**CNST 6308**

**PROJECT REPORT**

**ON**

**Analyzing Crashes Severity During Extreme Weather Conditions**

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**Analyzing Crashes Severity During Extreme Weather Conditions**

**Abstract:**

Road traffic accidents pose serious risks to everyone's safety and can cause harm, deaths, and financial losses. Numerous researchers have focused on the connection between severe weather and car accidents. This study attempts to examine how extreme weather events affect the frequency of traffic crashes by analyzing crash data. The historical crash records that were included in this study's dataset include information on each crash event's date, time, location, and weather. The first step in preprocessing data is to clean it, deal with missing values, and encode categorical variables. The number of crashes caused by extreme weather is then compared for each of the three periods to look for potential trends or patterns. The study examines the effects of numerous extreme weather events on crash occurrences throughout various periods, including heavy rain, snowstorms, fog, and extreme temperatures. Additionally, it investigates potential modifications in collision patterns that may have affected traffic volumes and driver behavior during these extreme weather conditions. The study models the association between extreme weather conditions and crash severity using statistical analyses and machine learning methods to get more insights. Additionally, it assesses the impact of elements like road design and driver behavior on the frequency of traffic accidents. A few models using machine learning algorithms and Neural Networks were trained to classify the severity of the crash using details on weather conditions. The results of this study can offer useful information to public safety organizations, transportation authorities, and politicians. Developing targeted initiatives to improve road safety and lower crash risks, especially during extreme weather events, can be made easier by understanding how extreme weather events affect traffic crashes during different times of the year. Overall, this research intends to clarify the intricate relationships between severe weather, and traffic accidents, advancing future efforts to increase traffic safety and prevent accidents.

**Introduction:**

Not only can traffic accidents create huge economic losses, but they also inflict unimaginable human agony. The impact of meteorological conditions on crash severity continues to be a crucial field of research despite continued efforts to increase road safety through the investigation of driver behavior, road infrastructure, and vehicle features. Extreme temperatures, rain, snow, fog, and other weather-related circumstances can make driving more dangerous and increase the likelihood of accidents. It is crucial to comprehend how these weather factors affect crash severity to create targeted interventions and raise the bar for driving safety. By examining the connection between meteorological conditions and the severity of traffic accidents and considering a variety of scenarios, this research aims to close this knowledge gap.

Recent changes in traffic safety serve as a further reminder of the importance of this study. Due to lockdowns and remote work arrangements, Extreme weather conditions apply significant changes in travel behavior, resulting in lower traffic numbers in some areas or higher crash rates in others. Even though there is less traffic overall, it is important to consider how weather-related factors could affect how serious incidents are during these difficult times. Furthermore, given that climate change is causing weather patterns to become more unpredictable, it is crucial to thoroughly analyze past accident data and associated meteorological records. This study will assist in analyzing the possible risks caused by extreme weather events as well as the effects of typical weather conditions, enabling authorities to put the right safety precautions in place.

An extensive dataset source from Kaggle, notably the US Accidents dataset, will be used to accomplish the research goals. This dataset includes a plethora of data about traffic accidents, such as the locations, dates, and severity levels of the occurrences, as well as pertinent weather information at the time of the incidents. We can perform a thorough study using sophisticated statistical modeling and machine learning approaches by utilizing this vast dataset. Policymakers, traffic safety authorities, and urban planners can make more informed decisions to improve road safety measures thanks to the research's practical consequences. The study's findings may also help develop predictive models that permit early warning systems for dangerous weather, lowering traffic accidents' frequency and severity.

As a result, this study aims to close the knowledge gap that exists on the relationship between the severity of a traffic accident and the weather. We seek to discover important insights that can inform road safety rules, enhance preventive measures, and contribute to a safer and more secure transportation environment for all by utilizing thorough data analysis and cutting-edge methodology.

A global status report on road safety states that 1.25 million people died in traffic-related incidents in 2013, with fatality rates rising in 68 nations compared to 2010 [3]. Driving conditions can be substantially impacted by weather events including heavy rain, hurricanes, tornadoes, and snowstorms, which can result in limited visibility, flooded roads, slick surfaces, and other dangerous scenarios. We want to analyze road accidents under these severe weather conditions using the full US Accidents [1,2] dataset obtained from Kaggle. This dataset provides a valuable resource for investigating the effects of weather on crash severity, aiming to improve road safety strategies and mitigate potential risks associated with adverse weather conditions.

**Related Work:**

There are many researchers on the same analysis, in which some were talking about different factors that affect the severity of crashes. There is a research by Vatanavongs, etc., (4) which utilized accident data on expressway networks from 2007 to 2010, in which Expressway Authority of Thailand (EXAT) as legislatively mandated unit has taken responsibility for the execution of nine expressways covering distances totaling over 207 km with a record of 2194 crashes. The chief objective of this study aims to forecast the accident severity by formulating a Multiple Logistic Regression Model to analyze the probability of injury accidents and fatal accidents in comparison with property damage-only accidents. Another analysis by Uddin etc., (5) crash data from the state of Ohio between 2011 and 2015 available from the Highway Safety Information System. To determine if weather conditions should be considered separately for truck safety analyses, parameter transferability tests are conducted; the results suggest that weather conditions should be modeled separately with a high level of statistical confidence. Yau etc., (6) examined factors causing accident severity of three vehicle types via logistic regression models; the research found that each vehicle type significantly exhibited different accident severity factors. In addition, the day of the week and time of the accident showed a significant relationship with accident severity levels of motorcycle type. Vehicles affect the crash type in our work, but differences among the accident severity levels are irrelevant. Concordant results were found with respect to the other factors. A logistic regression method was applied to a set of traffic collision data also for analyzing the factors that impact crashes severity at intersection (Chen etc.,). (7) Factors such as driver’s age and gender, time of day, and crash type, were found to be statistically significant. The study indicated that male drivers were more likely to be involved in an intersection crash leading to a fatal outcome than their female counterparts. Age, drivers aged 65 and above have higher odds of involvement in fatal intersection crashes than other age groups. In our study, gender appears as not significant, and drivers aged below 45 years have a lower probability to be involved in a front/side collision, and this probability decreases considering not many serious accidents. The research proposed by Theofilatos etc., (8) aims to identify and analyze the factors affecting accident severity differentiating between inside and outside urban areas. From the two binary logistic regression models developed, it appears that inside urban areas types of collisions, as well as the involvement of motorcycles, bicycles, buses, age groups, time of the accident, and location of the accident, seem to affect accident severity. Outside urban areas, types of collisions, weather conditions, time of the accident, one age group, and involvement of motorcycles and buses were found to be significant. In the same way, in our work inside urban areas, the probability of a not much serious accident increases. Kadilar etc., (9) developed a conditional logistic regression model to identify the factors, among drivers, roadway/environment, collision, and vehicle characteristics that could be associated with driver crash severity in Turkey. The results demonstrated that age, roadway condition, roadway type, time of day, collision location, and collision type were important determinants of accident severity. However, gender, roadway surface, and weather condition were found to have statistically insignificant effects on accident severity. Potoglou et al. (10) examined the associations between the severity of non-fatal accidents in the City of Palermo, and driver and accident characteristics, road conditions, and seasonality of accident severity. Findings from a mixed-effects logistic regression model highlighted that the severity of non-fatal accident injuries was significantly associated with drivers’ age and seasonality. A similar result was obtained in our study, where the weight of age on crash type is higher considering the not many serious accidents.

**Methodology:**

The US Accidents dataset from 2016 to 2023 was used as the data source for this analysis of crashes involving weather conditions. We first defined extreme weather conditions in the dataset and then filtered those out before conducting a comparative study using various data analysis techniques and exploratory analysis. Data collecting would be the first step, which would entail filtering out data that contained information regarding traffic crashes, such as crash date, time, location, severity, and so forth. Weather data would also be collected at the time and location of each data crash. The following step is data cleaning, in which we remove all garbage, null, and missing values from the accident dataset before aligning all available rows with the weather data based on date and location and aggregating the dates to the proper periods and geographic areas for analysis. We locate and extract the dataset's extreme weather occurrences, then we filter the crash data to only include the accidents that took place in these conditions.

**Data:**

For this study, we use the Kaggle dataset referred to as US accidents. It includes all of the United States' accident statistics from 2016 to 2023. This dataset of automobile collisions includes data from all 50 states in the union. Various APIs that provide streaming traffic incident (or event) data were used to collect the accident data between January 2019 and March 2023. These APIs transmit traffic data that has been gathered by several organizations, including the US and state transportation departments, law enforcement organizations, traffic cameras, and traffic sensors built into road networks. Approximately 7.7 million accident data with 46 attributes are currently included in the collection.

Table 1. Features considered in the Dataset.

|  |  |  |  |
| --- | --- | --- | --- |
| **#** | **Attribute** | **Description** | **Values** |
| 1 | ID | This is a unique identifier of the accident record. | Unique |
| 2 | Severity | Shows the severity of the accident, a number between 1 and 4, where 1 indicates the least impact on traffic (i.e., short delay as a result of the accident) and 4 indicates a significant impact on traffic (i.e., long delay). | Range(1 - 4) |
| 3 | Start\_Time | Shows the start time of the accident in the local time zone. | DateTime |
| 4 | End\_Time | Shows the end time of the accident in the local time zone. End time here refers to when the impact of the accident on traffic flow was dismissed. | DateTime |
| 5 | Start\_Lat | Shows latitude in GPS coordinates of the start point. | GPS coordinate |
| 6 | Start\_Lng | Shows longitude in GPS coordinates of the start point. | GPS coordinate |
| 7 | End\_Lat | Shows latitude in GPS coordinates of the endpoint. | GPS coordinate |
| 8 | End\_Lng | Shows longitude in GPS coordinates of the endpoint. | GPS coordinate |
| 9 | Distance(mi) | The length of the road extent affected by the accident. | mi |
| 10 | Description | Shows natural language description of the accident. |  |
| 11 | Number | Shows the street number in the address field. | int |
| 12 | Street | Shows the street name in the address field. | string |
| 13 | City | Shows the city in the address field. | string |
| 14 | County | Shows the county in the address field. | string |
| 15 | State | Shows the state in the address field. | string |
| 16 | Zip code | Shows the zip code in the address field. | int |
| 17 | Country | Shows the country in the address field. | string |
| 18 | Timezone | Shows the time zone based on the location of the accident (eastern, central, etc.). | string |
| 19 | Airport\_Code | Denotes an airport-based weather station which is the closest one to the location of the accident. | int |
| 20 | Weather\_Timestamp | Shows the timestamp of the weather observation record (in local time). | DateTime |
| 21 | Temperature(F) | Shows the temperature (in Fahrenheit). | F |
| 22 | Wind\_Chill(F) | Shows the wind chill (in Fahrenheit). | F |
| 23 | Humidity(%) | Shows the humidity (in percentage). | % |
| 24 | Pressure(in) | Shows the air pressure (in inches). | inches |
| 25 | Visibility(mi) | Shows visibility (in miles). | mi |
| 26 | Wind\_Direction | Shows wind direction. | string |
| 27 | Wind\_Speed(mph) | Shows wind speed (in miles per hour). | mph |
| 28 | Precipitation(in) | Shows precipitation amount in inches, if there is any. | in |
| 29 | Weather\_Condition | Shows the weather condition (rain, snow, thunderstorm, fog, etc.) | string |
| 30 | Amenity | A POI annotation indicates the presence of an amenity in a nearby location. | True/False |
| 31 | Bump | A POI annotation that indicates the presence of a speed bump or hump in a nearby location. | True/False |
| 32 | Crossing | [A POI annotation indicates the presence of a crossing in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:crossing) | True/False |
| 33 | Give\_Way | [A POI annotation indicates the presence of give\_way in a nearby location.](https://wiki.openstreetmap.org/wiki/Tag:highway%3Dgive_way) | True/False |
| 34 | Junction | [A POI annotation indicates the presence of a junction in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:junction) | True/False |
| 35 | No\_Exit | [A POI annotation indicates the presence of no\_exit in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:noexit) | True/False |
| 36 | Railway | [A POI annotation indicates the presence of a railway in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:railway) | True/False |
| 37 | Roundabout | [A POI annotation indicates the presence of a roundabout in a nearby location.](https://wiki.openstreetmap.org/wiki/Tag:junction%3Droundabout) | True/False |
| 38 | Station | [A POI annotation indicates the presence of a station in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:station) | True/False |
| 39 | Stop | [A POI annotation indicates the presence of a stop in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:stop) | True/False |
| 40 | Traffic\_Calming | [A POI annotation indicates the presence of traffic\_calming in a nearby location.](https://wiki.openstreetmap.org/wiki/Key:traffic_calming) | True/False |
| 41 | Traffic\_Signal | [A POI annotation that indicates the presence of traffic\_signal in a nearby location.](https://wiki.openstreetmap.org/wiki/Tag:highway%3Dtraffic_signals) | True/False |
| 42 | Turning\_Loop | [A POI annotation indicates the presence of turning\_loop in a nearby location.](https://wiki.openstreetmap.org/wiki/Tag:highway%3Dturning_loop) | True/False |
| 43 | Sunrise\_Sunset | Shows the period of day (i.e., day or night) based on sunrise/sunset. | Day/Night |
| 44 | Civil\_Twilight | [Shows the period of day (i.e., day or night) based on civil twilight.](https://en.wikipedia.org/wiki/Twilight#Civil_twilight) | Day/Night |
| 45 | Nautical\_Twilight | [Shows the period of day (i.e., day or night) based on nautical twilight.](https://en.wikipedia.org/wiki/Twilight#Nautical_twilight) | Day/Night |
| 46 | Astronomical\_Twilight | [Shows the period of day (i.e., day or night) based on astronomical twilight.](https://en.wikipedia.org/wiki/Twilight#Astronomical_twilight) | Day/Night |

The table displays the features that are taken into account in the dataset. Each accident is given a unique identifier, and extreme weather conditions like heavy rain, heavy thunderstorms, heavy snow, etc. are considered. According to the table, the crash severity is divided into 4 categories, with 1 denoting a minor crash and 4 denoting a major one. The latitude and longitude of the crash site have also been considered. The distance of the accident's impact on traffic flow, weather information including precipitation, humidity, pressure, and temperature, and driver vision. The time of day, the location of the crash facilities or a hospital, etc. Given that we have considered statistics from all US states.

Discussion of the Analysis:

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Fig 1. Bar Chart for Count of different types of Accidents during different Weather Conditions

A distinct pattern may be seen after carefully examining Figure 1, which shows the number of accidents broken down according to their relative severity categories. It is clear that the majority of crashes, across all scenarios, are characterized as having a type 2 severity. This prevalence of type 2 crashes is a noteworthy finding that necessitates additional research. From Fig 1. We can see that Rain has the most crashes that have occurred with 50% of the total crashes registered in the dataset. Then comes Fog with 20% of the crashes, Snowy conditions placed third with 14% of the crashes followed by Thunderstorm, Windy, and Hail with &.6%, 5.1%, and 1.4% respectively.

The picture also reveals a striking trend: Extreme Weather Conditions do not have a strong number of minor accidents, they have more of several accidents that are type 3 and 4 which are on the major side. This illustrates that extreme weather conditions which cause wet roads a,d lesser visibility can cause scenarios that can lead to accidents that have major concern than that of minor concerning accidents.

A graph of different colored bars

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Fig 2. Figure by weather conditions by month

Fig. 2 shows a detailed illustration of which month would have accidents in what kind of weather conditions, to start with January, we can see that Rainy conditions have the highest number of accidents occurring throughout the country. In February, We had accidents more than the previous month. So, this says the Department of Road Safety to take precautions so that the roads would not get wet in this kind of situation that makes vehicles lose traction and then have a severe accident.

The intricacies underlying this apparent tendency can be uncovered by researchers by digging deeper into the relevant factors, such as weather conditions, road kinds, and driving demographics. As a result, this study can help guide decisions about public policy, educational programs, and targeted interventions to address the rise in type 2 crashes and further decrease their occurrence, ultimately leading to an improvement in general road safety conditions.

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Fig 3. Count of Accidents during day or night in different Weather Conditions

From Fig 3. We can see that Rain has the most crashes that have occurred with 50% of the total crashes registered in the dataset. Then comes Fog with 20% of the crashes, Snowy conditions placed third with 14% of the crashes followed by Thunderstorm, Windy, and Hail with &.6%, 5.1%, and 1.4% respectively. In most weather conditions accidents occur during the daytime rather than at night. This may be because people don’t tend to travel at night a lot more than in the mornings. So, If we consider each weather individually, The number of Fog conditions is almost equal in both day and night time. Similarly, Hailstorm conditions have an equal amount of accidents during day and night time. Rainy conditions have several accidents that are higher during the day than at night. Similarly, Thunderstorm conditions and Windy conditions have accidents that are higher during the day than at night. But, In Snowy Conditions the accidents during the day are lesser than that of Night. This can be due to lack of visibility and judgment of the road or curve or a bump would be harder in these conditions.

A map of the united states

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Fig 4. Heatmap of Accidents Occurred Around USA.

A startling realization may be drawn from Figure 4, which lists the top 10 states in terms of the total number of crashes for the considered period. It should be noted that Florida, California, New York, and Pennsylvania consistently rank first in the number of crashes throughout this time.

When the State of California is considered It has almost 17.9% of the accidents that have occurred in the US, while Florida has 10.4% of crashes, and New York is third with 5.7% of the crashes. Pennsylvania and Texas have around 5% of the crashes each placing them at Fourth and Fifth positions of all the States in the Country. From Fig 4(B) We can see that the least affected area is South Dakota.

A map of the united states

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(a)Rain. (b)Fog

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(c)ThunderStorm (d)Snow

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(e)Windy (f) Hail

Fig 5. Heatmap of Weather Conditions In Different States

While following the heatmaps from Figure 5, In Rainy Weather conditions, States having Heavy Coastal Areas or near to Coast have the majority of crashes, while in Foggy conditions California has recorded the highest number of crashes. For Thunderstorm Conditions, The States that are near the Atlantic have recorded more amounts than the Pacific Side. States that are north have recorded a lot of crashes in Snowy Conditions.

**Crash Severity Prediction Model:**

To make a Severity Prediction model using weather data we have considered the columns that are mostly dependent on weather and the POI of the crash rather than all geographical positions. So, The table has been trimmed to 22 columns that consist of the following elements, ('Distance(mi)', 'Bump', 'Crossing', 'Give Way', 'Junction', 'No\_Exit', 'Railway', 'Roundabout', 'Station', 'Stop', 'Traffic Calming', 'Traffic Signal', 'Turning\_Loop', 'Temperature(F)', 'Wind Chill(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)', 'Wind Speed(mph)', 'Precipitation(in)', 'Weather\_Condition', 'Severity') columns as named in the dataset.

To make a prediction model we need to first train the model on historic data and then validate and test the model using the data. To first train a model we need to understand the data first. So, we have considered the above columns in the data frame let us see first how the values are ranged.

Then, we selected a few models to run on and selected the best model of the following models a) Random Forest Model, b) K-Neighbors Classifier Model, c) A Feed Forward Neural Network to be our algorithms for the model and trained the models on 80% of the data and tested on the 20% of the data. Our performance of the model is given by metrics like precision, recall, and F1-Score.

Precision = true positive / (true positive + false positive)

Recall = true positive / (true positive + false negative)

F1 - Score = 2 \* Precision \* Recall / (Precision + Recall)

Before, training the model steps like Data Cleaning, Data Preprocessing, Feature Selection, and Model Selection have taken place. As the dataset output column requires the value to be classified we used a classifier model.

**Results:**

The following table shows the result of all the training models and their metrics:

Table 2: Classification Metrics for the models under RUS

|  |  |  |
| --- | --- | --- |
| **Model** | **Metrics** | **Score** |
| **Random Forest** | Precision | 0.58 |
| Recall | 0.58 |
| F1-Score | 0.57 |
| **Decision Tree Classifier** | Precision | 0.48 |
| Recall | 0.49 |
| F1-Score | 0.48 |
| **K-Neighbors Classifier** | Precision | 0.38 |
| Recall | 0.38 |
| F1-Score | 0.37 |

The Above tables speak about the result of the prediction model made on the dataset and the testing results that have been obtained. This illustrates that all the prediction models did not have an impactful prediction with the random forest being the highest with 58% accuracy. Though we have tried to balance all the classes with random under-sampling this led to poor results.

Table 3: Classification Metrics for the models under SMOTE

|  |  |  |
| --- | --- | --- |
| **Model** | **Metrics** | **Score** |
| **Random Forest** | Precision | 0.77 |
| Recall | 0.81 |
| F1-Score | 0.78 |
| **Decision Tree classifier** | Precision | 0.75 |
| Recall | 0.74 |
| F1-Score | 0.75 |
| **K-Neighbors Classifier** | Precision | 0.74 |
| Recall | 0.82 |
| F1-Score | 0.75 |

The Above tables speak about the result of the prediction model made on the dataset and the testing results that have been obtained. This illustrates that all the prediction models did not have an impactful prediction with K-Neighbors being the highest with 82% accuracy.

**Conclusion:**

As this project speaks about analyzing crashes during extreme weather conditions these are the insights that we have concluded upon, (i) Most of the crashes have gone under due to wet road conditions like when there was rain or snow, or hails, etc.,. (ii) Months having colder weather have more accidents than months having hotter weather in a year. (iii) Overall accidents happen more during rain than during any other weather conditions. (iv) Most of the crashes happen during the day when we have extreme weather conditions, rather than at night. Except for snowy conditions where crashes happen a lot more during the night than during the day. (v) We have also analyzed the impact of different weather conditions in all states.

Finally, In Rainy Conditions States like CA, FL, TX and SC recorded most of the accidents, In Foggy Conditions states like CA, FL, SC and TX have the most,whereas in Thunderstorm Conditions, states like FL, SC, TX and LA recorded most of the crashes. In Snowy Conditions, States like MN, NY, PA, and MI have have recorded the most number of crashes. For, Conditions having Heavy Winds, CA, FL and TX have most of the crashes. In Hailstorm Conditions, States like NY, MN, PA will have most crashes. This analysis could help businesses like insurance to make their policy rates better and the local governance to be aware of the challenges that are upcoming in the coming days. Staes like WY, ID, SD, and AZ are mostly having lesser crashes in all of the weather conditions. People living in the mentioned states should take precautions in their appropriate weather conditions so that they would not be affected by these weather changes.

The accident severity prediction model using weather conditions metrics has not worked up to the mark, this might be because of the data being vastly imbalanced. If we see the severity count plot. We see that the Severity count of 2 is way superior to that of the other 3 severity classes. Having imbalances of this kind may result in poor results in prediction models. The prediction models made used algorithms like the random forest, decision tree, and K-Neighbors. Random Forest has the upper hand with 58% prediction accuracy. But, when considering SMOTE we have better accuracy results than RUS where K-Neighbors has the highest accuracy of 82%.

**Future Work:**

So, We have missed some important factors like driver details, for instance, the age of the driver involved in the accidents, the type of vehicles involved in the accidents, and the point of contact on the road or road types. The dataset has also missed the factors of the speed the vehicle is being traveled. By using these additional details we may have an even more accurate model or analysis in predicting crash severity. Our Models can be Fine-tuned even more as we have various hyperparameters to explore which could make more precise predictions.

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