SHINE: Using Machine Learning to Incorporate Social Vulnerability Indicators into Wildfire Risk Management

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Abstract
This study introduces SHINE, a novel tool designed for wildfire risk mitigation and adaptation planning. The name is derived from the tool's primary function in assessing the Susceptibility and Human Impact of Natural Emergencies. Leveraging 22 years of historical data from California, the tool employs a random forest initialized AdaBoost classifier to analyze the intersection of social vulnerability and wildfire risk. Six categories were derived by considering subsets of two from the four thematic areas identified by the Social Vulnerability Index from the U.S. Centers for Disease Control and Prevention. These categories were cross-referenced with spatial data on square kilometers burned by wildfires. The classifier, validated using 20 years of California data and tested on an additional 2 years of California data, demonstrated remarkable effectiveness. It achieved high accuracy and precision, with a mean accuracy of 99.22%, a precision of 99.40%, a recall of 98.87%, and an F1 score of 99.13% on the California test set. In a groundbreaking extension of our research, the classifier is further tested against 22 years of data from Oregon and Washington. On the Oregon test set, the model achieved a mean accuracy of 97.66%, a mean precision of 96.98%, a mean recall of 95.10%, and a mean F1 score of 95.99%. The model performed with a mean accuracy of 97.37%, mean precision of 96.96%, mean recall of 95.25%, and a mean F1 score of 96.06% on the Washington test set. The successful application of the classifier, trained on California data, to Oregon and Washington data demonstrates its adaptability and effectiveness across varied geographic and environmental contexts. This research showcases the potential of machine learning models in enhancing disaster risk reduction strategies and enabling targeted community-specific interventions.

1. Introduction
1.1. Wildfires
In recent years, the extremity of wildfires across the globe has emerged as a critical concern in the discourse on disaster risk reduction [1-4]. The frequency, intensity, and devastating impact of these fires present an urgent challenge for researchers, policy makers, and communities around the world. The 2019-2020 fire season in Australia, marked by a staggering 18.6 million hectares burned, set a precedent for the alarming scale and severity of wildfires [5,6]. This trend continued, with Canada witnessing a record-breaking 18.5 million hectares consumed by flames in the 2023 season an area twice the size of Portugal [7]. The same year, Greece grappled with 355 wildfires in a span of just five days, with 55 ignitions reported in a single 24-hour period [8]. Further compounding this global crisis, Maui, Hawaii, experienced the deadliest wildfire in over a century in the United States in 2023 [9,10]. The Mediterranean region and parts of North Africa were not spared, with Turkey enduring the worst of it in 2021, scorching 206,013 hectares – the most affected among countries in Europe, North Africa, and the Middle East. Italy and Algeria also faced severe wildfire seasons in 2017, with 159,537 and 134,273 hectares burned, respectively, marking Italy's season as the second worst in the European Union since 2000 [11].

1.2. Social Vulnerability
The number of important contributions in the area of social vulnerability of Cutter's research group offer crucial insights into the increased susceptibility of certain populations to environmental catastrophes [12-21]. Catastrophic wildfires throughout the world not only manifest themselves as environmental disasters, but

also reveal profound social inequalities that disproportionately affect the most vulnerable segments of society. In the 2009 Black Saturday wildfires in Australia, of the 173 lives tragically lost, 13% were children under 18 years of age and 16% were 70 and older [22]. This pattern of vulnerability among young and elderly people is repeated in Greece's 2017-2018 fire season, which saw the loss of 100 individuals, including 11 children and 45 elderly [23]. The 2007 wildfires in Greece highlighted the susceptibility of lower-income groups, with a majority of the 84 victims belonging to this demographic [23,24].

In the devastating 2017 fires in northern California, two-thirds of the victims were over the age of 65, a statistic echoed in Maui in 2023, where more than 60% of the deaths were in this age group [23,25]. In the 2018 Camp Fire, the deadliest fire in California's history, an astounding 80% of the victims were 65 years of age or older [26]. A comprehensive study by Rad et al. revealed a near 250% increase in the exposure of highly socially vulnerable individuals to fires across California, Oregon, and Washington between 2011-2021, compared to 2000-2010 [27]. Hino and Field's analysis of three decades of data across California communities showed that areas with higher fire experience tend to have lower average incomes than those with little to no fire experience [28].

Further studies corroborate these findings. Palaiologou's research in central North Washington, central California, and northern New Mexico demonstrated that areas with high social vulnerability, according to the Social Vulnerability Index, faced disproportionate exposure per burned area [23]. In mainland Portugal, Oliveira et al. used classification trees and random forests, revealing that parishes with higher fire density had more overcrowded buildings and those with larger burned areas had a higher proportion of elderly residents [29]. Kapuka and Hlásny's study across Namibia linked districts with high social vulnerability to more frequent and severe natural hazards, including wildfires [30]. Chas-Amil et al. investigated the spatial coincidence of social vulnerability and wildfire risk in Spain and found that locations with high social vulnerability and high wildfire risk tend to have relatively high percentages of elderly people [31].

1.3. Machine Learning in Wildfire Vulnerability Analysis
In the United States, with nearly 69,000 wildfires reported in 2022 burning more than 7.5 million acres a significant increase from 2021 - the urgency of understanding and minimizing wildfire risks has become paramount [32-34]. As the impacts of climate change intensify, understanding and mitigating the risk posed by wildfires has become more crucial than ever [35-39]. Recognizing that certain subpopulations bear a disproportionate burden during such disasters, this research builds upon the emerging body of work on the intersection of wildfire risk and social vulnerability [40]. Previous studies, such as those of Rad et al., have laid the groundwork for identifying the complex relationship between sociodemographic characteristics and the impacts of wildfires [27]. Andersen and Sugg combined socioeconomic and physical data at the tract level on wildfires from 1985 to 2016 to identify

the intersection of social and physical vulnerability to wildfires in western North Carolina, USA [41]. Yadav et al. analyzed the sociodemographic characteristic of communities affected by wildfires in California during 2010 – 2020 and found that urban areas were statistically and increasingly more affected statewide by wildfires [42].

This study aims to deepen this understanding by leveraging machine learning techniques to analyze social vulnerability indicators in relation to historical wildfire data in California, Oregon, and Washington. Over the past few decades, California has experienced some of the most devastating wildfires in its history, with significant impacts on communities, economies, and ecosystems [43-45]. These events have underscored the need for more sophisticated risk assessment and management strategies [46-49]. Traditional approaches to wildfire risk management have focused primarily on environmental and climatic factors. However, there is growing recognition of the importance of social vulnerability factors in shaping communities' wildfire risk profiles. The Centers for Disease Control and Prevention (CDC) has identified four key thematic areas of social vulnerability: socioeconomic status, household composition and disability, minority status and language, and type of housing and transportation [50]. These themes provide a comprehensive framework for understanding how various social factors contribute to vulnerability in the face of wildfires.

This study uses 22 years of data that combine the social vulnerability percentile rankings and square kilometers burned by wildfires at the census tract level in California, Oregon, and Washington. Through the application of a random forest initialized AdaBoost classifier, our aim was to identify vulnerable subpopulations with increased susceptibility to fire risk. Social vulnerability, characterized by the exposure of a population and its ability to cope with disasters, along with its degree of social, economic and demographic susceptibility to harm from hazards, plays a pivotal role in disaster outcomes [19]. Information on social vulnerability is essential to mitigate losses and ensure equitable and effective fire recovery and anticipatory planning. Differential access to social, political and economic resources critically affects the ability of individuals and communities to mitigate, adapt to, and recover from fire events. As wildfires continue to pose significant challenges, the incorporation of social vulnerability considerations into disaster risk management is imperative to build resilient and equitable communities.

2. Materials and Methods
2.1. Data Selection and Feature Engineering
In our study, we used a dataset compiled by Rad et al., encompassing data on social vulnerability and wildfires [27]. For the analysis of social vulnerability, we employed percentile rankings from 2000 to 2021 for each census tract in California, Oregon, and Washington, originally sourced from the US Centers for Disease Control and Prevention (CDC) [51]. Furthermore, our research incorporated historical data on square kilometers burned by wildfires in these states, also spanning 2000 to 2021. These wildfire data were

initially collected by the US National Interagency Fire Center (NIFC) [52].

We used several feature engineering steps to optimize the data set for analysis. The wildfire data was originally categorized into separate columns according to the size of the fires: small, medium, and large. Recognizing the need for a more straightforward approach to data interpretation, we transformed these columns into a singular binary indicator of 'fire/no fire.' This transformation involved summing the square kilometers burned by fires in all three size categories for each record. Records where the sum exceeded zero were labeled as '1', indicating the presence of a wildfire, while those with no burned area were labeled as '0', indicating no wildfire. This binary format greatly simplified the representation of wildfire occurrences, enhancing the model's ability to discern patterns related to wildfire risk A.5.

Another modification involved addressing inconsistencies in the column naming conventions of the data set, which had evolved over the 22-year period [50,53,54]. To ensure coherence and facilitate model training, we standardized the column names to reflect the most recent terminology. This uniformity across the dataset was instrumental in enabling accurate comparisons and analyses over the years. To encapsulate the overall vulnerability within each theme, we created new columns representing each thematic area and populated them with the highest percentile ranking of the indicators pertinent to that theme. Additionally, we observed inconsistencies in the classification of the 'limited English' variable, which alternated between the household composition theme and minority status theme over the years. To maintain consistency in our analysis, we classified this variable under the theme of minority status / language for all years.

The categorization strategy for our multiclass classification task was designed to reflect the underlying dimensions of social vulnerability identified by the Centers for Disease Control and Prevention (CDC) A.3. Specifically, we utilized the CDC's framework, which delineates four principal thematic areas that contribute to social vulnerability: socioeconomic status, household composition and disability, minority status and language, and housing type and transportation. Within these broad themes, we further focused on the 15 subdimensions of vulnerability as detailed in the 2018 CDC Social Vulnerability Index (SVI) documentation [55] A.4.

To create our category labels, we methodically paired subsets of the main CDC-identified thematic areas, combining two themes at a time. This method allowed us to construct category labels that represent the intersecting and overlapping nature of vulnerability factors [56,57]. Each label represents a specific intersection of two thematic areas, providing a more detailed perspective on the different dimensions of vulnerability. Each census tract in our dataset was then evaluated against these paired thematic areas, and assigned a category label that best represents its most significant areas of vulnerability. By assigning each census tract to a category label based on its most pronounced areas of vulnerability, we aimed to capture the complex interplay of social factors that can exacerbate disaster risk.

2.2. Machine Learning Algorithms

In our study, we used an AdaBoost classifier initialized with a random forest base estimator to perform multiclass classification. This approach represents an advanced form of ensemble learning, combining multiple machine learning techniques to achieve superior predictive performance [58]. To provide a comprehensive understanding of our methodology, the following sections will discuss the foundational principles of the applied ensemble learning methods.

2.2.1. Decision Trees

The basic principles of decision trees are an essential foundation for understanding the advanced ensemble learning methods applied in our study. At its core, the decision trees partition the feature space into a set of rectangles and fit a simplified model within each. Each rectangle represents a node in the tree [59]. The Classification and Regression Trees (CART) method, a widely used approach for both regression and classification, exemplifies this process [60]. The primary advantage of CART, especially in the context of a recursive binary tree, is its interpretability and the complete description of the feature space partition through a single tree structure [59,61].

A dataset consists of N observations, each with p inputs (x_i) and a corresponding response (y_i), thus forming pairs (x_i, y_i) where $x_i = (x_{i1}, x_{i2}, ..., x_{ip})$. The CART algorithm decides the best splitting variables and points for the dataset, thereby determining the tree's topology. Binary splits are favored as they avoid rapid data fragmentation, ensuring adequate data availability at subsequent levels. Upon identifying the optimal split, the data is partitioned into two regions, and the splitting process is recursively applied to each resulting region. In any given node m, representing a region R_m with N_m observations, the proportion of class k observations is denoted as $\hat{p}_{mk} = \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i = k)$, with I being the indicator function. The classification at each node m is then determined by $k(m) = argmax_k \hat{p}_{mk}$, essentially assigning the majority class in node m to the observations.

A significant challenge in tree-based methods is their high variance. Minor changes in the dataset can lead to vastly different tree structures. This instability is attributed to the hierarchical nature of tree construction, where errors in top-level splits propagate throughout the tree. To counteract this, the methodology used in this study incorporates a form of bagging (Bootstrap Aggregating) to stabilize variance and improve model reliability [59].

2.2.2. Random Forests

Random forests are an extension of the bagging technique, or bootstrap aggregation, which is a method aimed at reducing the variance of a prediction function. In the context of classification, bagging involves a "committee" of trees where each tree contributes

a vote for the predicted class [59]. Random forests, introduced by Breiman, modify bagging by constructing a large collection of de-correlated trees [62]. The core idea of random forests is to improve the reduction in variance achieved through bagging by reducing the correlation between individual trees in the ensemble. This is crucial because while bagging significantly reduces variance, it does not address the potential high correlation between trees, which can limit the benefits of the ensemble [59].

In random forests, the reduction of the correlation between trees is accomplished by altering the tree-growing process. For each tree, a subset of input variables is randomly selected before each split. This randomness ensures that each tree in the forest is built from a different perspective of the data. In a classification context, each tree in the random forest contributes a vote towards the predicted class. The final decision is based on the majority vote across all trees. An underlying indicator-vector function, represented as $f(x)$, is used, where $G(x) = \arg\max_k f_k(x)$. The bagged classifier then selects the class that receives the majority of votes across all trees. The training process involves creating multiple bootstrap datasets from the original training data, $Z = \{(x_i, y_i)\}_{i=1}^{N}$. Each of these datasets is of the same size as the original dataset and is used to grow a decision tree. This process is repeated B times to produce a diverse ensemble of B trees. Random forests address the inherent instability of decision trees, which can exhibit high variance and sensitivity to small changes in the data. Additionally, the random selection of features for each tree split reduces the correlation between trees, enhancing the prediction accuracy of the ensemble [59].

2.2.3. AdaBoost
AdaBoost (Adaptive Boosting), a concept introduced by Freund and Schapire, combines the outputs of multiple "weak" classifiers to create a strong and accurate classifier [63]. A weak classifier has an error rate slightly better than random guessing. While it shares some similarities with bagging, boosting's approach is distinct. It focuses on sequentially applying weak classification algorithms to modified versions of data, generating a series of classifiers whose predictions are then combined by a weighted majority vote.

The error rate is calculated as $err = \frac{1}{N} \sum_{i=1}^{N} I(y_i \neq G(x_i))$, where I is an indicator function, N is the number of observations, yi is the actual class, and x_i are the predictor variables. In the boosting process, each classifier $G_m(x)$ in the sequence is influenced by the performance of its predecessors. At each iteration m, weights $w_1, w_2, ..., w_N$ are assigned to training observations, starting with equally weighted training samples. Misclassified observations have their weights increased, while correctly classified ones have their weights decreased. This iterative process emphasizes difficult-to-classify observations, forcing each new classifier to focus on them [60]. The final prediction is a weighted majority vote of all classifiers: $G(x) = sign\left(\sum_{m=1}^{M} \alpha_m G_m(x)\right)$. Here, $\alpha_1, \alpha_2, ...$

., αM are weights calculated by AdaBoost, giving more influence to accurate classifiers [59].

This implementation of AdaBoost employs the SAMME algorithm for multiclass classification. In binary classification, the random guessing error rate is 0.5, making it easier for weak learners to achieve better accuracy. However, in multiclass classification with K classes, the error rate of random guessing is $\frac{K-1}{K}$, making it harder to maintain an error rate less than 0.5. SAMME (Stagewise Additive Modeling using a Multi-class Exponential loss function) modifies AdaBoost to better suit multi-class problems by adding the term $\log(K-1)$ to the weight calculation. The weight $\alpha(m)$ for each classifier is now calculated as $\alpha(m) = \log\left(\frac{1-err(m)}{err(m)}\right) + \log(K - 1)$. This adjustment allows for the positive contribution of each classifier as long as its accuracy is better than $\frac{1}{K}$, not strictly above 0.5 [64].

2.2.4. Adaboost With Random Forest
In our study, we used an approach that capitalizes on the strengths of the random forest and AdaBoost algorithms. By utilizing random forests as the base estimators within AdaBoost, we leverage the algorithm's inherent robustness against overfitting and its ability to create a diversified set of classifiers. AdaBoost's sequential model building approach, where each successive model focuses on the errors of the previous ones, brings a high level of precision and adaptability to our classifier. This methodology, developed using the scikit-learn library, takes advantage of the complementary attributes of these two powerful algorithms to create a multiclass classification model that is robust and accurate [65].

Our random forest model consisted of 10 decision trees. This number strikes a balance between model complexity and the ability to capture diverse aspects of the data. The trees were restricted to a maximum depth of 10 layers from the root to the node, which helps to control overfitting while maintaining the depth required for capturing complex patterns. To measure the quality of a split in tree growth, we used the Gini index: $\sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk})$. This criterion is sensitive to changes in node probabilities, offering a nuanced approach to node splitting compared to the misclassification rate [60].

Upon establishing the random forest base, we incorporated these models into the AdaBoost framework. Our AdaBoost model was configured to construct 50 classifiers by boosting. This number was chosen to create a comprehensive ensemble. Each of these classifiers was a random forest, ensuring that the robustness of the bagging is intertwined with the refinement process of boosting. In this setting, each subsequent classifier in AdaBoost pays more attention to the instances that were misclassified by the earlier classifiers, thereby enhancing the model's overall accuracy and adaptability. The model was trained on 20 years of data for the state of California and subsequently tested on 3 independent test datasets:

1) California, 2020 - 2021, 2) Oregon, 2000 – 2021, and 3) Washington, 2000 – 2021.

2.3. Evaluation Metrics

The model's performance was evaluated based on accuracy, precision, recall, and F1 score. In a multiclass setting, accuracy is calculated as the number of correct predictions divided by the total number of predictions: $Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$, where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives. Precision is the ratio of correctly predicted positive observations to total predicted positive observations: $Precision = \frac{TP}{TP+FP}$. High precision relates to the low false positive rate. In the context of our study, it reflects the model's ability to correctly identify a particular vulnerability category without incorrectly classifying other categories as belonging to it. Recall is the ratio of correctly predicted positive observations to all observations in the actual class: $Recall = \frac{TP}{TP+FN}$. It shows the model's ability to find all relevant cases within a category.

In the case of wildfire vulnerability, a high recall indicates that the model is effective in identifying most of the census tracts for a specific category. The F1 score is the weighted average of precision and recall: $F_1 = \frac{2*Precision*Recall}{Precision+Recall}$ Therefore, this score takes into account both false positives and false negatives [66].

2.4. Cross-Validation

Monte Carlo cross-validation and 10-fold cross-validation methods were applied to assess the model's reliability and to mitigate overfitting. The dataset comprising 20 years of California data on social vulnerability and wildfire incidence was randomly split into different subsets for each validation iteration. Monte Carlo cross-validation, also known as random subsampling validation, involves randomly partitioning the dataset into a training set and a test set multiple times. In the first round, the split was 50% for training and 50% for testing. This means that half of the data is used to train the machine learning model and the other half is used to evaluate its performance. Model performance is assessed using accuracy, precision, recall, and the F1 score as evaluation metrics. The splitting, training, and evaluation steps were repeated 9 more times, with a different random split each time. This resulted in a total of 10 trials for the 50/50 data split. The entire process was then repeated for different training/testing splits: 60%/40%, 70%/30%, and 80%/20%. For each split ratio, the model was trained and evaluated 10 times and the mean and standard deviation for each of the performance metrics was calculated. Repeating the process multiple times with different splits helps mitigate the variance in model performance that can result from a single random split [67]. Next, the stability and reliability of the model were assessed using 10 fold cross-validation. The 10-fold cross-validation method involves dividing the data into 10 equal subsets (or 'folds'). The model is then trained on 9 folds and tested on the remaining fold. This process was repeated 10 times, with each fold used exactly once as the test set [68].

3. Results

The models generated from each of the ten iterations across four distinct training split ratios were saved for evaluation on three separate, independent test sets. This methodical approach allowed for a comprehensive assessment of the robustness and effectiveness of the models in various testing scenarios.

3.1. California 2020 – 2021 Test Set

In the California test set, models trained on different splits of California training data exhibited notable accuracy and consistency. Models trained on a 50/50 split of California training data displayed remarkable performance with a mean accuracy of 98.26% and a standard deviation of 1.00%. The precision was high at 98.34% (SD = 1.11%), and the recall rate stood at 97.48% (SD = 1.37%), demonstrating the models' ability to effectively identify vulnerability categories. The mean F1 score, a critical metric for the balance between precision and recall, was 97.90% with a standard deviation of 1.25%. Models trained on a 60/40 split showed better performance, achieving a mean accuracy of 98.89% (SD = 0.69%) and a mean F1 score of 98.70% (SD = 0.86%). For the 70/30 split, mean accuracy was 99.19% (SD = 0.22%), indicating robust performance across various training data splits. The highest performance was recorded in the 80/20 split, where the model achieved a mean accuracy of 99.22% (SD = 0.13%), precision of 99.40% (SD = 0.14%), recall of 98.87% (SD = 0.23%), and F1 score of 99.13% (SD = 0.18%) 1.
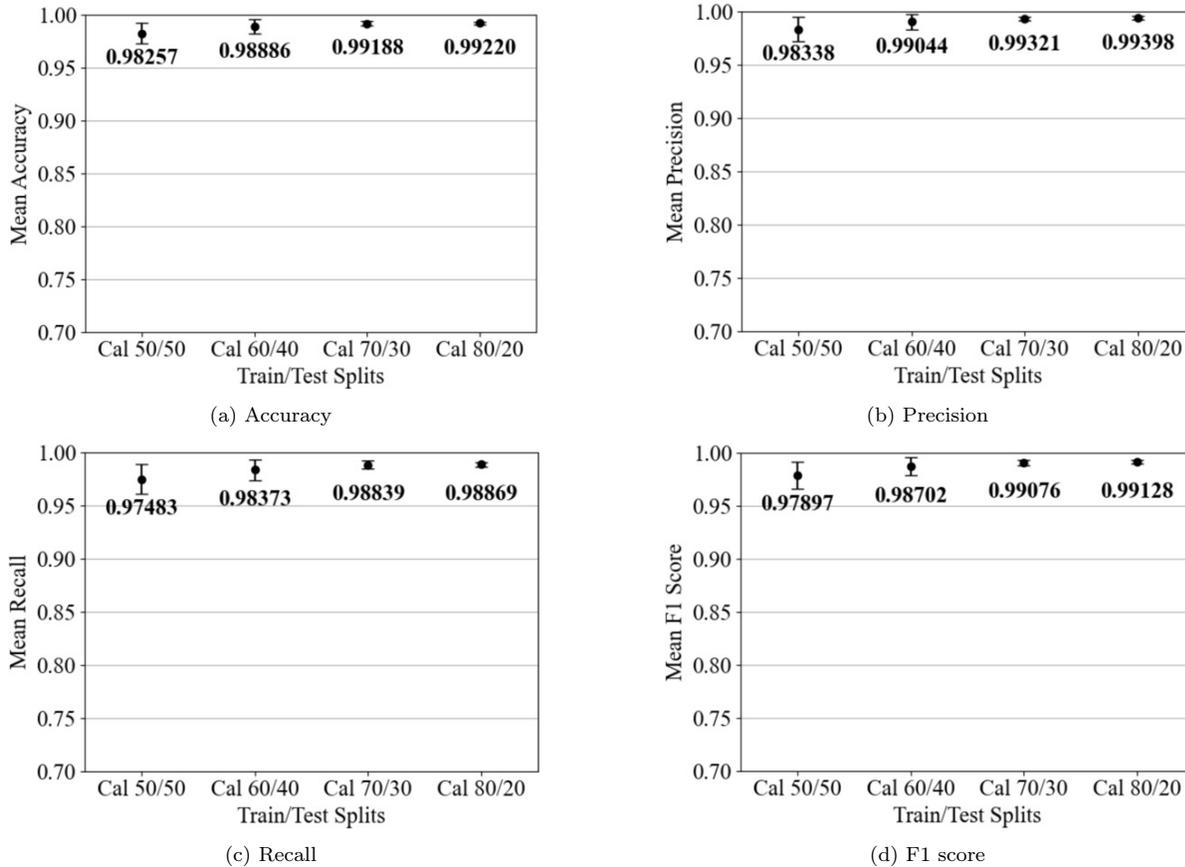
(a) Accuracy

(b) Precision

(c) Recall

(d) F1 score

Figure 1: Performance Metrics of Models Trained on Various Splits of California Data (2000-2019) and Tested on California data (2020-2021)

3.2. Oregon 2000 – 2021 Test Set

For the Oregon test set, covering data from 2000 to 2021, models trained on a 50/50 split of the California data achieved a mean accuracy of 97.49% (SD = 0.23%). This high level of accuracy was complemented by a mean precision of 96.91% (SD = 0.32%) and a mean recall of 94.91% (SD = 0.58%), indicating the models' effectiveness in various sce- narios. The mean F1 score for this split was 95.84% (SD = 0.41%). The consistency of the models was evident, as the 60/40 split models maintained similar performance levels, with a mean accuracy of 97.50% (SD = 0.19%) and an F1 score of 95.88% (SD = 0.36%). The 70/30 split demonstrated a mean accuracy of 97.58% (SD = 0.11%), highlighting the models' effectiveness in diverse test conditions. Moreover, the 80/20 split models showcased their robustness with a mean accuracy of 97.66% (SD = 0.25%), mean precision of 96.98% (SD = 0.43%), and an impressive mean recall of 95.10% (SD = 0.88%), illustrating their adaptability to different data distributions 2.
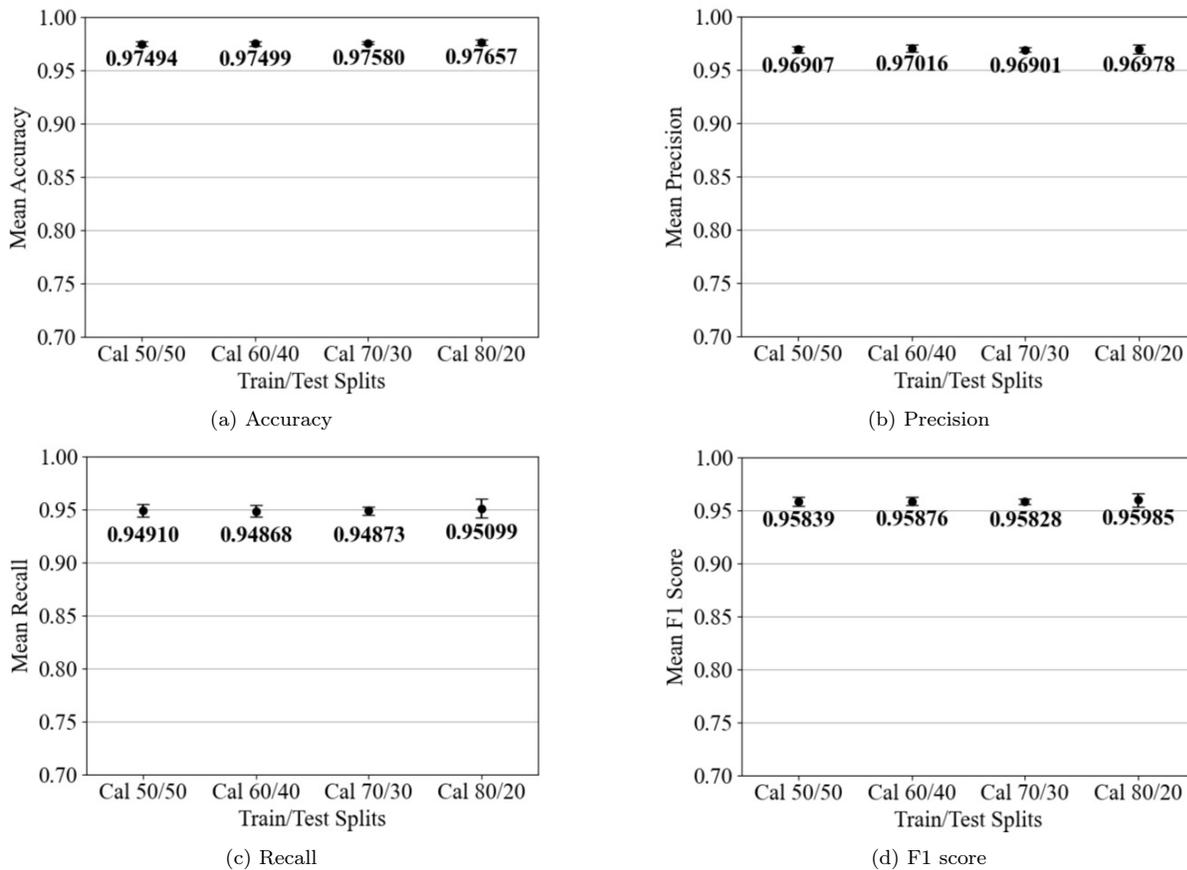
(a) Accuracy

(b) Precision

(c) Recall

(d) F1 score

Figure 2: Performance Metrics of Models Trained on Various Splits of California data (2000-2019) and Tested on Oregon data (2000-2021)

3.3. Washington 2000 – 2021 Test Set

On the Washington test set, using data from 2000 to 2021, models trained on a 50/50 split of the California training data exhibited a mean accuracy of 97.17% (SD = 0.16%), mean precision of 96.64% (SD = 0.33%), and mean recall of 95.16% (SD = 0.34%), with a mean F1 score of 95.86% (SD = 0.29%). This demonstrates the models' effective generalization to different geographical contexts. Increasing the training data to a 60/40 split resulted in a mean accuracy of 97.23% (SD = 0.18%), precision of 96.97% (SD = 0.21%), recall of 95.25% (SD = 0.42%), and F1 score of 96.06% (SD = 0.25%). The 70/30 split improved the model's performance, achieving a mean accuracy of 97.30% (SD = 0.16%), precision of 96.96% (SD = 0.21%), recall of 95.14% (SD = 0.42%), and F1 score of 96.00% (SD = 0.29%). The 80/20 split models maintained this trend with a mean accuracy of 97.37% (SD = 0.12%), further demonstrating the models' effectiveness across diverse test sets 3.
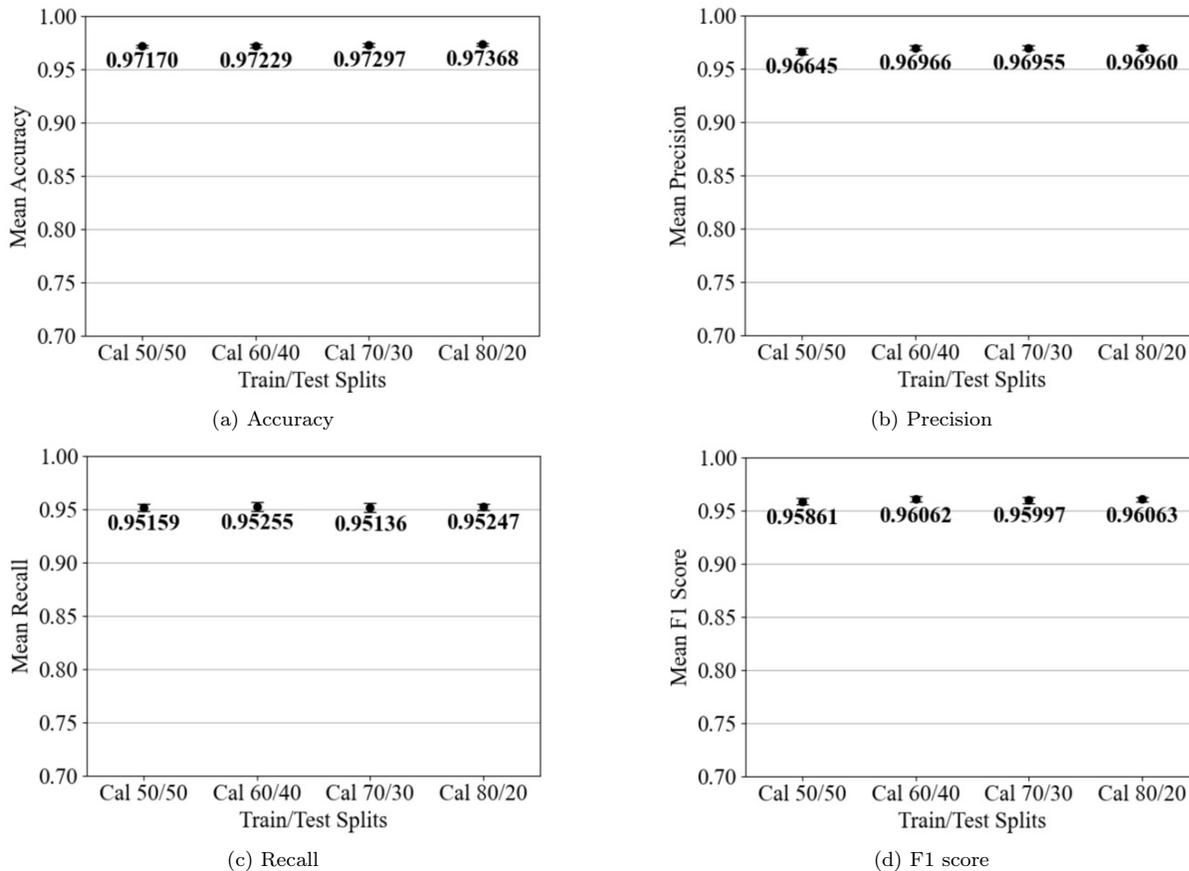
Figure 3: Performance Metrics of Models Trained on Various Splits of California Data (2000-2019) and tested on Washington data (2000-2021)

3.4. Monte Carlo Cross-Validation Results

The Monte Carlo cross-validation approach was crucial to providing a reliable estimate of model performance, considering the inherent variability in training data splits. It should be noted that Monte Carlo validation data differ from test data, as it involves repeated random sampling of the training data to validate model performance. This approach offers a more nuanced understanding of model reliability, as it simulates a variety of training scenarios.

For models trained on a 50/50 split of California training data, the Monte Carlo validation yielded compelling results. The mean accuracy stood at 99.17% (SD = 0.46%), accompanied by a mean precision of 99.25% (SD = 0.47%), mean recall of 98.99% (SD = 0.59%), and a mean F1 score of 99.12% (SD = 0.53%). These metrics indicate a consistently high performance across different aspects of classification. Models trained on a 60/40 split

of the California data further reinforced the reliability of our approach. The mean accuracy was 99.35% (SD = 0.26%), with mean precision at 99.44% (SD = 0.26%), mean recall at 99.23% (SD = 0.33%), and the mean F1 score at 99.33% (SD = 0.29%). The minimal standard deviation highlights the stability of model performance across multiple iterations of validation. For the 70/30 split, the mean accuracy was noted at 99.35% (SD = 0.31%), mean precision at 99.43% (SD = 0.32%), mean recall at 99.20% (SD = 0.39%), and the mean F1 score at 99.31% (SD = 0.36%). This consistency in high performance across different metrics showcases the model's robustness. Finally, models trained on an 80/20 split of the California data achieved a mean accuracy of 99.59% (SD = 0.10%), with mean precision at 99.67% (SD = 0.08%), mean recall at 99.52% (SD = 0.14%), and a F1 score at 99.60% (SD = 0.11%). These results not only affirm the model effectiveness but also their reliability in diverse training scenarios.

Split	Accuracy		Precision		Recall		F1 Score	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
50/50	0.9917	0.0046	0.9925	0.0047	0.9899	0.0059	0.9912	0.0053
60/40	0.9935	0.0026	0.9944	0.0026	0.9923	0.0033	0.9933	0.0029
70/30	0.9935	0.0031	0.9943	0.0032	0.9920	0.0039	0.9931	0.0036
80/20	0.9959	0.0010	0.9967	0.0008	0.9952	0.0014	0.9960	0.0011

Table 1: Results of Monte Carlo Cross-Validation for Models Trained on California Data (2000-2019)

3.5. 10 Fold Cross-Validation Results

In addition to Monte Carlo cross-validation, ten-fold cross-validation was utilized to evaluate the performance of machine learning models trained for multiclass classification using California training data. The ten-fold cross-validation method ensures robust validation by dividing the data into ten parts, using each part once as the validation set, while the remaining parts form the training set. The results of each fold demonstrate consistent high performance in all metrics. Specifically, the first fold achieved an accuracy of 99.74%, pre- cision of 99.78%, recall of 99.70%, and an F1 score of 99.74%. The second fold showed even higher results with an accuracy of 99.87%, precision of 99.90%, recall of 99.87%, and an F1 score of 99.88%. This trend of exceptional performance continued throughout all folds,

although there was a slight decrease in the fifth through tenth folds, with accuracies ranging from 99.36% to 99.49%, precision from 99.48% to 99.54%, recall from 99.16% to 99.39%, and F1 scores from 99.32% to 99.46%.

Aggregating the results of all folds, the overall mean accuracy stands at 99.58% (SD = 0.19%), mean precision at 99.65% (SD = 0.16%), mean recall at 99.40% (SD = 0.25%), and mean F1 score at 99.57% (SD = 0.21%). These results underline the robustness and reliability of the model, showcasing its effectiveness in classifying vulnerability categories across diverse subsets of data. The consistency across folds highlights the model's stability and its ability to generalize well across different subsets of the training data 2.

Fold	Accuracy	Precision	Recall	F1 Score
1	0.9974	0.9978	0.9970	0.9974
2	0.9987	0.9990	0.9987	0.9988
3	0.9984'	0.9986	0.9981	0.9984
4	0.9976	0.9983	0.9973	0.9978
5	0.9949	0.9954	0.9939	0.9946
6	0.9943	0.9950	0.9929	0.9939
7	0.9941	0.9952	0.9926	0.9939
8	0.9947	0.9955	0.9939	0.9946
9	0.9936	0.9948	0.9916	0.9932
10	0.9940	0.9952	0.9925	0.9939
Mean	0.9958	0.9965	0.9940	0.9957
Std. Deviation	0.0019	0.0016	0.0025	0.0021

Table 2: Results of 10 Fold Cross-Validation for Models Trained on California Data (2000-2019)

4. Discussion

4.1. Technological Innovations in Wildfire Risk Management

The landmark interagency agreement signed on November 8 2023, by key U.S. federal agencies – the Environmental Protection Agency (EPA), the U.S. Department of Agriculture (USDA), the U.S. Department of the Interior (DOI), and the Centers for Disease Control and Prevention (CDC) – represents a significant stride in the collective approach to wildfire risk management and community protection [69]. This joint effort aligns seamlessly with the priorities outlined in the Wildland Fire Mitigation and Management Commission Report presented to Congress on September 27, 2023. The report, one of the most comprehensive reviews of the wildfire system to date, highlights seven critical

themes essential to improving wildfire management, notably the modernization of tools for informed decision making. A key recommendation from the report is the establishment of an interagency joint office, known as a "fire environment center." The report directly states: "The proposed center would address the widely recognized lack of timely, manager-focused models, technologies, assessments, and forecasts to support operational decision-making and short- and long-term planning [70]."

In this context, the development of a classifier as a decision-making tool for wildfire risk management could prove to be a valuable asset. SHINE, with its focus on identifying socially vulnerable populations, aligns with the agreement's broader

goal of advancing health equity and addressing the unique needs of different communities. In the often dynamic and resource-constrained environment of wildfire risk management, a tool specifically aimed at identifying vulnerable populations could help decision makers prioritize efforts and optimize resource allocation effectively. Using machine learning to harness its power, decision makers can rapidly analyze data and identify actionable insights. This research underscores the potential of technology to deliver solutions that are not only effective but also equitable, thereby enhancing the resilience of our communities in the face of ever-evolving challenges. Our classifier has shown outstanding results, underscoring its potential as an asset in the domain of wildfire risk management. The exceptionally high mean accuracy of the model across various test sets is a testament to its strong predictive power in accurately classifying the six vulnerability categories derived from thematic areas of the CDC. The model also demonstrated a remarkably high precision, recall, and F1 score.

To affirm these findings, the model was rigorously validated using both Monte Carlo and 10-Fold cross-validation methods. The consistent performance across these diverse valida- tion methods further highlights the model's robustness and generalizability. This consistency is paramount, confirming that the model is reliable and effective in different datasets and conditions. Overall, these performance results signify that the classifier has the ability to deliver reliable, accurate, and consistent predictions, making it a valuable tool for identifying socially vulnerable populations, thus enhancing wildfire preparedness and response strategies.

It is important to note that the tool is built using CDC data, which are national data. Although we present our results on states in the western United States, this generalizes to all states in the nation. This broad applicability underscores the versatility and relevance of SHINE in various geographical contexts, enhancing its utility as a nationwide decision- making tool for wildfire risk management.

Figure 4: SHINE, a Novel Tool for Wildfire Risk Mitigation Planning

4.2. Tailored Strategies for Risk Reduction

The high accuracy of the model in classifying vulnerability categories underscores the potential for tailored community-level wildfire mitigation, planning, response, and recovery programs. The classifier's ability to highlight specific subsets of social vulnerability indicators can inform the development of targeted mitigation strategies. For example, individuals with limited English proficiency may struggle to access vital information during wildfire emergencies due to language barriers [71]. Recognizing this vulnerability, it becomes essential to develop inclusive mitigation strategies and ensure the accessibility of crucial information to all members of the community [72]. For communities with a higher concentration of individuals with limited English proficiency, the model's insights could lead to the implementation of multilingual emergency communication systems and educational materials,

ensuring that vital information is accessible during wildfire emergencies.

For populations 65 years and older, specific needs arise in the context of preparedness and response to wildfires [73,74]. Mobility limitations, chronic health conditions, and the need for regular medication are factors that can complicate evacuation and recovery [75]. Identifying areas with a higher concentration of older adults enables emergency services to allocate resources more effectively, providing accessible transportation and targeted health services during and after wildfires. Economic vulnerabilities, such as poverty, low income, or unemployment, significantly impact the ability of individuals and communities to prepare for, respond to, and recover from wildfires [76-79]. These populations may lack resources for essential activities such as home hardening or

purchasing insurance [80-82]. Targeted financial aid programs and affordable housing solutions are critical in mitigating these economic vulnerabilities and aiding in recovery [83-85].

Residents in mobile home communities face increased risks due to the vulnerability of their homes to wildfires [86,87]. Identifying these communities enables the allocation of resources to improve fire safety regulations, offer fire risk education, and provide resources for home hardening [88-90]. In areas where many residents do not have access to personal vehicles, evacuation can be difficult [91]. Emergency services must plan effective evacuation strategies, including transportation options and assistance programs, to ensure the safety of these populations [92]. Populations living in group quarters require specialized evacuation plans and safety protocols due to the unique challenges posed by these living arrangements [93]. Tailoring strategies to these settings ensures the safety and well-being of residents in dormitories, nursing homes, or shelters.

For minors, ensuring informed guardians and having evacuation and emergency plans in schools are crucial aspects of disaster preparedness [94, 95]. Similarly, single parents may face additional challenges during evacuation, underscoring the need for support networks and intracommunity cooperation [96-99]. Educational levels, specifically the lack of a high school diploma, can also influence the ability to cope and recover from disasters [100,101]. Addressing these educational disparities is essential in formulating effective mitigation and recovery strategies [102,103]. Individuals with disabilities may require personalized evacuation assistance and disability-friendly emergency shelters. Ensuring that these needs are met is crucial in the planning and response phases of wildfire management [104].

Lastly, areas with high levels of crowding or multiunit structures necessitate specific evacuation strategies to manage the safe evacuation of all residents [105]. Staggered evacuation plans and clear communication within densely populated communities are essential to avoid chaos and ensure safety [106]. The classifier's ability to highlight specific subsets of social vulnerability indicators can inform the development of targeted strategies that address the unique needs and risks of diverse populations, ultimately improving the resilience and safety of the community in the face of wildfires [71].

4.3. Health Impacts of Wildfire Smoke
It is worth noting that the impact of wildfires extends well beyond their immediate perimeters, affecting air quality and health in vast regions [107,108]. This phenomenon was starkly observed when Prof. Johnston from the University of Tasmania reported that 80% of Australians were affected by smoke from Australia's 2019-2020 wildfire season, leading to thousands of hospital admissions and emergency room visits [109]. Similarly, Canada's 2023 fire season, with 45 million acres burned, saw health impacts from smoke felt as far as New York, Florida and even across the Atlantic in Britain and Spain [7,110]. This transboundary impact of wildfire smoke illustrates its far-reaching consequences.

Wildfire smoke, laden with fine particles and gases, travels great distances, degrading air quality far from the fire's origin [111]. Studies have shown a disproportionate impact on vulnerable communities. Rappold et al. identified that communities with higher percentages of older adults, poverty, and lower education levels experience greater exposure to smoke [112]. Wettstein et al. linked smoke exposure to increased emergency department visits for cardiovascular and cerebrovascular problems, particularly among adults over 65 years of age [113]. Aguilera et al. found that wildfire-specific PM2.5 caused a significant increase in respiratory hospitalizations [114]. Similarly, Dohrenwend et al. reported a surge in respiratory illness-related emergency department visits during the 2007 Southern California wildfires [115]. Heaney et al.'s evaluation of California's 2004-2009 wildfire seasons revealed an increase in cardiorespiratory visits, notably a 10.3% rise in asthma cases among children aged 0-5 years and increased visits for cardiovascular diseases in those over 65 [116]. These findings underscore the importance of considering both direct and indirect impacts of wildfires, especially for socially vulnerable populations.

5. Conclusion
It is imperative to contextualize our findings within the broader framework of wildfire risk management. The Wildland Fire Mitigation and Management Commission Report, presented to Congress, emphasizes the necessity of advanced tools in this realm. The report recommends that "The fire environment center should provide real-time science-based, and data-rich scientific and technical analytic services, decision support, and predictive services to inform land and fuels management, community risk reduction, and fire management and response [70]." This encapsulates the essence of our research, which utilizes machine learning techniques to identify vulnerable subpopulations for increased wildfire risk susceptibility. The use of a random forest initialized AdaBoost classifier, validated with Monte Carlo and K-Fold Cross-Validation methods, has enabled the classification of these subpopulations with high accuracy, precision, recall, and F1 score. Identifying populations with heightened vulnerability allows for the creation of targeted mitigation strategies that address the specific needs and challenges of these communities. By pinpointing areas of higher susceptibility, resources for fire prevention, education, and emergency response can be allocated more efficiently. This ensures that the most vulnerable populations receive the necessary attention and support, both in terms of preventive measures and in response to fire events.

This study highlights the potential for machine learning techniques to improve our understanding of social vulnerability in disaster contexts. Understanding which communities are most vulnerable allows for targeted interventions. This ensures that the most vulnerable populations receive the necessary attention and support, both in terms of preventive measures and in response to fire events. As we continue to face the challenges posed by wildfires, the integration of innovative approaches will be crucial in safeguarding communities, especially those most vulnerable, thereby fortifying our collective resilience against these ever-evolving threats.

Category	Areas of Heightened Vulnerability	SVI Indicators
0	Housing/Transportation, Minority Status/Language	Mobile homes Group quarters No vehicle Crowding Multiunit structures Limited English Minority
1	Socioeconomic Status, Minority Status/Language	Mobile homes Group quarters No vehicle Crowding Multiunit structures Limited English
2	Socioeconomic Status, Housing/Transportation	Mobile homes Group quarters No vehicle Crowding Multiunit structures Limited English Crowding Multiunit structures Limited English
3	Household Composition/Disability, Housing/Transportation	Mobile homes Group quarters No vehicle Crowding Multiunit structures Limited English Crowding Multiunit structures Limited English
4	Household Composition/Disability, Minority Status/Language	Mobile homes Group quarters No vehicle Crowding Multiunit structures Limited English
5	Socioeconomic Status, Household Composition/Disability 18	Mobile homes Group quarters No vehicle Crowding Multiunit structures Limited English Minority Limited English

Table A.3: Key Social Vulnerability Indicators Per Classification Category

Indicator	Description	Theme
Below poverty	Percentile of the proportion of persons below poverty	Socioeconomic status
Unemployed	Percentile of the proportion of civilian (age 16+) unemployed	
Income	Percentile of per capita income	
No HS diploma	Percentile of the proportion of persons with no high school diploma (age 25+)	
Age 65 or older	Percentile of the proportion of persons aged 65 and older	Household Composition & Disability
Age 17 or younger	Percentile of the proportion of persons aged 17 and younger	
Disability	Percentile of the proportion of persons aged 5 and older with a disability	
Single Parent	Percentile of the proportion of single parent households with children under 18	
Minority	Percentile of the proportion minority	Minority Status & Language
Limited English	Percentile of the proportion of persons (age 5+) who speak English "less than well"	
Multiunit structures	Percentile of the proportion of housing in structures with 10 or more units	Housing Type & Transportation
Mobile homes	Percentile of the proportion of mobile homes	
Crowding	Percentile of the proportion of households with more people than rooms	
No vehicle	Percentile of the proportion of households with no vehicle available	
Group Quarters	Percentile of the proportion persons in group quarters	

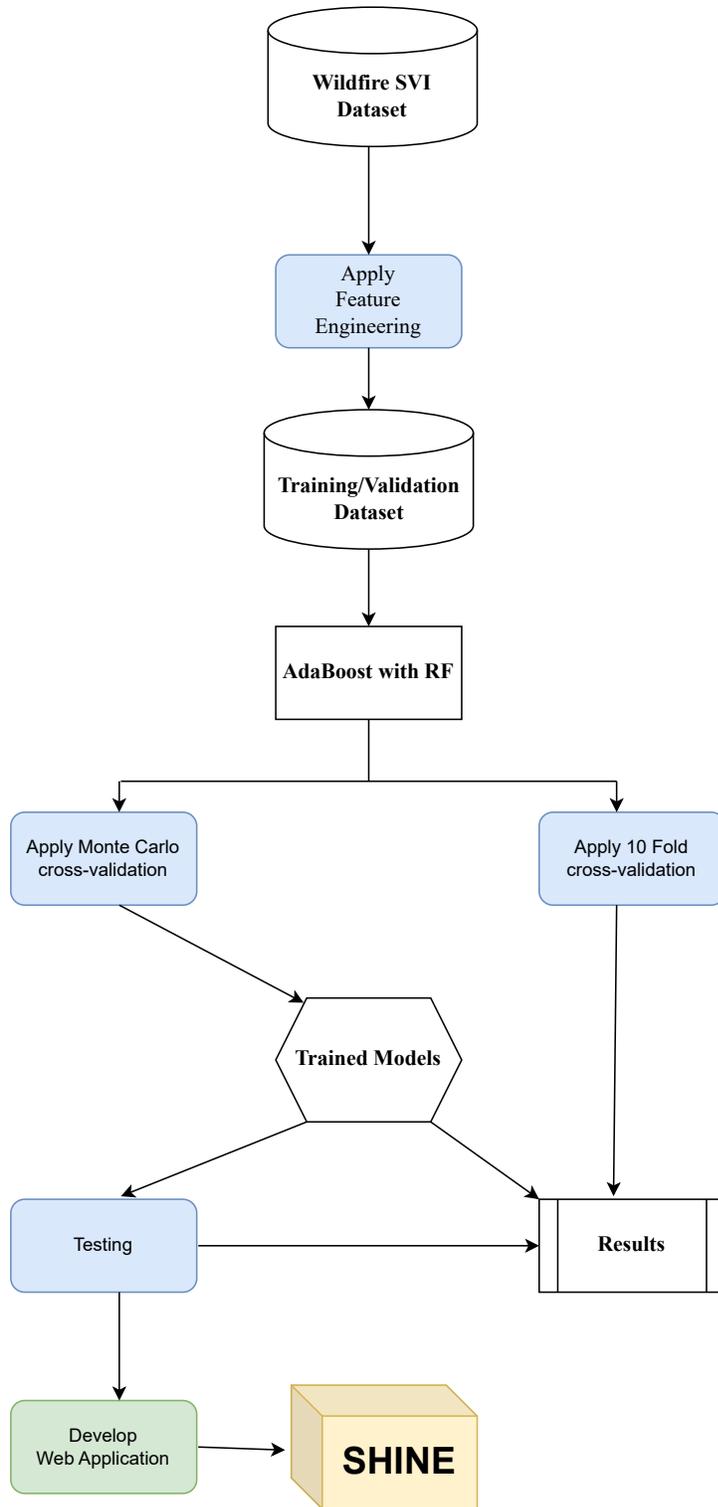**Table a.4: description of social vulnerability indicators (sources: u.s. Cdc [50, 54])**

Figure A.5: Wildfire Risk Susceptibility Classification Framework

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