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RESEARCH ARTICLE

Social Media Sensors for Weather-Caused Outage Prediction Based on Spatio–Temporal Multiplex Network Representation

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ABSTRACT This study investigates severe weather events that lead to power outages. Despite extensive research on using social media during disasters, little work has focused on combining social media information with power outage data. To address this limitation, we propose a novel and effective approach to enhance the prediction accuracy of weather-related power outages by learning a spatio-temporal multiplex network that integrates information on the impact of inclement weather on the residents extracted from their social media posts with relevant weather, geographic, and grid topology data. In the multiplex network framework, the outage risk is estimated using logistic regression, neural network, support vector machine, random forest, xgboost, and decision tree classifiers through which machine learning models are applied separately on individual layers and jointly on multiplex networks representing layers capturing information related to weather, lightning, and vegetation. Experiments were conducted to predict the risk for weather-related power outages three hours in advance at a county level in five states of the Pacific Northwest region from November 2021 to April 2022. Evidence suggests that using vegetation information improves the quality of all models compared to relying on weather and lighting layers alone. Integrating an additional layer on the impact of inclement weather on the community residents retrieved from public social media posts (Twitter, Reddit) with weather, lightning, and vegetation layers improves the accuracy of outage prediction by $5\% - 7\%$. The results demonstrate that the proposed spatio-temporal multiplex network-based approach offers beneficial insights for predicting power outages three hours ahead at the county level.

INDEX TERMS Multiplex network, power outage, spatio–temporal, social media, weather, machine learning.

I. INTRODUCTION

A. BACKGROUND

A severe weather has become more common and more intense; therefore, it is important to consider its impact on critical infrastructure and quality of life. The observations made by social network users, and the content they share, provide possibly useful information about weather-related disruptive events and the impact they have on services. This study considers the possibility of using such social sensors to improve the assessment of the impacts of extreme weather on power system infrastructure to estimate the risk such events might cause.

Severe weather poses an increasing threat to the stability of power system infrastructure. Severe conditions, like freezing rain [1], can create issues leading to events such as blackouts.

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Eaton's Blackout Tracker is one example of an effort to track the impact of severe weather conditions which shows weather issues were responsible for about 30% of power outages in the United States between 2000-2001 [2].

Social media has gained popularity as tool to communicate about emergencies; similarly, the occurrence of severe weather has increased in recent years. As a result or as a result of such growth, social media networks have become an integral tool for society, allowing for rapid dissemination of important information during severe weather events [3], [4], [5]. For example, over 20 million tweets were posted about Hurricane Sandy on Twitter between October 27 and November 1, 2012 [6]. The impact these tools have on society will only grow as the user bases of these websites increase. As it stands, 23% of Americans say they use Twitter, and 18% regularly visit the Reddit website [7].

The data shared on social media sites can also provide information back to observers interested in weather-related impact on infrastructure in specific areas in addition to its impact on human behavior [8]. For example, researchers were able to leverage content posted on the photo-sharing site Flickr, to build datasets of geo-located, time-stamped photos from U.S. National Parks. These images, when labeled with weather conditions (rain, snow, overcast, extreme heat, cold), can be used to improve models of the impact that weather has on park attendance [9]. The growing body of online social content should be explored, and its utility to existing methods of predicting and modeling power system disruptions should be analyzed. Historically, hazard probability is assessed based on data on historical power outages and weather data extracted from real-time weather forecasts [10]. The hypothesis considered in our study is that these two types of data, while useful, could be enhanced and improved by incorporating features built based on observations of social sensors. These social sensors, which represent users' experience at specific locations, can be considered a component of a larger, multiplex network. This study seeks to indicate that social sensors can be combined with typical weather datasets to produce a more informative spatio-temporal multiplex network representation. In addition, it shows that the utility of such a network by answering the following research questions:

- RQ1: How can severe weather events impact social media usage?
- RQ2: How will the spatio-temporal multiplex network-based knowledge representation improve the power outage prediction accuracy compared to weather features?

B. CONTRIBUTION

The main contributions of this paper are summarized as follows:

1- Weather data has many missing values, and the missingness mechanism is not entirely random. Researchers have addressed the challenge of learning from such data for decades. However, the benefit of integrating weather data with noisy information extracted from many social media posts is insufficiently studied. The main contribution of this study is to develop a principal framework for integrating such multi-modal data for improved spatio-temporal regression.

2- This study fills the gaps in weather data by incorporating information from social media. We examine the impact of social media usage on electricity loss over five months in the states of the Pacific Northwest region (Idaho, California, Montana, Washington, and Oregon).

3- We propose a county-level spatio-temporal multiplex network methodology for integrating geographic and social media data.

C. PAPER ORGANIZATION

Related work is discussed in Section II while methodology is described in Section III, which also includes comprehensive information on data collection and multiplex social-power network creation. An in-depth analysis of social media data and multiplex social-power networks is presented in Section IV. A detailed evaluation of power outage events is presented in Section V followed by conclusions included in Section VI.

II. RELATED WORK

Power outages significantly affect the economy and residents of the impacted area. Some power outages may be prolonged and necessitate a long time to be repaired, especially the ones that occur in rural areas [11]. Power outage causes can be categorized into four main categories: natural, accidental, malicious, and emerging threats [12]. Further, the power system operations are classified into the following: the normal operating state, alert state, emergency state, and extreme state [13].

In a blackout, restoring power will require much work to fix the distribution lines. Therefore, it is crucial to develop models to predict the risk of outages before storms occur. Often, people formulate the problem as a classification task using statistical tools such as quantile regression forests. Besides, Bayesian additive regression tree models are also used to predict power outages [14]. Further, a combination of models and algorithms is proposed to predict hurricane-related power outages by integrating a Random Forest prediction model with a Bayesian mass-balance multi-scale model and by combining mixture models, re-sampling, and cost-sensitive learning [15], [16]. Previous studies also predicted power outage risk using machine learning [17]. Some work focused on predicting power outages using common machine learning tools, such as logistic regression model [19], a Bayesian network-based framework [20], graph-based models [21], [22], [23], and xgboost [24]. On the other hand, some research treats power outage prediction as a regression problem. They focus on predicting the risk caused by the transmission lines distribution and vegetation information using the Gaussian conditional random fields ($GCRF$) [39]. $GCRF$ is a structured regression model that shows improvement in performance in many domains, such as patients' behavior prediction [40]. Several deep-learning models are developed to address the uncertainties of wind speed forecasting models, such as Rough autoencoder (RAE) [49] and interval probability distribution learning (IPDL) [50]. Furthermore, a novel deep temporal dictionary learning (DTDL) [51] was proposed for the problem of energy disaggregation.

Weather data plays an essential role in predicting outages [41]. Such data is retrieved from weather stations [42], satellites [43], and lightning databases [44]. Integrating diverse datasets can create value, as each dataset may bring a different characteristic. For example, a predictive model is developed based on machine learning by integrating transmission lines and vegetation data [45]. Nowadays, social media plays an essential role in predicting future events, and for natural language processing applications, it reported that social networks could add meaningful information that helps enhance the desired prediction [46].

Since weather data contains numerous missing values, learning from such data is challenging. Our work is different in that we take advantage of combining weather data with information from social media. We consider the effect of social networks (multiplex networks) and social media data to predict power outages three hours ahead. To our knowledge, our study is among the first to address predicting power outages by considering social sensors in a multiplex representation. In particular, we quantify the benefits of learning a spatio-temporal multiplex network that consists of data collected from six sources: power outages, Bonneville Power Administration transmission lines topology, weather, lightning, vegetation, and social media data (Reddit and Twitter).

TABLE 1. List of abbreviations addressed in the paper, along with the complete form.

Abbreviation	Full Writing
$GCRF$	Gaussian Conditional Random Fields
BPA	Bonneville Power Administration
$FIPS$	Federal Information Processing Standards
$ASOS$	Automated Surface Observing Systems
$NOAA$	National Oceanic and Atmospheric Administration
$NHGIS$	National Historical Geographic Information System
$NLCD$	National Land Cover Database
T	Twitter
R	Reddit
G	Graph
V	Vertex
E	Edge
L	Layer
T	Time
W	Weight
Avg	Average
DC	Degree Centrality
CC	Closeness Centrality
EC	Eigenvector Centrality
SCF	Square Clustering
CF	Clustering Coefficient
$TFIDF$	Term Frequency-Inverse Document Frequency
$SMOTE$	Synthetic Minority Oversampling Technique
LR	Logistic Regression
NN	Neural Network
SVM	Support Vector Machine
DT	Decision Tree
RF	Random Forest
XGB	XGBoost
Acc	Accuracy
$F1$	F1 score
$C - Layer$	Classification layers
$SetA$	Weather features
$SetB$	Lightning features
$SetC$	Weather, lightning, and vegetation features
$TMNO$	Twitter multiplex network outages
$RMNO$	Reddit multiplex network outages
$RTMNO$	Reddit and Twitter multiplex network outages

III. METHODOLOGY

Figure 1 illustrates the pipeline of the proposed approach to construct the Spatio Temporal Multiplex Network that includes information captured at Twitter and Reddit. Our proposed framework consists of three stages: 1) Spatio-temporal data collection: in this step, we select candidate counties with power substations. Then at the candidate counties, we collect BPA transmission lines, power outage events, weather, and lightning data for the period when the power outages occurred. We also collect vegetation data. 2) Social media data collection: we collect relevant tweets and Reddit posts as described in section III-A for each step when a power outage occurs. 3) Finally, we construct Twitter and Reddit Multiplex networks and integrate geographic, temporal, and social media information. Table 1 shows the list of abbreviations addressed in the manuscript and the complete forms.

A. DATA COLLECTION

To identify the spatial aspect of our problem, we start by collecting power outage data, followed by transmission lines, weather, lighting, vegetation, and spatio-temporally collocated social media activities. This section provides a description of the data collection process.

1) POWER OUTAGES

We collect information on reported power outages from Bonneville Power Administration (BPA),[1] from November 2021 to April 2022 in four states located in the northwest of the United States (Idaho, California, Montana, Washington, and Oregon). In this work, we are only interested in power outages caused by severe weather conditions. During this period, we observed that the weather caused the first power outage on November 18, 2021, and the last on April 4, 2022. Additionally, the geographical location of the outage was manually identified (counties and states). To map each location to the correct county, we create a dictionary that links every county to its Federal Information Processing Standards (FIPS)[2] code. As a result, we identified 337 weather-related outages with a total duration of 231163 minutes and an average outage duration of 686 minutes.

[1]https://www.bpa.gov/
[2]https://www.nist.gov/itl/fips-general-information

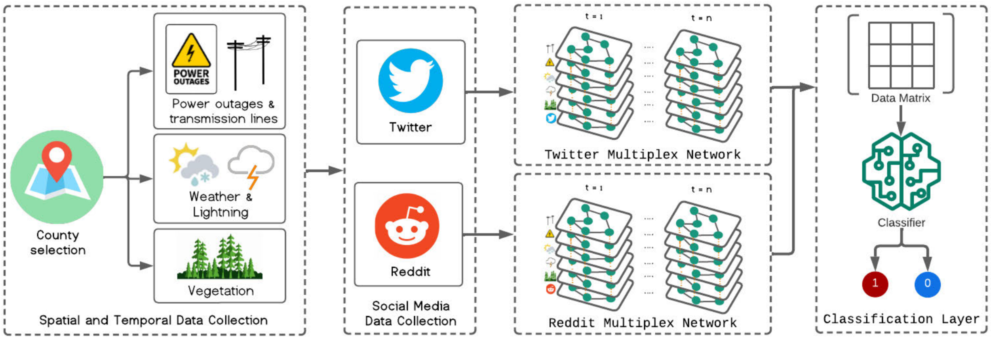

FIGURE 1. **Twitter and reddit multiplex network construction pipeline.**

2) BPA TRANSMISSION LINES

A critical aspect of the power system is the transmission lines structure which links power stations together. This structure is an essential factor in predicting power outages. Therefore, we added the transmission lines to our data using the BPA maps, in which we extracted the transmission lines that connect power substations. A total of 15,000 miles of transmission lines are owned and operated by BPA. In this work, we focus on the transmission lines for the five selected states. We filter the transmission lines based on the counties that were affected by power outages. The final observation considers a total of 267 unique transmission lines.

3) WEATHER DATA

We collect the weather data from the Automated Surface Observing Systems (ASOS)[3] for the five selected US states between November 2021 and April 2022. The ASOS database includes hourly information retrieved from the weather station sensors; the database contains data about weather station location, sky conditions, obstructions to vision, pressure, ambient temperature, wind, and precipitation accumulation for point locations. However, each power station is not linked to a particular county; therefore, we map each station to its county and state using latitude and longitude. We collected more than 8 million in observations from 348 unique stations in the five states.

4) LIGHTNING

During storms, lightning strikes can affect utility assets and cause faults. The ASOS database does not report any information from the National Oceanic and Atmospheric Administration (NOAA)[4] public database for the selected county and period. The NOAA public database provides daily information on the total count of lightning strikes within a 0.1 degree grid cell. The data also contains the latitude and longitude in which the lightning strike occurs, which we utilize to map the lightning strike events to its particular county and state. We focus on observing lightning strikes during the power outage period between November 18, 2021, and April 4, 2022. As a result, 21 counties from the five states were affected by 179 lightning strikes.

5) VEGETATION

The landscape of the geographic location plays an essential role in predicting power outages. For instance, a location with tall trees might have an increased risk of power line faults compared to grass-based locations. Therefore, for the selected states, we collected vegetation data from National Historical Geographic Information System (NHGIS),[5] which provides a land covering summary from the National Land Cover Database (NLCD). NLCD has a spatial resolution of 30 meters derived from Landsat satellite images. In addition, this is the only data that is publicly accessible. They provide environmental summaries for the years 2001, 2006, and 2011; as a result, we collected data from the most recent version of the NLCD, which is the 2011 version. We focus on collecting the land cover features such as deciduous forests, evergreen forests, and mixed forests. The main challenge in the data collection process is county identification. To map the vegetation data to its correct county, we create a county dictionary using the GISJOIN identifier[6] provided by [36].

6) SOCIAL MEDIA DATA

The main objective of this paper is to understand the effect of social media activities in predicting power outages. Therefore, we collected social media activities from two leading platforms, Twitter and Reddit, using weather and power-outage-related keywords such as power outage, outage, blackout, weather, storm, and more [26]. This subsection describes this data.

a: TWITTER

Using weather and power outage-related terms, we collect English-language tweets relating to power outages using scrape.[7] During the power outage period between November 18, 2021, and April 4, 2022, we collect more than 8 million in power outage-related tweets worldwide. Using the location information in the user profile, we filter the tweets based

[3] https://www.weather.gov/asos/
[4] https://www.ncei.noaa.gov/
[5] https://www.nhgis.org/
[6] https://www.nhgis.org/geographic-crosswalks
[7] https://github.com/JustAnotherArchivist/snscrape

on geographical location using our US states and US cities dictionaries. Lastly, we utilize our county dictionary to map each tweet with its corresponding county using FIPS code. As a result, we ended up with $11.16K$ weather and power outage-related tweets from the five selected states from $11.15K$ unique users.

b: REDDIT

Using Reddit API, we focus on collecting data from counties' subreddits, which allows for identifying locations on Reddit. During the power outage period between November 18, 2021, and April 4, 2022, we collect all posts and comments from these subreddits, and then filter posts and comments by weather and power outage keywords. We collect $70.78K$ posts, and after filtering based on our keyword selection, we use the remaining $14.89K$ posts from $14.1K$ unique users.

B. MULTIPLEX SOCIAL-POWER NETWORK CREATION

Let G be a Multiplex Network that consists of $G = (V, E, L, T)$, where, $V = \{v_1, v_2, ..., v_n\}$ is the set of vertices (counties), $E = \{e_1, e_2, ..., e_m\}$ is set of edges, $L = \{l_1, l_2, l_3, l_4, l_5, l_6\}$ set of layers, and $T = \{t_1, t_2, ..., t_k\}$ represent a set of time steps. In our formulation, there are the following six layers in the network, $l1$= BPA transmission line layer, $l2$= power outage layer, $l3$= weather layer, $l4$= lightning layer, $l5$= vegetation layer, and $l6$= social media layer. Based on the multiplex network definition, all vertices $\{v_1, v_2, ..., v_n\}$ in all layers L are from the same vertex sets; in other words, $V \in \mathbb{V}$ where $\mathbb{V}$ represent all selected counties. In addition, an inter-layer connection links vertex v with itself in another layer, and the intra-layer connections represent the different types of interaction between the vertices. Each edge e is associated with a weight $\omega \in \Omega$, where $\Omega \in \mathbb{R}$ is a real number greater than or equal to 1, and it represents the strength of the connection between vertices (v, u) in the i^{th} layer. E in each layer l_i represent a different type of relationship between V explained as follow:

1) **BPA transmission line layer** (E_{l_1}): vertices (u_{l_1}, v_{l_1}) are connected if two vertices (counties) share the same BPA transmission line. In l_1, the edge weight, ω= the number of shared BPA transmission lines.
2) **Power outage layer** (E_{l_2}): vertices (u_{l_1}, v_{l_1}) are connected if a power outage accrues in both vertices (counties) on the same date since we are only taking the co-occurrence into account while ignoring the edge weight ω (0 or 1 value is assumed).
3) **Weather layer** (E_{l_3}): we assume that a power outage is highly correlated with the weather condition; therefore, vertices (u_{l_3}, v_{l_3}) are connected if a power outage accrues in both vertices (counties) and report severe weather in condition. The edge weight, $\omega = 1$.
4) **Lightning layer**(E_{l_4}): vertices (u_{l_4}, v_{l_4}) are connected if a lightning strike accrues in both vertices (counties) on the same date. In addition, in l_4, the edge weight, ω= the total count of lightning strikes during the day.
5) **Vegetation layer** (E_{l_5}): in this layer, we link two vertices (u_{l_5}, v_{l_5}) (counties) if they share the same vegetation properties. In order to do so, we calculate the Euclidean distance between each pair of vertices and decide if a link will occur based on a threshold (λ). The threshold represents how similar two counties'

Algorithm 1 Multiplex Network Construction

```
procedure Construct_Multiplex_Network(V, L, T)
    Multiplex_Network ← Ø
    for layer ∈ L do
        if layer = l1 then
            for each pair of vertices (u, v) ∈ V do
                shared_lines ← calculate_shared_BPA_lines(u, v)
                if shared_lines > 0 then
                    add_edge(Multiplex_Network, u, v, layer, shared_lines)
        else if layer = l2 then
            for each pair of vertices (u, v) ∈ V do
                if power_outage_occurs(u, t) and power_outage_occurs(v, t) then
                    add_edge(Multiplex_Network, u, v, layer, 1)
        else if layer = l3 then
            for each pair of vertices (u, v) ∈ V do
                if power_outage_occurs(u, t) and power_outage_occurs(v, t) and severe_weather_condition(t) then
                    add_edge(Multiplex_Network, u, v, layer, 1)
        else if layer = l4 then
            for each pair of vertices (u, v) ∈ V do
                total_lightning_strikes ← calculate_total_lightning_strikes(u, v, t)
                add_edge(Multiplex_Network, u, v, layer, total_lightning_strikes)
        else if layer = l5 then
            for each pair of vertices (u, v) ∈ V do
                euclidean_distance ← calculate_euclidean_distance(u, v)
                if euclidean_distance ≥ λ then
                    add_edge(Multiplex_Network, u, v, layer, 1)
        else if layer = l6 then
            for each pair of vertices (u, v) ∈ V do
                social_activities_count ← calculate_social_activities_count(u, v, t)
                add_edge(Multiplex_Network, u, v, layer, social_activities_count)
    return Multiplex_Network
```

vegetation features are $\mathbf{V}(u)$ and $\mathbf{V}(v)$ as shown in the following equation:

$$e(u_{l_5}, v_{l_5}) = \begin{cases} 1 & \text{if Eculidean}(\mathbf{V}(u), \mathbf{V}(v)) \geq \lambda, \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

We test different thresholds of (λ) and find that a threshold of 0.5 gives the best performance.

6) **Social media layer** (E_{l_6}): an edge is formed between vertices (u_{l_6}, v_{l_6}) if both vertices (counties) possess some social activities in the time period of the power outage. Note that in l_6 the edge weight ω represents the number of social activities during t time, where social activities represent the number of tweets in the Twitter multiplex network and the number of Reddit comments in the Reddit multiplex network.

Algorithm 1 shows Multiplex Network Construction. Each iteration within the loop has the same asymptotic time complexity, hence $O(|V|^2 + |V|^2 + |V|^2 + |V|^2 + |V|^2 + |V|^2) = O(|V|^2)$. As a result, the algorithm has a quadratic time complexity of $O(|V|^2)$, where $|V|$ is the number of vertices in the set V. Model code is available on GitHub.[8]

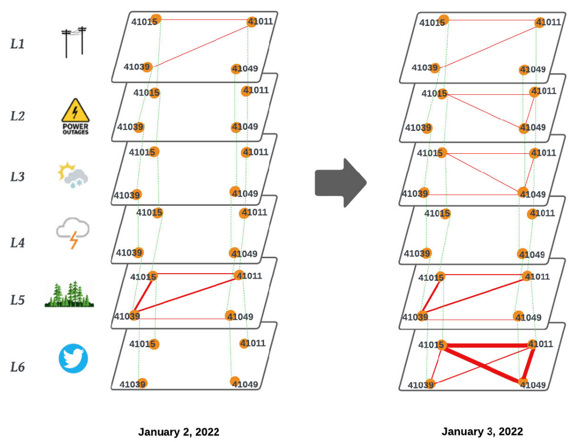

FIGURE 2. Spatio-temporal visualization of Twitter multiplex network over two days period (January 2nd and January 3rd, 2022). The outages occurred on January 3rd. We zoomed over four counties in Oregon State: 41011 represents Coos County, 41015 represents Carry County, and 41039 represents Lane County. The county's FIPS represents every node. The edge represents the link between the nodes, and the weight is represented by the width of the edge. In the right figure (January 3rd), we can see major structural differences, with higher interaction between the nodes, compared to the left figure (January 2nd), when there was no power outage in any of the zoomed counties. Most especially in the social media layer, we can observe that the counties that experienced power outages at the same time period tend to have high social media interaction. The strong interaction refers to the weight, which represents the number of tweets on Twitter and the number of Reddit comments.

The spatio-temporal multiplex network-based approach uniquely represents structural differences among different features that might cause a power outage, such as weather, lightning, and vegetation. In addition, to how the power outage events are discussed on social media. To demonstrate, Figure 2 shows a zoomed example of our multiplex graph for four Oregon counties in two consecutive days. The zoomed counties are as follows: 41011 represents Coos County, 41015 represents Carry County, and 41039 represents Lane County. The six layers represent BPA transmission lines, power outages, weather conditions, lightning, vegetation, and social media activities on Twitter. The power outage occurred in three counties on January 3rd, the network on the right, while there were no power outages the day before, the network on the left. Looking to the day when the power outage occurred (January 3rd), we observed that counties that share the same BPA transmission lines are more likely to be affected by the power outage from their neighboring county. In addition, severe weather conditions are visible in the network compared to the day before, when there was no power outage in any of the counties. Most importantly, the social media layer demonstrates a high volume of interaction across the affected counties, compared to the day before, January 2nd, where the power outage did not occur in any of the zoomed counties. Note that we only connected social media posts related to power outages and severe weather conditions.

[8]https://github.com/RAljurbua/Weather-caused-outage-prediction/

IV. ANALYSIS

A. SOCIAL MEDIA DATA ANALYSIS

Reddit features consist of post id, author name, text, number of comments, date, and time. A large fraction of posts (78%) were California-related. The state of Oregon accounted for 7.9% of all Reddit posts, while 5% of posts were from Idaho and Washington, and 3.7% were from Montana.

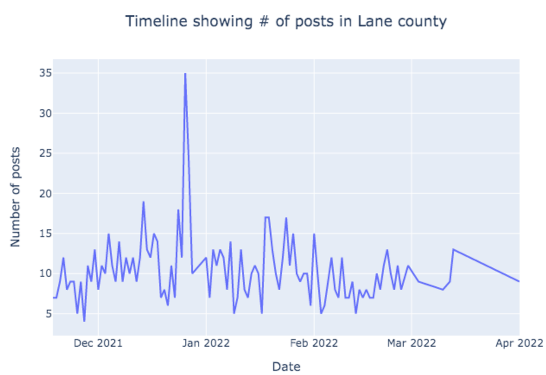

FIGURE 3. Reddit: Number of posts during the power outage period between November 18, 2021, and April 4, 2022 (Example from Lane County, Oregon).

Due to the user-curated nature of Reddit, the only way to identify county-related posts is through county-related subreddits, which may or may not exist depending on the whims of the users interested in those counties. We observed that not all counties in the five selected states have a county subreddit. Table 2 shows the number of counties per state on Reddit and county-related subreddits on the site. Social media engagement was much higher in California than in the other states considered in this work. California has the largest number of counties represented on Reddit (38 counties out of 58). This contrasts the least represented states of Idaho (8 out of 44) and Montana (8 out of 56).

TABLE 2. County-Related Subreddits vs Actual State Counties.

State	# of counties	# counties subreddits
California	58	38
Idaho	44	8
Washington	39	15
Oregon	36	7
Montana	56	8

Twitter data includes features such as tweet id, conversation id, username, date, time, tweet, and likes. The majority of tweets (around 50%) belong to the state of California, while only 2.9% of tweets belong to the state of Idaho. The state of Oregon represents 16.6% of tweets, and around 28% of the tweets originate from Washington. The state with the smallest number of tweets is Montana, with less than 2% of tweets.

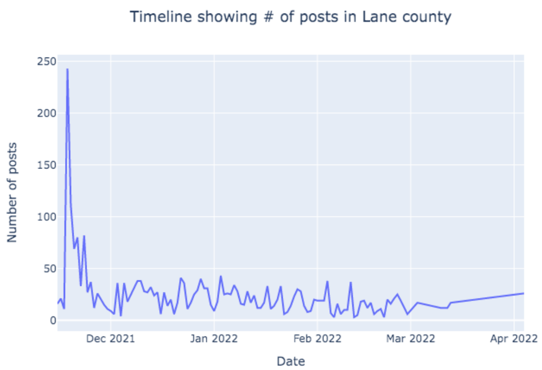

FIGURE 4. Twitter: Number of tweets during the power outage period: November 18, 2021, to April 4, 2022 (Example from Lane County, Oregon).

TABLE 3. Social media statistics: Number of posts Mined per State during the power outage period between November 18, 2021, and April 4, 2022.

State	Twitter	Reddit
California	5597	11620
Idaho	330	762
Washington	3162	767
Oregon	1859	1187
Montana	202	561

It is evident that the people of California seem to be more engaged on social media compared to the remaining four states. Table 3 shows the collected data grouped by the number of counties per state based on weather and power outages keywords and during the power outages between November 18, 2021, and April 4, 2022.

In November 2021, a powerful storm affected the Pacific Northwest region, ravaging Oregon and inflicting many power outages. While system malfunctions or other maintenance-based issues may cause outages, Oregon and nearby states also face additional sources of downtime. Major weather events, like the Nov 2021 storm, also introduce excessive ice on transmission lines, causing additional issues leading to outages. As such, the Nov 2021 storm caused Lane County, Oregon, to experience a major power outage. This severe weather event provides a case study in which we observed the online behaviour of residents using data mined from Reddit and Twitter during the outage period. Figure 3 shows the Reddit activity of Lane County, Oregon, during and after the major power outage of Nov. 18, 2021, while Figure 4 shows the Twitter activity of Lane County, Oregon, during the same period. We can observe that people in Lane County are more engaged in Twitter during the power outage period. However, the Reddit activity change is less evident. The most temporally-adjacent spike in weather-related Reddit activity to the date of the outage is a month later, well after the start of the outage. This difference in response time and quantity does make some sense, given the nature of communication on each site and the differences between them. Reddit permits long, in-depth discussions, while Twitter usually contains short texts, often used for breaking news and real-time updates. In short, this data makes sense given that past work has shown Twitter to function as a real-time news source [37].

B. MULTIPLEX SOCIAL-POWER NETWORK STRUCTURE ANALYSIS

In this section, we report the results of the topological structure analysis in constructed weighted multiplex networks. When analyzing such a network, it is essential to understand different centrality measures. Therefore, we consider the following proprieties, Degree Centrality (DC), Closeness Centrality (CC), and Eigenvector Centrality (EC). In addition, we study Square Clustering (SCF) and Clustering Coefficient (CF). In all these measures, we report the average value. Degree Centrality is shown in the following equation as follows:

$$C_D(G) = \frac{\sum_{i=1}^{|V|}[C_D(v*) - C_D(v_i)]}{|V|^2 - 3|V| + 2}, \tag{2}$$

where (v) is a vertex of the graph (G). DC measures the node connectivity in terms of the number of edges that each node has; it indicates the importance of the node and the existence of potential hubs. A high degree of centrality means that this node is more central compared to the other nodes. Closeness Centrality (CC) value suggests how to distance a certain node to the other nodes in the network. Specifically, the node with the shortest distance implies a high Closeness Centrality, which is important to identify nodes that can be potential candidates for information spread. It can be calculated as follows:

$$C(v) = \frac{N-1}{\sum_u d(u, v)}, \tag{3}$$

where N is the number of nodes in the graph and $d(u, v)$ is the distance between vertices u and v. Eigenvector Centrality (EC) accounts for the neighbor's importance. In other words, EC calculates the node centrality according to the centralities

TABLE 4. Twitter and Reddit multiplex network topological structure. L = number of layer, V= number of nodes, E= number of total edges, *coupling E*= number of coupling edges, *avg*(*DC*)=average degree centrality, *avg*(*CC*)=average closeness centrality, *avg*(*EC*)=average eigenvector centrality, *avg*(*SCF*)=average square clustering, *avg*(*CF*)=average clustering coefficient for the social media layer ($l6$).

Multiplex Network	L	V	E	$coupling\ E$	$avg(DC)$	$avg(CC)$	$avg(EC)$	$avg(SCF)$	$avg(CF)$
Twitter	6	882	$365K$	4410	0.940	0.300	0.007	0.272	0.773
Reddit	6	606	$354K$	3030	1.931	0.284	0.010	0.315	0.823

of its neighbors. We can calculate it using this formula:

$$x_v = \frac{1}{\lambda} \sum_{u \in M(v)} x_u = \frac{1}{\lambda} \sum_{u \in G} a_{v,u} x_u, \tag{4}$$

while $A = (a_{v,u})$ is the adjacency matrix of graph G. $M(v)$ is the set of the neighbors for the node v, and λ is a constant. In our analysis, we utilize the extended version of each measure to a multiplex network, which calculates the centrality for a v with respect to l_i. We then aggregate the values by calculating the average Centrality (*avg*). The average Clustering Coefficient ($avg(CF)$) represents the average number of edges of all nodes within their neighborhood. The average clustering coefficients of all the vertices v are calculated as follows:

$$\bar{C} = \frac{1}{n} \sum_{i=1}^{n} C_i, \tag{5}$$

where C is the graph's global clustering coefficient. It is based on the number of closed triplets (3×the number of triangles) divided by the total number of triplets. n is the number of vertices. $Avg(CF)$ measures how well the nodes tend to form clusters [27], where a value close to 1 means that nodes in the network have a high tendency to form clusters, while a score close to 0 means otherwise. Here we report the $avg(CF)$ for the social media layer in Twitter and Reddit network.

Finally, *Average Square Clustering* ($avg(SCF)$) extends the definition of Clustering Coefficient, in which it calculates the probability of two neighbors linked to a common neighbor that is different from a v node neighbors forming a square shape connection [28]. Following is the calculation of the Square Clustering:

$$C(v) = \frac{\sum_{u=1}^{k_v} \sum_{w=u+1}^{k_v} q_v(u,w)}{\sum_{u=1}^{k_v} \sum_{w=u+1}^{k_v} [a_v(u,w) + q_v(u,w)]}, \tag{6}$$

where $q_v(u, w)$ refer to the number of common neighbors of u and w other than v. Similarly to CF, a value closer to 1 represents a high presence of Square Clusters, and a value closer to 0 means otherwise.

Both networks have six layers: the BPA transmission line, power outage, weather, lightning, vegetation, and social network (Twitter or Reddit). The number of connected nodes V is shown in Table 4. Although the first five layers are the same in both multiplex networks, the number of edges E in the Twitter multiplex network is larger than in the Reddit multiplex network. This indicates that when a power outage occurs, people tend to share information and discuss the disruptive event more on Twitter compared to Reddit. An important property of a multiplex network is coupled edges ($coupling\ E$) which capture the transitions of the nodes between adjacent layers [18]. The network with the higher number of coupled edges tends to be more saturated and have richer connections compared to networks with low or non-coupled edges. In our case, we can see that both Twitter and Reddit multiplex networks consist of fewer coupled edges than the total number of edges E. We can explain this because there are only six layers in the network, and the number of nodes is small compared to the edges. Comparing Twitter and Reddit multiplex network structures (Table 4), we see that both networks have similar properties. For example, both networks have a small $avg(CC)$ of 0.300 and 0.284 and a small $avg(SCF)$ of 0.272 and 0.315, respectively. Further, we distinguish that the $avg(EC)$ for Twitter and Reddit multiplex networks is small and varies between 0.007 and 0.010 alternately. The $avg(CF)$ for the social media layer varies between 0.773 and 0.823, respectively, suggesting that the social media layer in both networks tends to form clusters, representing the main characteristic of a small-world network. According to $avg(DC)$, we observe that the Reddit network has a significantly larger centrality than the Twitter network, meaning that the Reddit network contained more hubs.

V. EVALUATION ON PREDICTING POWER OUTAGE EVENTS

Our objective is to assess if the multiplex network and social media information could help improve the accuracy of power outage prediction. Here, we learn from the annotated dataset according to the power outage that occurred due to weather-related events. Counties and states experience different numbers of weather-related power outages. Therefore, for a given data point representing a timestamp, if a county experiences a power outage event during that time, these data points are labeled as 1, and 0 otherwise.

A. BASELINE

To understand the effect of the multiplex network on power outage prediction, we use row features as a baseline that we collect from different sources such as weather, lightning, and vegetation. Since we have many features, we form a feature selection step to remove irrelevant information from the data and select the most suitable features that improve the performance of the classification model. In this process for the weather data, for the prediction, we select air temperature, dew point temperature, wind direction, wind speed, apparent temperature, humidity, wind gust, pressure, precipitation, and ice accretion over 6 hours. Then, in a prediction model as explanatory variables, we use daily average and standard deviation for each selected weather feature. For the vegetation data, we focus on three land cover features that can be useful for power outage prediction: deciduous forests, evergreen forests, and mixed forests. In addition, for the lightning data, we count the total number of lightning strikes in every county daily. Finally, with the aim of extracting informative features from social media text (Twitter- Reddit), we apply TF-IDF [38]. TF-IDF refers to "Term Frequency-Inverse Document Frequency," and it determines the importance of the words in the text based on a numerical statistic. We focus on applying TF-IDF on weather and power-outage-related keywords.

B. MULTIPLEX NETWORK

The structural and connectivity features embedded within the multiplex network carry valuable information that could enhance the classification model predictions. The multiplex network has information regarding the transmission lines and counties' similarities in terms of landscape and social activities on Twitter and Reddit. We use a modified version of Node2Vec [30] that obtains the graph feature representation for multiplex networks. Node2Vec maps the graph nodes to low-dimensional vectors while preserving the graph structure. To avoid high dimensional feature vector issues, we choose to set the vector length produced by Node2Vec to 100. Then, we concatenate the graph features with the weather, lightning, and vegetation features. Once we obtain the feature vectors, we feed them to the classification model to perform the prediction.

C. EXPERIMENTAL SETUP

Since power outages are not an everyday event, our dataset is imbalanced by nature; we have a total of 4051 events, of which only 4.4% represent a power outage event, while 95.5% of the data represents a typical daily event. To address the imbalanced issue, we tested different data balancing techniques, such as oversampling, undersampling, and Synthetic Minority Oversampling Technique (*SMOTE*) [31]. We found that utilizing (*SMOTE*) is sufficient for addressing the imbalance in our application because it generates synthetic samples from the same distribution as the minority class.

Our learning approach is supervised machine based. For the classification layer, we test different well-known machine learning algorithms, such as logistic regression (*LR*) [32], neural network (*NN*) [35], support vector machine (*SVM*) [33], random forest (*RF*) [48], xgboost (*XGB*) [47], and decision tree (*DT*) [34] classifiers.

We split the data into training and testing sets; we use 75% of the data for training and 25% for testing. The split results in imbalanced sets with 3038 instances for training with daily events of 2903 and 135 power outages, whereas the testing set revealed 1013 examples. Note that we randomly split the data and solved the imbalance issue in the training data to avoid data leaks. Therefore, SMOTE solved our imbalanced issue by generating more examples for the small class in our training set, resulting in 2903 instances for both classes.

For each of the used models, we test different hyperparameters. We aim to find the optimal hyperparameters of a model that provide the best predictions and therefore, we use grid search. Table 5 lists the hyperparameters set for all classifiers. Since the purpose of this paper is not to build a neural network model, we use the general case of Xavier initialization.

TABLE 5. Selected hyperparameters for every binary classifier.

Classifier	Hyperparameter
LR	(classifier-C: 100)
NN	(hidden layer sizes: 50, activation: relu, solver: lbfgs)
SVM	(kernel: rbf, classifier- C: 100, gamma: 1)
RF	(max depth:10)
DT	(max depth:10)
XGB	(max depth:10)

Further, our second research question is: How will the spatio-temporal multiplex network-based knowledge representation improve the power outage prediction accuracy compared to weather features? To answer this, we use different sets of baseline classifiers using weather, weather and lightning, and weather, lightning, and vegetation attributes.

In order to study the effect of social media information (Twitter, Reddit), we further scrutinized the impact of social media by adding experiments that combine weather, lightning, and vegetation with Twitter, then Reddit. Additionally, we combine weather, lightning, and vegetation with Twitter and Reddit. Then, we compare baseline models to our proposed multiplex network.

Our primary analysis compared the predictive ability relative to the logistic regression, neural network, support vector machine, random forest, xgboost, and decision tree model in terms of the F1 score ($F1$), defined as the measure of a test's accuracy on a dataset. It measures the harmonic mean of precision and recall. Also, the F1 score gives a less biased metric than accuracy since it offers equal weights for false positives and false negatives. Recall is the measure of the model that correctly identified true positive cases, and precision is the ratio of the true positive cases to all positive cases. Further, we compare the accuracy (Acc), defined as the percentage of correct predictions for the test data.

D. VALIDATION

We use k-fold cross-validation to evaluate predictive models. K different subsets (folds) divide the dataset. For the k-fold cross-validation, we use 5-fold cross-validation to split the dataset for training and testing. Figure 5 overviews the repeated 5-fold cross-validation. We average and report the results of all ten repetitions of each experiment, along with the corresponding standard deviations, to measure the stability of the model.

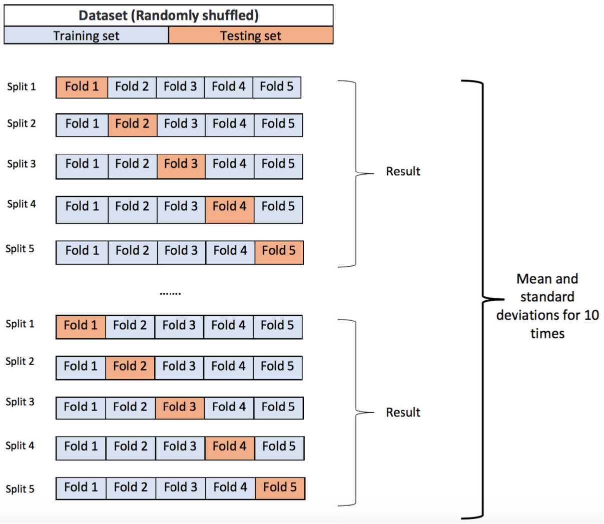

FIGURE 5. An overview of the repeated 5-fold cross-validation procedure. We repeat all experiments ten times; then, we report the mean and standard deviation results from all runs.

E. RESULTS AND DISCUSSION

After collocating data from the six sources: power outages, Bonneville Power Administration transmission lines topology, weather, lightning, vegetation, and social media data (Reddit and Twitter). We address the main contribution of this work by considering Reddit and Twitter spatio-temporal multiplex network representation to predict power outages three hours ahead. In this section, we compare the performance of the machine learning models with weather, lightning, and vegetation features as baselines. To examine the effect of social media on power outage predictions, we further add social media features. Finally, we examine each model's performance on Twitter and Reddit multiplex networks to understand the advantage of addressing the network structure effect on prediction.

Table 6 summarizes the average accuracy and F1 score along with standard deviations of 10 repeated experiments with different values of initial values for parameters of the models replaying on baseline attributes and social media information. We can see that the combined features that consist of weather, lightning, and vegetation (Set C) obtain better results as compared to using weather and lightning features only (Set B). These findings indicate that vegetation features are among the leading causes of power outages, including forest trees growing or falling into overhead lines, which also is a significant contributor to power faults. Further, we can observe that social media information collected from Twitter or Reddit yields better results than combined weather, lightning, and vegetation features (improvement of 2% to 4%). This indicates that social media features carry essential information that helps the model predict power outages. Indeed, the combined social media information (Twitter or Reddit), along with weather, lightning, and vegetation features, outperformed all models, showing the highest performance among the features in the analysis.

Figure 6 shows the confusion matrix for all models using weather, lightning, and vegetation, along with social media information features.

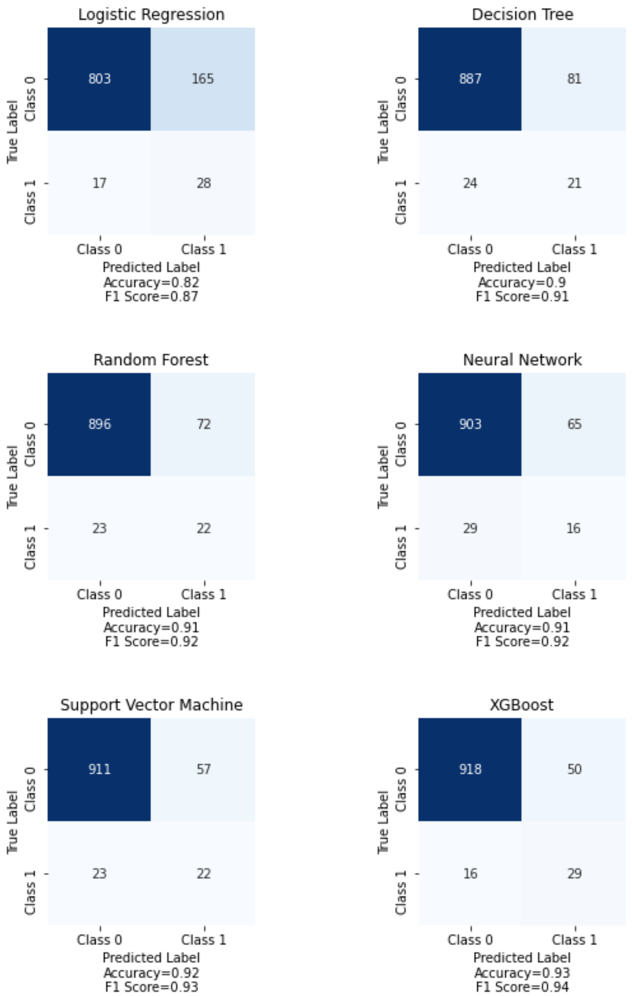

FIGURE 6. Confusion matrix for all models using weather, lightning, vegetation along with social media information features.

To understand the effect of different baseline features, we analyze the predictive significance of these features in interpretable classification models based on logistic regression, support vector machine, random forest, xgboost, and decision trees. Table 7 shows the top 10 features when using weather, lightning, vegetation, and social sensors features. We can see that the wind speed and gust appear among the top features in both explainable models. This indicates that although weather features alone did not outperform other features, they still carry essential information that helps the model predict power outages. In addition, social sensors' features appear in the top 10 features in both models. Thus, it can be concluded that social sensors provide valuable information in predicting power outages. User verification on Twitter refers to the credibility and reliability of a Twitter account. In addition, it reduces the probability that bot accounts write the tweet or generate fake news. Verified users interact and engage more with discussed events. They

TABLE 6. The comparison of the average accuracy and average F1 score of logistic regression model (*LR*), decision tree model (*DT*), random forest model (*RF*), neural network model (*NN*), support vector machine model (*SVM*) and xgboost model (*XGB*) where: (*Acc*)= Accuracy, (*F*1)= F1 score. Baselines are: (*SetA*)= weather features, (*SetB*)= weather and lightning features, (*SetC*)= weather, lightning, and vegetation features. Social sensors are Twitter(*T*) and Reddit(*R*). Note that standard deviations in all models between [0.006, 0.02].

	Baselines						The proposed approach					
Features	$SetA$		$SetB$		$SetC$		$SetC+R$		$SetC+T$		$SetC+R+T$	
Classification layer	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
LR	0.73	0.81	0.74	0.82	0.75	0.82	0.79	0.85	0.81	0.86	**0.82**	**0.87**
DT	0.83	0.87	0.84	0.88	0.85	0.88	0.87	0.90	0.88	0.90	**0.90**	**0.91**
RF	0.84	0.88	0.85	0.88	0.86	0.89	0.88	0.90	0.89	0.91	**0.91**	**0.92**
NN	0.84	0.88	0.85	0.88	0.86	0.89	0.89	0.91	0.90	0.91	**0.91**	**0.92**
SVM	0.85	0.88	0.86	0.89	0.87	0.89	0.90	0.91	0.91	0.92	**0.92**	**0.93**
XGB	0.86	0.88	0.87	0.89	0.88	0.90	0.91	0.92	0.92	0.93	**0.93**	**0.94**

also provide insight based on their expertise; therefore, we believe that for the previously mentioned reasons, the user verification feature was shown in the top 10 important features.

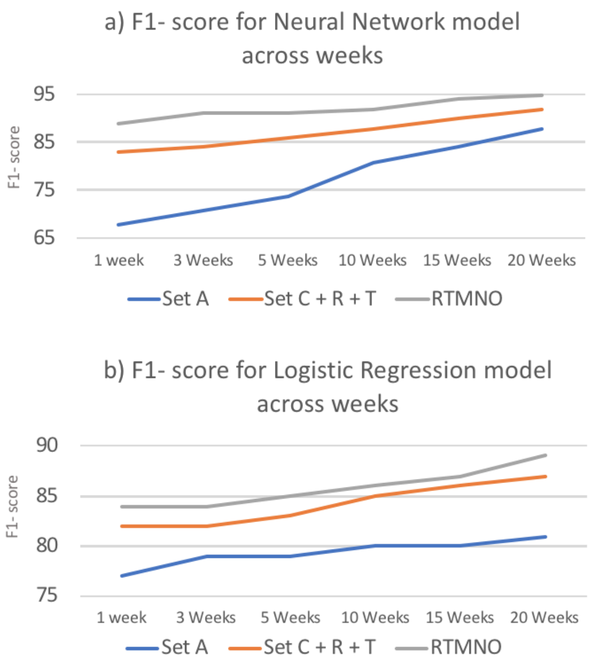

FIGURE 7. Outage prediction performance using F1- score for Neural Network and Logistic Regression models across weeks.

To address the power of multiplex network structure, we compare the best feature set from Table 6 with the network structure. Table 8 reports the average F1 score of that comparison. The results provide evidence that the network structure and social media information derived from Twitter and Reddit outperform the best feature set from Table 6. These results support our hypothesis that social media information and multiplex network structure improve the prediction of power outages. Comparing the two social platforms, Twitter slightly outperforms Reddit, which is expected since the Twitter network (TMNO) is more extensive than the Reddit network (RMNO). In addition, using combined Reddit and Twitter multiplex features (RTMNO) shows the best performance with the highest accuracy and F1 score. In addition, we observe a consistent pattern across

TABLE 7. Top 10 features per model and their predictive significance.

Model	Features	Score
LR	Twitter (user verified)	12.2
	Twitter (quote count)	12.0
	Reddit (TFIDF-power)	10.4
	Twitter (TFIDF-outage)	7.4
	Twitter (Tweets' likes)	5.3
	Wind speed	5.2
	Reddit (TFIDF-rain)	4.5
	Air temperature	3.8
	Wind gust speed	3.4
	One-hour precipitation	2.8
DT	Twitter (user verified)	0.21
	Mixed forest	0.09
	Twitter (TFIDF-wind)	0.09
	Wind gust speed	0.08
	Reddit (TFIDF-rain)	0.06
	One-hour precipitation	0.05
	Twitter (TFIDF-outage)	0.04
	Reddit (TFIDF-wind)	0.03
	Wind speed	0.01
	Reddit (TFIDF-power)	0.01
SVM	Twitter (TFIDF-wind)	0.04
	Twitter (user verified)	0.04
	Reddit (TFIDF-wind)	0.04
	Wind gust speed	0.03
	Wind speed	0.02
	Reddit (TFIDF-storm)	0.02
	Twitter (TFIDF-blackout)	0.02
	Twitter (Tweets' likes)	0.02
	Twitter (TFIDF-power)	0.01
	Reddit (TFIDF-cold)	0.01
RF	Twitter (TFIDF-wind)	0.09
	Mixed forest	0.08
	Twitter (user verified)	0.07
	Twitter (TFIDF-outage)	0.06
	Reddit (TFIDF-rain)	0.04
	Wind gust speed	0.04
	Reddit (TFIDF-rain)	0.04
	Reddit (TFIDF-wind)	0.03
	One-hour precipitation	0.03
	Twitter (Retweet count)	0.02
XGB	Twitter (TFIDF-wind)	0.18
	Reddit (TFIDF-power)	0.05
	Twitter (TFIDF-outage)	0.05
	Twitter (user verified)	0.04
	Reddit (Number of comments)	0.04
	Wind gust speed	0.04
	Mixed forest	0.04
	Reddit (TFIDF-rain)	0.03
	Reddit (TFIDF-blackout)	0.02
	One-hour precipitation	0.02

different classification models. For example, the best feature set for logistic regression is Reddit and Twitter networks, which is true for all other classification models (neural network, support vector machine, random forest, xgboost, and decision tree). Note that the best classification results are obtained by the xgboost followed by the support vector machine model with performance improvement up to 10% versus alternative models considered. Random forest and neural networks obtain good results. However, our dataset contains fewer training examples than are generally needed to train deep learning models properly. The decision tree model behaves slightly lower than neural networks but is much easier to explain. In addition, the logistic regression model is the least accurate in conducted experiments, as expected by its simpler representation.

To highlight the advantage of the proposed approach (RTMNO), we scrutinize the performance of outage prediction when using different amounts of training data measured in weeks. Figure 7 (a) shows the result of evaluating the predictions of the baseline when using weather data (Set A), adding social media information (Set C + R + T), and proposed multiplex network (RTMNO) using neural network and logistic regression as prediction layers. We split the training data temporally into five sub-datasets: one week, two weeks, five weeks, ten weeks, and fifteen weeks, and the full dataset of twenty weeks. We observe that we need at least five weeks of data is needed for Set A to improve outage prediction using the neural network predictor. Comparing the baselines with Reddit and Twitter data (Set C + R + T) enhances the prediction performance, which indicates that social sensors' information improved the prediction performance from 5%-14%. However, the results indicate that the proposed spatio-temporal multiplex network (RTMNO) consistently outperforms all baselines. As for the logistic regression predictor shown at Figure 7 (b), which does not require a lot of training examples, we found that the baseline and the proposed approach performance is consistent with sight improvement in the F1 score when we increase the number of training examples. Overall, our proposed multiplex network (RTMNO) outperforms all baselines.

We conduct machine-learning experiments to predict weather-related power outages three hours ahead by collecting power outage data, weather, lightning, vegetation, and social media information from Twitter and Reddit. Our findings are consistent and reliable in all models shown by the small standard deviation value. This result provides evidence that the proposed models are stable and robust in predicting weather-related power outages.

However, our study also has several limitations. First, our analysis is based on geographical location. Future improvements might be possible by including better ways to connect a geographic location to online content. Twitter provides "built-in" functionality allowing geographically fenced content collection, but this feature does not exist on Reddit. Secondly, user age distribution affects user engagement in social media. Therefore, different subsets of a target geographic area's population may be present in different online communities not considered in this study. Future work could consider ways to expand the multiplex network to include social data sources across more age groups. NLCD data collected for vegetation is based on outdated information. However, this method may not be revised to capture the dynamics of vegetation structure accurately. The goal is to address this limitation in future research by utilizing up-to-date datasets. Finally, to better understand our findings, in future research, we will also apply statistical measures to understand the correlation between results.

TABLE 8. The comparison of the average F1 score of the classification layers($C - Layer$): logistic regression model (LR), decision tree model (DT), random forest model (RF), neural network model (NN), support vector machine model (SVM), and xgboost model (XGB). We compare weather, lightning, and vegetation, social media information features with different network models. Twitter multiplex network outages($TMNO$), Reddit multiplex network outages ($RMNO$) and Reddit and Twitter multiplex network outages ($RTMNO$) are network models. Note that the standard deviations in all models were between [0.005, 0.02].

	The proposed model			
C-Layer	$SetC+R+T$	$RMNO$	$TMNO$	$RTMNO$
LR	0.87	0.88	0.88	**0.89**
DT	0.91	0.92	0.93	**0.94**
RF	0.92	0.92	0.93	**0.95**
NN	0.92	0.92	0.93	**0.95**
SVM	0.93	0.94	0.95	**0.97**
XGB	0.94	0.95	0.96	**0.98**

VI. CONCLUSION

In this study, we address the problem of predicting weather-related power outages three hours ahead with the aid of online social media data. We find a positive correlation between severe weather events that cause electricity loss and information on the impact of inclement weather on the community residents extracted from two prominent social media platforms (Reddit and Twitter). Therefore, we quantify the benefit of integrating such people's behavior information in common machine learning models for weather-related outage prediction (logistic regression, neural networks, support vector machines, random forest, xgboost, and decision trees). The results show that information extracted from social sensors is helpful for outage risk estimation. The most considerable benefit is evident when using the xgboost, which acquires the highest accuracy (0.93) and the highest F1 score (0.94).

We investigate whether the proposed multiplex networks could learn better than simpler networks relying on the weather features and whether the network structure enhances the model performance compared to using only weather features. Our study demonstrates that machine learning models for this task perform better when they include network-based formulations and inputs. We show that our spatio-temporal multiplex network is a novel and effective way to encode online social media information into such a network-based approach, which can improve the accuracy of a predictive model for power outages.

Our future work shall develop a method to predict disruption risk by integrating data collected over time at multiple spatial resolutions through a hierarchical spatio-temporal multiplex network. Further, a demanding prospect on the horizon pertains to establishing a systematic risk prediction framework tailored toward predicting the duration of power outages. It involves extending the prediction time interval to 3, 6, 12, and up to 24 hours. Another future direction is studying how outages affect people and how they discuss it on social media platforms.

In conclusion, we provide novel insights to predict weather-related power outages three hours ahead, and our results show that spatio-temporal multiplex network features can improve the efficacy of weather-related power outage prediction.

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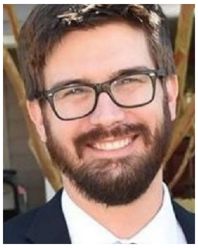

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