. FARSITE: a fire area simulator for fire managers. *The Proceedings of The Biswell Symposium*, pages 55–56, 1994.

[7] Shruti Lall and Bonolo Mathibela. The application of artificial neural networks for wildfire risk prediction. *International Conference on Robotics and Automation for Humanitarian Applications, RAHA 2016 - Conference Proceedings*, 2017.

[8] Hao Liang, Meng Zhang, and Hailan Wang. A Neural Network Model for Wildfire Scale Prediction Using Meteorological Factors. *IEEE Access*, 7:176746–176755, 2019.

[9] Ashima Malik, Megha Rajam Rao, Nandini Puppala, Prathusha Koouri, Venkata Anil Kumar Thota, Qiao Liu, Sen Chiao, and Jerry Gao. Data-Driven Wildfire Risk Prediction in Northern California. *Atmosphere*, 12(1):109, 2021.

[10] By Hariharan Naganathan, Sudarshan P Seshasayee, Jonghoon Kim, Wai K Chong, and Jui-sheng Chou. Wildfire Predictions : Determining Reliable. 16(4), 2016.

[11] Rylan Perumal and Terence L.Van Zyl. Comparison of Recurrent Neural Network Architectures for Wildfire Spread Modelling. *2020 International SAUPEC/RobMech/PRASA Conference, SAUPEC/RobMech/PRASA 2020*, 2020-Janua, 2020.

[12] David Radke, Anna Hessler, and Dan Ellsworth. Firecast: Leveraging deep learning to predict wildfire spread. *IJCAI International Joint Conference on Artificial Intelligence*, 2019-Augus:4575–4581, 2019.

[13] Krishna Rao. How artificial intelligence helps monitor forest dryness. https://aws.amazon.com/blogs/publicsector/how-artificial-intelligence-helps-monitor-forest-dryness/.

[14] J. C. Sanderlin and J. M. Sunderson. A simulation for wildland fire management planning support (FIREMAN). pages 233–249, 1975.

[15] Younes Oulad Sayad, Hajar Mousannif, and Hassan Al Moatassime. Predictive modeling of wildfires: A new dataset and machine learning approach. *Fire Safety Journal*, 104(September 2018):130–146, mar 2019.

[16] Jeremy Storer and Robert Green. PSO trained Neural Networks for predicting forest fire size: A comparison of implementation and performance. *Proceedings of the International Joint Conference on Neural Networks*, 2016-Octob:676–683, 2016.

[17] Dieu Tien Bui, Quang Thanh Bui, Quoc Phi Nguyen, Biswajeet Pradhan, Haleh Nampak, and Phan Trong Trinh. A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area. *Agricultural and Forest Meteorology*, 233:32–44, feb 2017.

[18] Guoli Zhang, Ming Wang, and Kai Liu. Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China. *International Journal of Disaster Risk Science*, 10(3):386–403, 2019.