Interpretable Machine Learning for Modeling Weather-Related Power Outages in Central Florida

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BACKGROUND

Extreme weather events often cause power grid disruptions across the United States, with a 10-fold increase in power outages between 1984-2012. Modeling weather-related power-outages is challenging due to grid quality, vegetation, and weather conditions such as wind, precipitation, etc. Limited granular outage data further complicates the modeling. In this study, we propose weather-outage models based on machine learning algorithms for Orange County in Central Florida as a case study.

We test various models, including Random forest, Gradient boosting, Extreme gradient boosting, Artificial neural networks, and Long short-term memory using weather variables as predictors and the duration of power outage as predictand. We also build different ensemble models combining different algorithms.

DATA

Power outage data was collected from the Environment for the Analysis of Geo Located Energy Information (EAGLE-I) managed by ORNL for the Department of Energy. Data is available at the county level from November 2014 to 2022 at 15-minute intervals providing the number of customers experiencing an outage in a county.

The different weather variables used in this study have varying spatial and temporal resolution (see Table 1). All datasets were converted to county level spatial resolution and daily temporal resolution by through resampling methods to obtain homogenous data sets to be used for further preprocessing and analysis.

Table 1: Selection of weather variables collected from CONUS404, ERA5, and other sources.

Variable	Spatial res.	Temporal res.	Source
Eagle-I	County level	15 minutes	DOE & ORNL
Precipitation (TP, MP)	4*4 km grid	Hourly	CONUS404
Temperature (T)	4*4 km grid	Hourly	CONUS404
Wind Speed (WS)	4*4 km grid	Hourly	CONUS404
Soil Moisture (SM)	4*4 km grid	Hourly	CONUS404
Leaf Area Index (LAI)	4*4 km grid	Hourly	CONUS404
Lightning (LIS)	--	Count	NLDN
CAPE	28 *28 km grid	Hourly	ERA5
Hurricane Path	--	6 hourly	HURDAT
MSL (sea level pressure)	28*28 km grid	Hourly	ERA5
Hail	0.75° × 0.75°	Daily	NOAA NCEI

METHODOLOGY

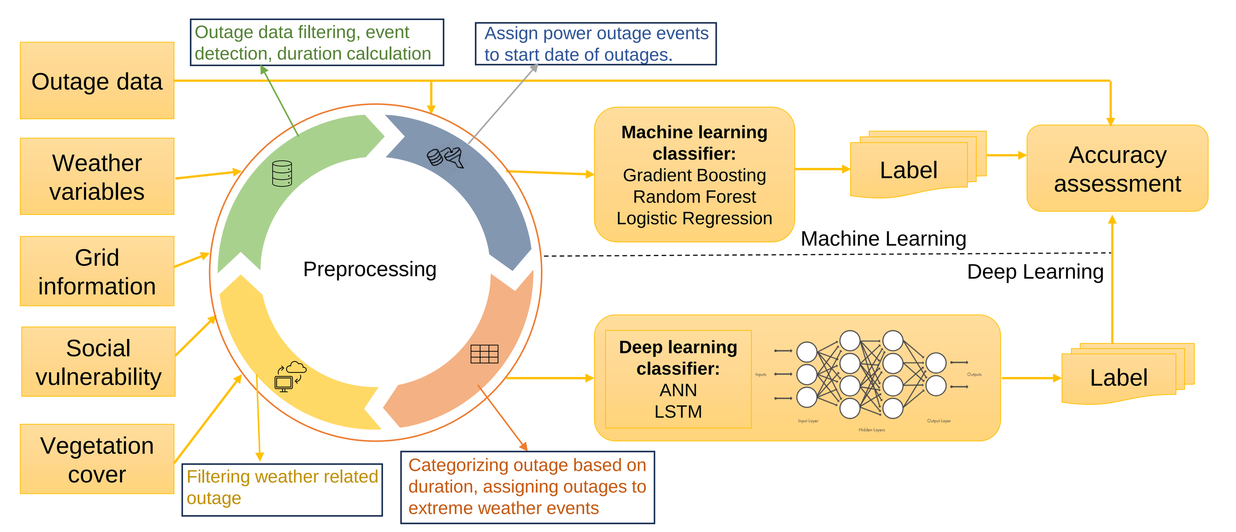

Fig. 1: Workflow adopted in this study, including different weather and power outage variables, preprocessing steps, classification methods used, and accuracy assessment applied for each method. Note that grid information and social vulnerability index were not considered for the preliminary results shown here.

Filtering is carried out to distinguish weather-related power outages from "other" outages (e.g., minor outages from daily system operations). This is done by setting a threshold of customers affected and linking outages to severe weather events. Afterwards, outage durations are derived and classified into class 0 (no outage), class 1 (minor outage with <4-hour duration), and class 2 (major outage with >4-hour duration). Data preprocessing also includes categorizing predictor variables by applying percentile-based thresholds to use for model building.

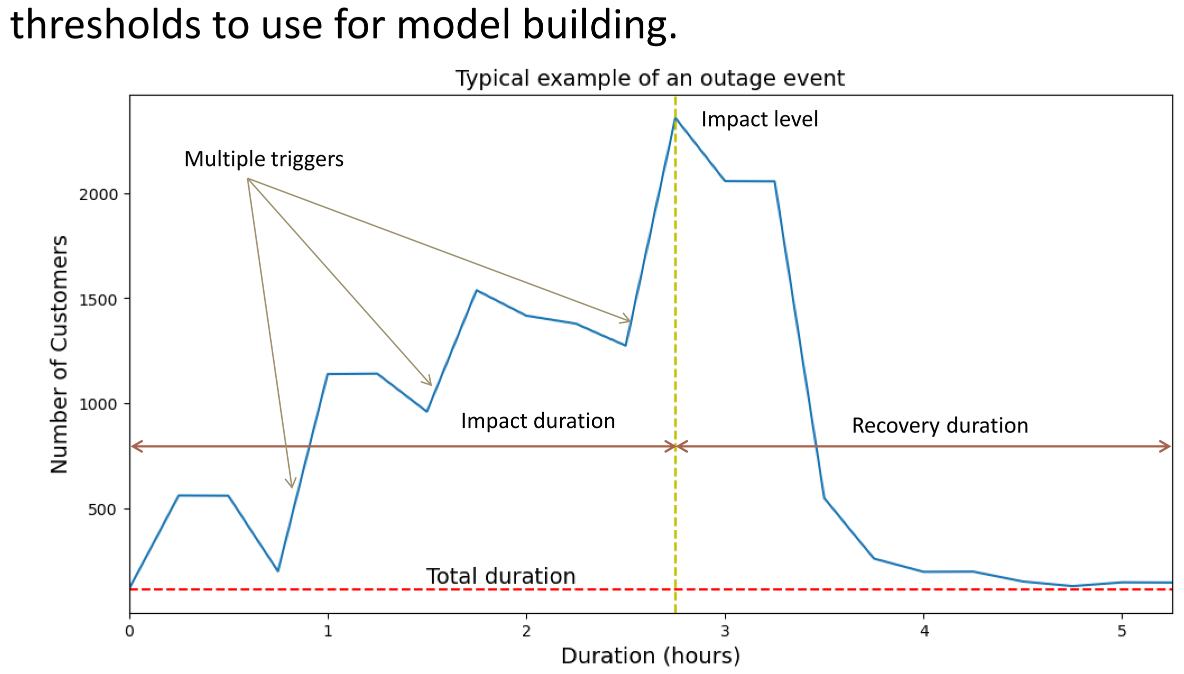

Fig. 2: Typical example of a power outage event with multiple triggers, impact duration, and recovery duration. Red dotted line shows the minimum number of customers affected (above the threshold we use to consider it an "event") and total event duration. The impact level represents the maximum number of customers affects and separates impact and recovery duration.

MODEL BUILDING

Model building includes selecting appropriate models, training the models (including train-test split, regularization), model evaluation (precision, recall, F1), model tunning (hyperparameters tunning, 5-fold cross validation), and building ensemble models (stacking classifier, voting classifier). Evaluation metrics such as accuracy score provide average scores across outage classes and can be heavily affected by model performance for a single class. Hence, we derive precision, recall, and F1 scores for each class separately to avoid potential bias in the model evaluation.

RESULTS

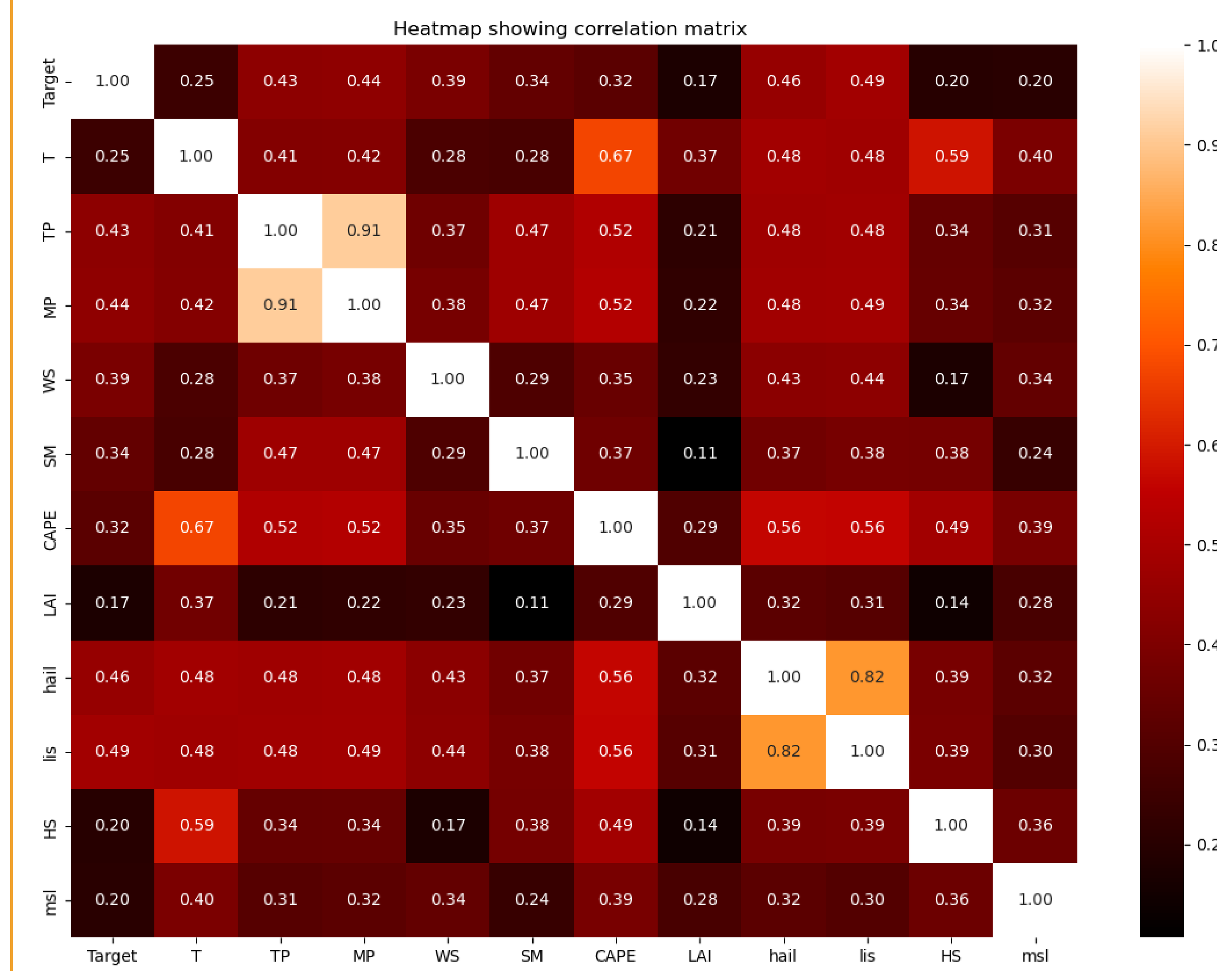

Fig. 3: Correlation matrix for different predictor variables and the target variable. Matrix shows that TP (total prcp), MP (mean prcp), wind speed, lightning (LIS), and hail have strong positive correlation with the target variable (power outage duration).

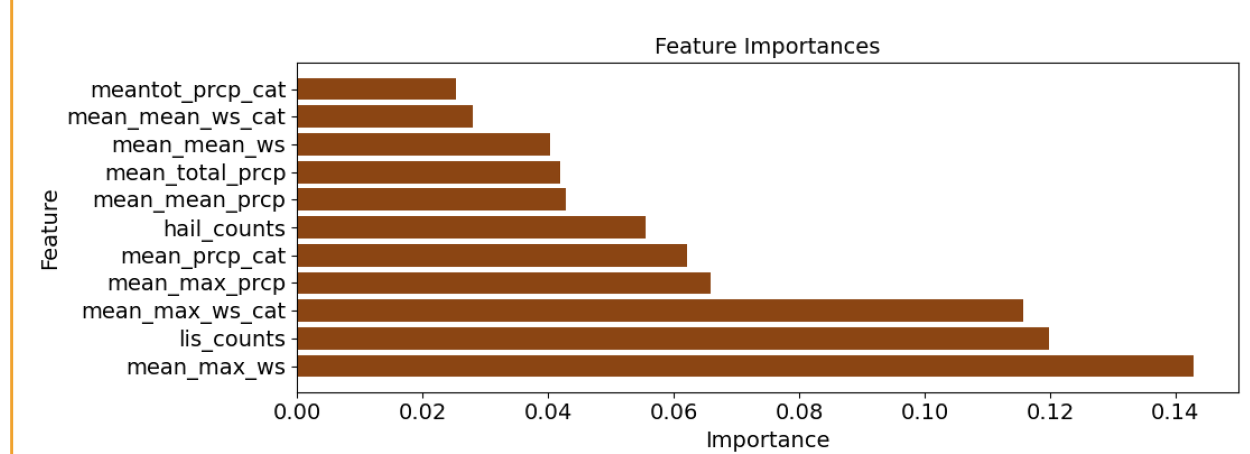

Fig. 4: Importance of the top 11 predictor variables used to build random forest-based power outage model. Results show that precipitation, wind speed, lightning, and hail contribute most.

Table 2: Precision (Pre.), recall (Re.), and F1 scores for extreme gradient boosting classifier (yellow), voting classifier (brown), and stacking classifier (black). Voting classifier and stacking classifier consist of random forest, gradient boosting, and extreme gradient boosting models and in stacking classifier logistic regression was used as intermediate classification method.

	XGBoost classifier			Voting classifier			Stacking classifier		
Class	Pre.	Re.	F1	Pre.	Re.	F1	Pre.	Re.	F1
0	0.99	1	0.99	0.99	1	0.99	0.99	1	0.99
1	0.74	0.67	0.7	0.73	0.69	0.71	0.78	0.64	0.7
2	0.72	0.77	0.74	0.72	0.75	0.74	0.71	0.82	0.76

Results show that the best model achieves above 80 percent accuracy in identifying diverse power outage classes including no outage, minor outage, and major outage events.

CONCLUSIONS

- Out of the tested models, ensemble models show better performance compared to single models.
- Stacking classifier performs best among all the tested models.
- Minor and major outage class prediction is challenging because the duration of power outages does not solely dependent on the intensity of extreme weather.
- Using county level data imposes limitations because the gird is not uniform within a county and the same weather event likely leads to outages in some areas and not others.

WAY FORWARD

In the next step, we aim to ingest outage data with higher spatial resolution, extend the modelling domain to other counties, and integrate social vulnerability data and grid characteristics into the modeling framework. The ultimate goal is to identify hotspots of weather-related outages enabling the development of targeted intervention strategies (e.g., placement of PV systems and storage) to improve resilience of disadvantaged communities, especially in the face of climate change.

Future efforts to improve weather-related power outage modeling should:

- Consider finer resolution power outage data at census tract or zip code levels along with detailed grid information.
- Leverage NASA night-time imagery (especially Black Marble products) as proxy for coarse resolution power outage data to identify vulnerable communities.

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