Optimizing Fayetteville Law Enforcement Deployment with Accident Hot Zone Prediction

Problem Setting:

Every day on my drive home from work, I frequently encounter traffic at certain spots due to accidents. This results in long commutes and unpleasant experiences, especially when driving a manual stick car. I often wonder, "Why aren't the police deployed to quickly resolve these accidents? This happens several times a week. Is the police department aware of this issue? Can they pre-deploy officers or implement preventative measures to reduce the likelihood of these accidents occurring again?" Apparently, the City of Fayetteville faces a significant challenge in managing road safety due to the limited resources available. Therefore, they must efficiently deploy law enforcement to areas and times where accidents are most likely to occur and where the severity of these accidents is highest. Efficient resource allocation can improve response times, potentially reduce accident severity, and enhance overall public safety (and reduce my commute time every day). This challenge lies in predicting both the occurrence and severity of accidents to ensure optimal deployment of law enforcement resources.

Problem Definition:

1. Predict the occurrence of traffic accidents in different locations and times within the City of Fayetteville.

2. Assess the likely hot zones of these accidents to prioritize law enforcement deployment effectively.

Key questions to be answered through this project include:

- Which areas and times have the highest likelihood of traffic accidents?
- What factors contribute most to the occurrence of accidents?
- How can the Fayetteville Police Department allocate resources to reduce accident response times and improve public safety?

Dataset Source:

The primary dataset for this project is sourced from the City of Fayetteville's open data portal. The dataset can be accessed at:

https://data.fayettevillenc.gov/datasets/faync::accidents/about

Data Description:

The accident dataset contains records of traffic accidents reported by the Fayetteville Police Department from 2015 to the present. The dataset includes the following columns:

acci_id: Unique identifier for each accident

Date: Date of the accident

dtg_utc_diff: Time difference from UTC

Year: Year of the accident

Month: Month of the accident

Wk_Yr: Week of the year

Julian: Julian date

DoW: Day of the week

Hour: Hour of the day

YMD: Year-Month-Day format of the date

fatality: Indicator of whether the accident resulted in a fatality

contrcir1: Contributing circumstance of the accident

DMVCrashID: DMV crash identifier

X: Longitude of the accident location

Y: Latitude of the accident location

The dataset consists of 90,287 rows, each representing an individual accident record.

Data Cleaning and Data Preprocessing:

1. Identified a column containing mostly blank entries and I decided to drop it completely.

```
# Count blank values in 'xmlretrn'
blank_count = (accidents_data['xmlretrn'] == ' ').sum()
# Count null values in 'xmlretrn'
null_count = accidents_data['xmlretrn'].isnull().sum()
# Count unique values in 'xmlretrn'
unique_count = accidents_data['xmlretrn'].nunique()
unique_values_xmlretrn = accidents_data['xmlretrn'].unique()
print(unique_values_xmlretrn)
# Print the results
print(f"Blank values in 'xmlretrn': {blank_count}")
print(f"Null values in 'xmlretrn': {null_count}")
print(f"Unique values in 'xmlretrn': {unique_count}")
```

```
[' ' nan '107686003' ... '107713067' '107713070' '107714339']
Blank values in 'xmlretrn': 81303
Null values in 'xmlretrn': 447
Unique values in 'xmlretrn': 7668
```

```
# The xmlretrn column contains mostly blank entries and a few unique numeric values. Not sure what'
accidents_data.drop(columns=['xmlretrn'], inplace=True)
accidents_data.head()
```

2. Converting 'Date' and 'dtg_utc_diff' columns to datetime format as a common practice for analyzing datetime data.

```
# Convert Date column to datetime format
accidents_data['Date'] = pd.to_datetime(accidents_data['Date'])
# View the cleaned dataset
accidents_data.info()
accidents_data.head()
```

```
# Convert 'dtg_utc_diff' to datetime format
accidents_data['dtg_utc_diff'] = pd.to_datetime(accidents_data['dtg_utc_diff'], errors='coerce')

# view the cleaned dataset
accidents_data.info()
accidents_data.head()
```

3. Identify zero values in 'X' and 'Y' columns and remove them from the data frame.

```python
# Check for zero values in 'X' and 'Y'
zero_x_count = (accidents_data['X'] == 0).sum()
zero_y_count = (accidents_data['Y'] == 0).sum()

# Check for null values in 'X' and 'Y'
null_x_count = accidents_data['X'].isnull().sum()
null_y_count = accidents_data['Y'].isnull().sum()

print(f"Zero values in 'X': {zero_x_count}")
print(f"Zero values in 'Y': {zero_y_count}")
print(f"Null values in 'X': {null_x_count}")
print(f"Null values in 'Y': {null_y_count}")
```

```
Zero values in 'X': 903
Zero values in 'Y': 903
Null values in 'X': 0
Null values in 'Y': 0
```

```python
# Remove rows where 'X' or 'Y' are zero
accidents_data = accidents_data[(accidents_data['X'] != 0) & (accidents_data['Y'] != 0)]

# Verify the removal by checking for zero values again
zero_x_count_post = (accidents_data['X'] == 0).sum()
zero_y_count_post = (accidents_data['Y'] == 0).sum()

print(f"Zero values in 'X' after removal: {zero_x_count_post}")
print(f"Zero values in 'Y' after removal: {zero_y_count_post}")
```

```
Zero values in 'X' after removal: 0
Zero values in 'Y' after removal: 0
```

4. Convert X and Y from UTM to WGS 84 latitude and longitude coordinates for future map operations.

```python
# Define the projection transformer from UTM Zone 17N to WGS 84
transformer = Transformer.from_crs('epsg:3632', 'epsg:4326', always_xy=True)

# Define a function to apply transformation
def convert_coordinates(row):
    lon, lat = transformer.transform(row['X'], row['Y'])
    return pd.Series([lon, lat], index=['longitude', 'latitude'])

# Apply the conversion function to the entire DataFrame
accidents_data[['longitude', 'latitude']] = accidents_data.apply(convert_coordinates, axis=1)

# Check the first few entries to confirm the conversion
print(accidents_data[['longitude', 'latitude']].head())
```

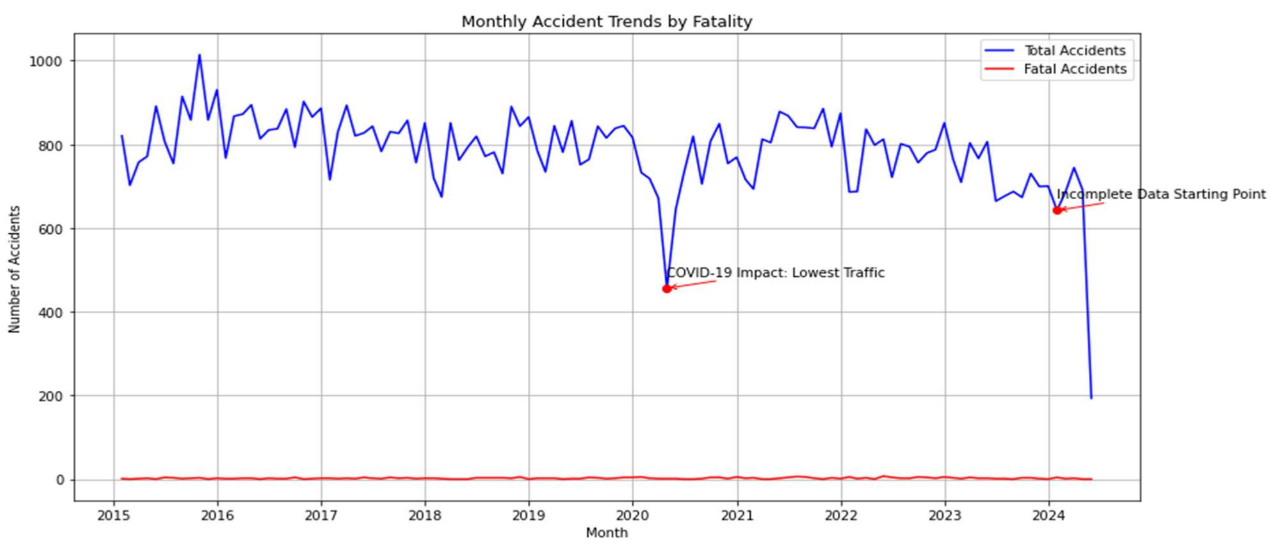
```
   longitude   latitude
0 -78.914625  35.031896
1 -78.982501  35.044178
2 -78.979894  35.036341
3 -78.899743  35.136187
4 -78.978539  35.077483
```

5. We skipped the descriptive analysis because our data contains only location and time, no need to calculate mean, median, mode or standard deviation.

Exploratory Data Analysis (EDA)

1. Visualize the occurrences of accident (Total accidents and Fatal accidents) over time to have a better understanding of the overall accidents in Fayetteville.

```
# Define the time periods
covid_period_start = pd.Timestamp('2020-01-01', tz='UTC')
covid_period_end = pd.Timestamp('2021-01-01', tz='UTC')
incomplete_data_start = pd.Timestamp('2024-01-01', tz='UTC')
incomplete_data_end = pd.Timestamp('2024-05-10', tz='UTC')

# Find the minimum points within these periods
covid_min_date = time_series_data.loc[covid_period_start:covid_period_end, 'Total Accidents'].idxmin()
covid_min_value = time_series_data.loc[covid_min_date, 'Total Accidents']

incomplete_data_min_date = time_series_data.loc[incomplete_data_start:incomplete_data_end, 'Total Accidents'].idxmin()
incomplete_data_min_value = time_series_data.loc[incomplete_data_min_date, 'Total Accidents']

# Plotting
plt.figure(figsize=(14, 7))
plt.plot(time_series_data.index, time_series_data['Total Accidents'], label='Total Accidents', color='blue')
plt.plot(time_series_data.index, time_series_data['Fatal Accidents'], label='Fatal Accidents', color='red')

# Annotations
plt.scatter([covid_min_date, incomplete_data_min_date], [covid_min_value, incomplete_data_min_value],
            color='red', marker='o', zorder=5)
plt.annotate('COVID-19 Impact: Lowest Traffic',
             xy=(covid_min_date, covid_min_value),
             xytext=(covid_min_date, covid_min_value + 30),

             arrowprops=dict(arrowstyle="->", color='red'))

plt.annotate('Incomplete Data Starting Point',
             xy=(incomplete_data_min_date, incomplete_data_min_value),
             xytext=(incomplete_data_min_date, incomplete_data_min_value + 30),

             arrowprops=dict(arrowstyle="->", color='red'))

plt.title('Monthly Accident Trends by Fatality')
plt.xlabel('Month')
plt.ylabel('Number of Accidents')
plt.legend()
plt.grid(True)
plt.show()
```

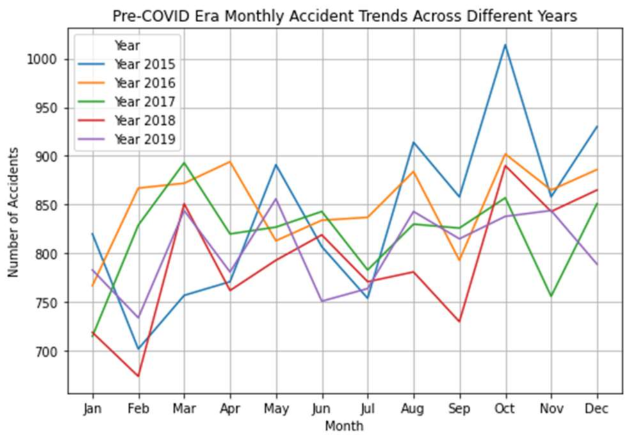


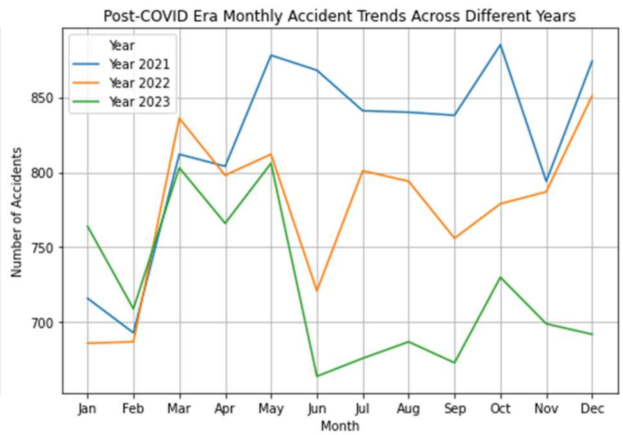
Result: The first significant dip of low number of accidents happened between 2020 to 2021, this is mainly because it's COVID-19 era and the state implemented control measures that resulted in low traffic during that period. The second significant decrease is after 2024, this mainly because of incomplete data collection of this year. Both dips are annotated on the graph.

2. To avoid the impact from covid-19 abnormality and the incompletion dataset from 2024, I'll break down the datasets to prior COVID from 20150101 to 20191231, post COVID from 20210101 to 20231231 to analyze the accident under normal conditions.

```python
# Filter the data for the specified ranges

# Filtering the Pre-COVID data
pre_covid_data = accidents_data[(accidents_data['dtg_utc_diff'] >= '2015-01-01')
                                & (accidents_data['dtg_utc_diff'] <= '2019-12-31')]

# Filtering the Post-COVID data
post_covid_data = accidents_data[(accidents_data['dtg_utc_diff'] >= '2021-01-01')
                                 & (accidents_data['dtg_utc_diff'] <= '2023-12-31')]
```

```python
# Lets drill down to monthly accidents changes to see the seasonal pattern

# Group the data by year and month and count the number of accidents in each group
monthly_accidents_pre_covid = pre_covid_data.groupby([pre_covid_data['dtg_utc_diff'].dt.year,
                                                      pre_covid_data['dtg_utc_diff'].dt.month]).count()['OBJECTID'].unstack(0)
monthly_accidents_post_covid = post_covid_data.groupby([post_covid_data['dtg_utc_diff'].dt.year,
                                                        post_covid_data['dtg_utc_diff'].dt.month]).count()['OBJECTID'].unstack(0)
# Set up a figure with two subplots (one for Pre-COVID and one for Post-COVID) horizontally aligned
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14, 5))

# Plotting Pre-COVID data
for year in monthly_accidents_pre_covid.columns:
    axes[0].plot(monthly_accidents_pre_covid.index, monthly_accidents_pre_covid[year], label=f'Year {year}')
axes[0].set_title('Pre-COVID Era Monthly Accident Trends Across Different Years')
axes[0].set_xlabel('Month')
axes[0].set_ylabel('Number of Accidents')
axes[0].set_xticks(range(1, 13))
axes[0].set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
axes[0].legend(title='Year')
axes[0].grid(True)

# Plotting Post-COVID data
for year in monthly_accidents_post_covid.columns:
    axes[1].plot(monthly_accidents_post_covid.index, monthly_accidents_post_covid[year], label=f'Year {year}')
axes[1].set_title('Post-COVID Era Monthly Accident Trends Across Different Years')
axes[1].set_xlabel('Month')
axes[1].set_ylabel('Number of Accidents')
axes[1].set_xticks(range(1, 13))
axes[1].set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
axes[1].legend(title='Year')
axes[1].grid(True)

# Display the plot
plt.tight_layout()
plt.show()
```





Result: We can see the total number of accidents are slightly decreased each year, this indicates our city is generally proceeding to a better and safer place for road traffic.

We can see that there are certain months accidents will increase significantly, such as Feb to Mar, Apr to May, and will continually increase slightly from Jun till Dec.

We can see that from Jan to Feb the number of accidents will decrease significantly as well as Jun to Jul, Oct to Nov.

My assumption of these observations is that: a. Seasonal Weather conditions can significantly impact driving conditions. For instance, rainy or icy conditions might contribute accidents rate. b. Vacation season and tourist season: Fayetteville is near several military bases and historic sites, might experience seasonal tourist inflows. c. Behavioral factors: during holidays, increased alcohol consumption might also lead to spikes in accident.

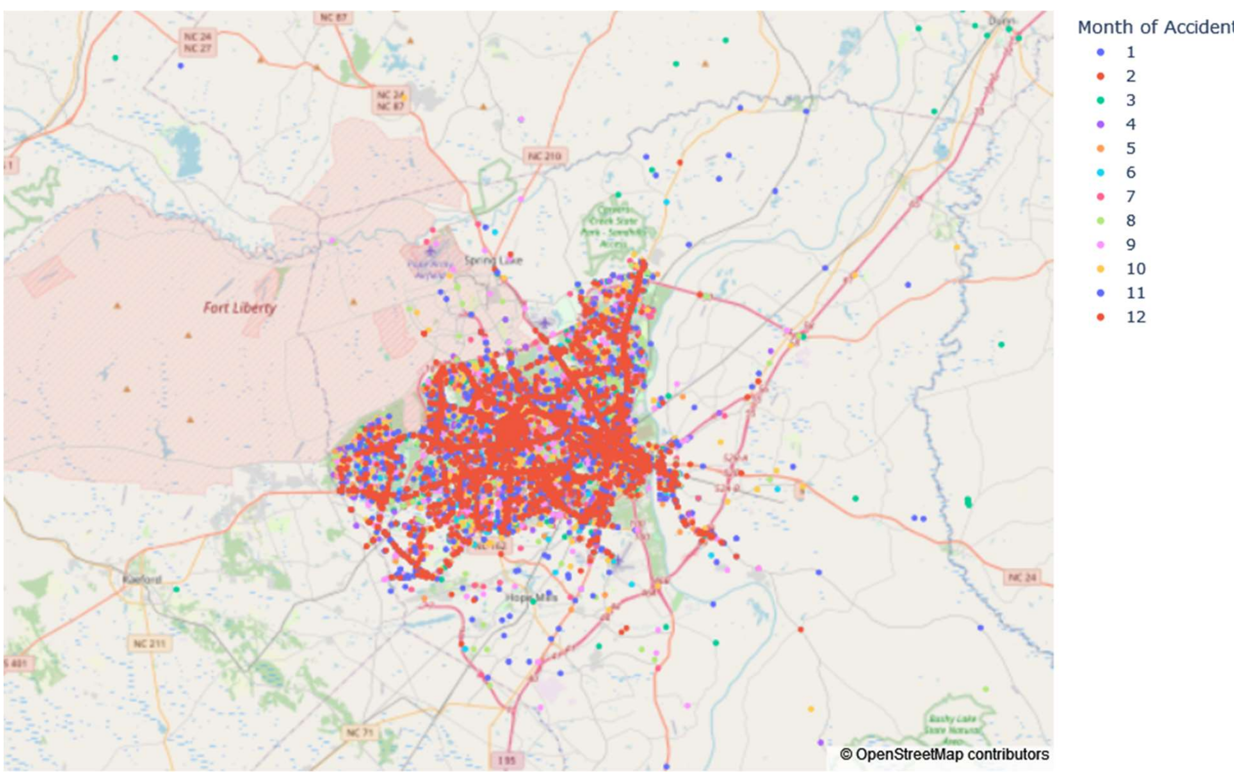
From online research, I'm not able to find local weather data, traffic volume statistics or possible behavioral studies to further substantiate these hypotheses, however, I can continue to mine the data to drill down more on specific period and locations to identify high risk area for better deployment strategy.

3. Visualize accidents on the heatmap to see the distribution of it over the entire city throughout the months:

```python
# First, lets combine pre-covid and post-covid data together to ensure there's no outlier's influence.

# Combine pre-COVID and post-COVID data
combined_data = pd.concat([pre_covid_data, post_covid_data])

# Ensure the data is sorted by date if necessary
combined_data.sort_values('dtg_utc_diff', inplace=True)

# Reset index for the new combined dataframe
combined_data.reset_index(drop=True, inplace=True)
```

```python
# Drop rows where longitude or latitude are NaN or infinite
combined_data = combined_data[(combined_data['X'].notnull()) & (combined_data['Y'].notnull())]
combined_data= combined_data[np.isfinite(combined_data['X']) & np.isfinite(combined_data['Y'])]
```

```python
# Plot on map to see hotspots.

# Create new column 'month' for visualizing different hotspot by month difference
combined_data['month'] = combined_data['dtg_utc_diff'].dt.month
# Define a color map by month, to visualize and identify hot spot.
fig = px.scatter_mapbox(combined_data, lat="latitude", lon="longitude",
                        color=combined_data['month'].astype(str),  # Convert month to string for discrete color scale
                        labels={'color': 'Month of Accident'},
                        hover_data={"OBJECTID": True, "month": True},
                        zoom=10, center={"lat": combined_data['latitude'].mean(), "lon": combined_data['longitude'].mean()},
                        height=600)

# Update mapbox style to a publicly available style
fig.update_layout(mapbox_style="open-street-map")
fig.update_layout(margin={"r": 0, "t": 0, "l": 0, "b": 0})

# Show the figure
fig.show()
```

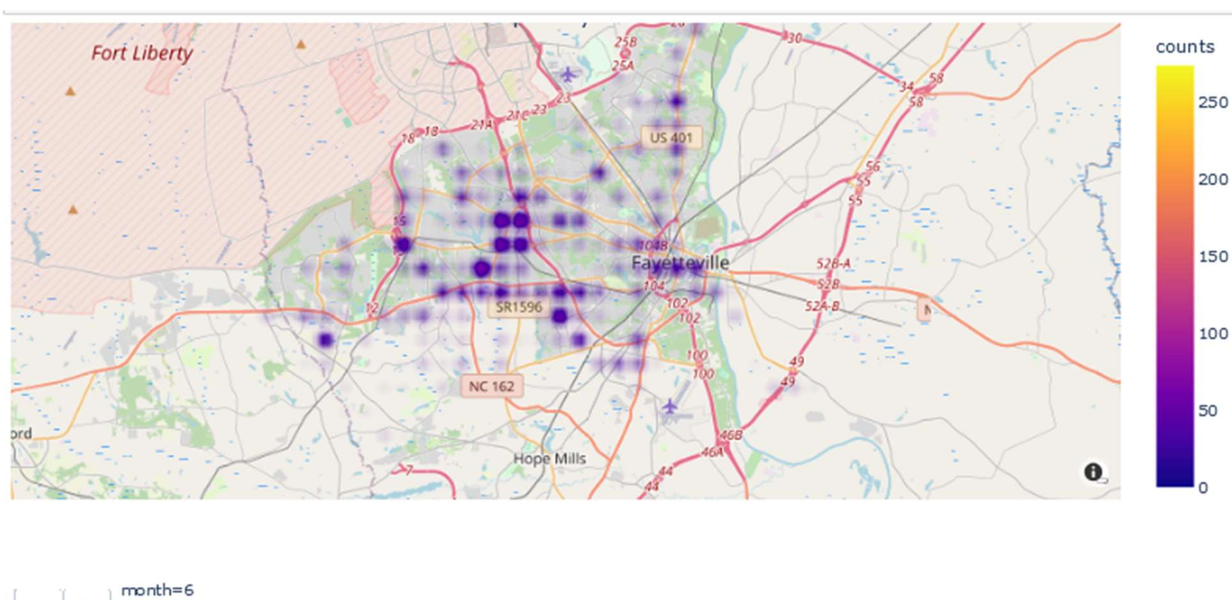


Result: This visualization is hard to interpretate due to the density. I'm going to group the accident location into bins to represent "hot" spots by month on the heat map. In this step, each bin represents approximately 1.11 km by 1.11 km area. In this way, the Fayetteville PD can see where the hot spots across the year are. Potentially, they could allocate resources to be able to respond to accidents quicker and more efficiently.

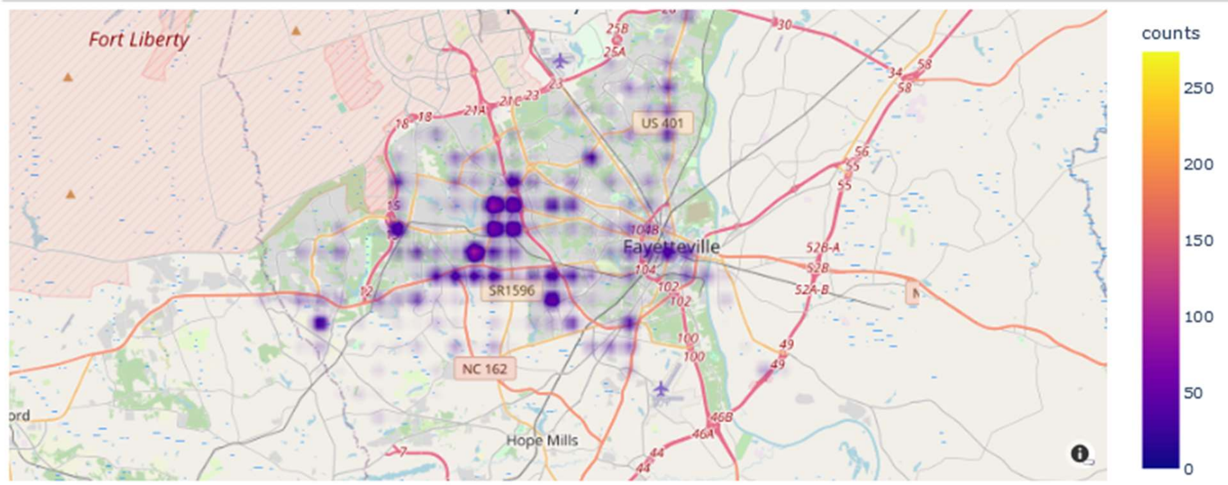
4. Visualize the hotspots over the heatmap per each month:

```python
# Visualize hotspots changes per each month.

# Create grid bins
combined_data['latbin'] = np.floor(combined_data['latitude'] * 100) / 100
combined_data['lonbin'] = np.floor(combined_data['longitude'] * 100) / 100
# Convert 'month' to string for better handling in Plotly

# Aggregate data by bins and month
binned_data = combined_data.groupby(['latbin', 'lonbin', 'month']).size().reset_index(name='counts')
# Sort binned_data by 'month' to ensure the animation frames are in the correct order
binned_data = binned_data.sort_values('month')

# Visualize using Plotly
fig = px.density_mapbox(binned_data, lat='latbin', lon='lonbin', z='counts', radius=12,
                        center={"lat": combined_data['latitude'].mean(), "lon": combined_data['longitude'].mean()},
                        zoom=10, mapbox_style="open-street-map",
                        animation_frame='month',  # Ensure this is the string-typed 'month'
                        range_color=[0, binned_data['counts'].max()],
                        title='Interactive Visualization of Accident Hotspots by Month')

# Update layout if needed
fig.update_layout(margin={"r": 0, "t": 0, "l": 0, "b": 0})

# Show the figure
fig.show()
```

Hot Spots during Month of June

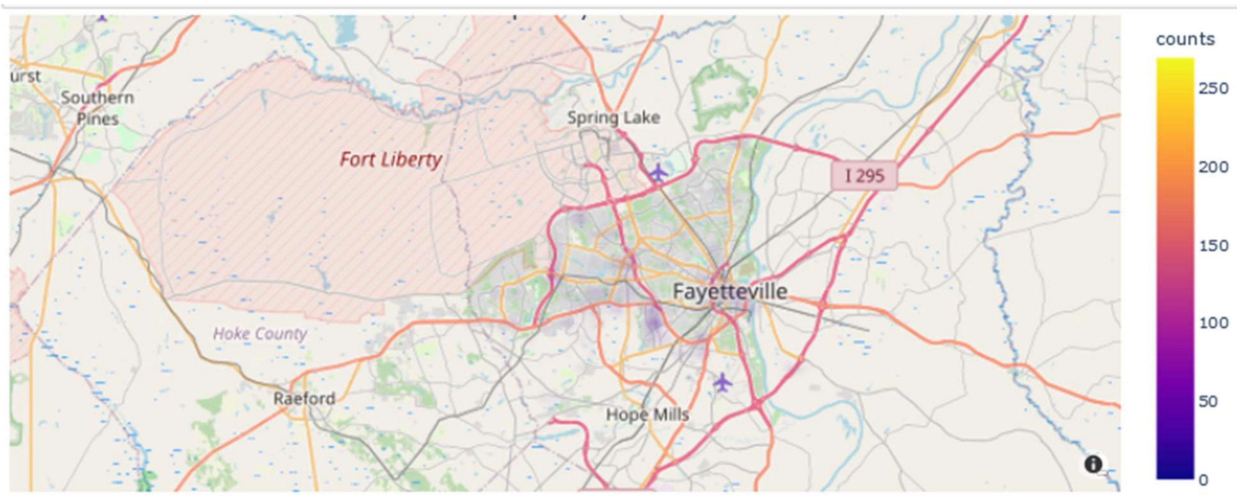


Hot Spots during Month of December



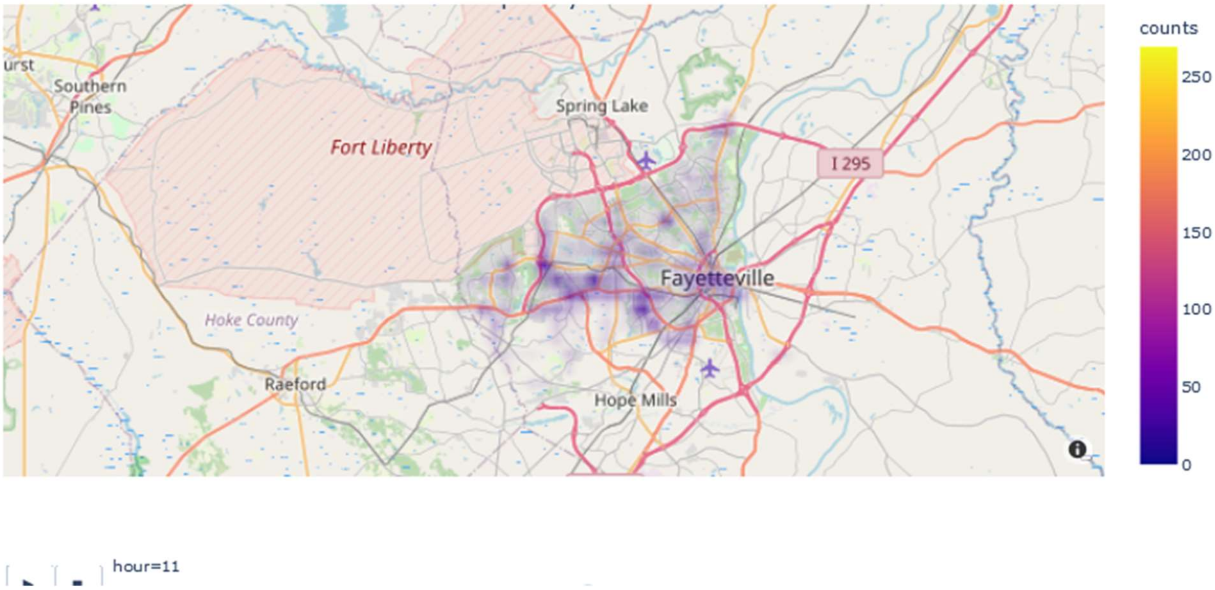
month=12

Hot Spots during 10 am

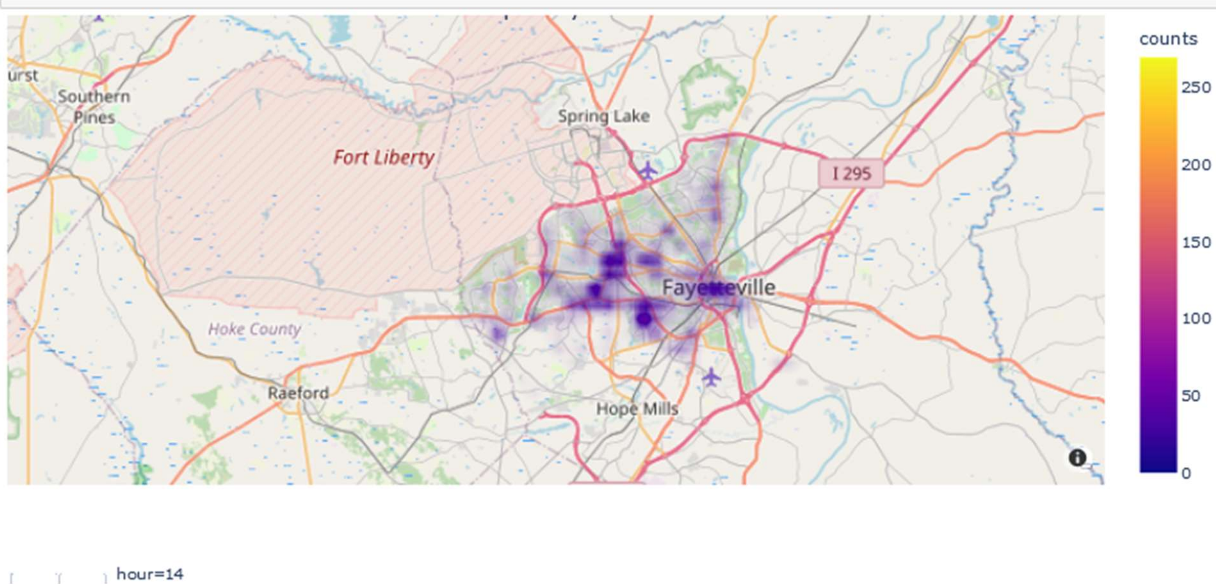


hour=10

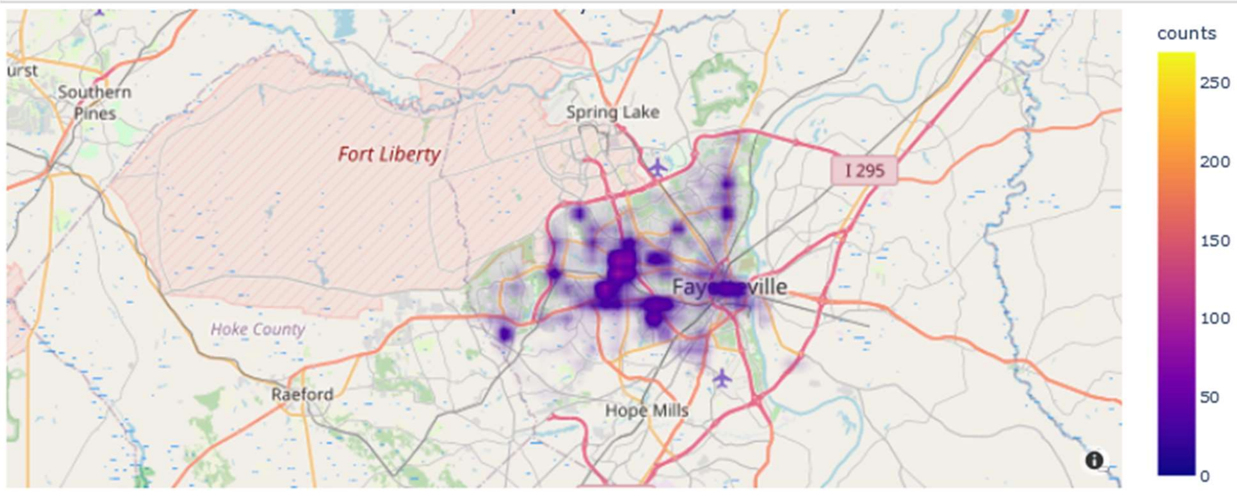
Hot Spots during 11 am



Hot Spots during 2 pm



Hot Spots during 4 pm



hour=16

Result: Multiple hotspots are generally similar across the year, such as the intersection of Skibo Road and Cliffdale Road, which is accurate that I personally encountered accidents happened at that intersection multiple times since I moved to this City. My assumption is that if certain hotspots are always there across the year, that indicates it possibly because of the route usage or road conditions that lead to its high rate of accidents. More research needs to be done to find the root cause and implement preventative measures to lower the accident chance. Furthermore, different month indeed has different hot spots showing respectively, which indicates the contribution of seasonal factors to the total number of accidents in certain areas. For instance, between June and December, the accidents on the same intersection mentioned before increased almost 30%.

Accidents rate start increasing from 11 am and reach at the highest rate from 4 pm to 9 pm.

These hotspots do not necessarily represent accurate center of the accident hubs, but it can be utilized for better resource allocation in conjunction with field investigation and expertise.

Feature Engineering & Selection

1. Adding feature ‘is_hotspot’. I need this binary feature to be used for our model to predict the Y value. The goal here is to we will have necessary features to develop model to predict most likely hotspots so the FPD can pre-deploy officers to prevent accidents from occurring.

```python
# Create more Accurate daytime features
combined_data['day'] = combined_data['dtg_utc_diff'].dt.day
combined_data['hour'] = combined_data['dtg_utc_diff'].dt.hour
combined_data['month'] = combined_data['dtg_utc_diff'].dt.month
# Aggregate data to count accidents per spatial-temporal bin
aggregated_data = combined_data.groupby(['latbin', 'lonbin', 'hour','month']).size().reset_index(name='counts')

# Define a threshold to identify hotspots
threshold = 9 # If a area has more than 9 accidents per that hour in that particular month, I called it hotspot.

# Create the target variable
aggregated_data['is_hotspot'] = (aggregated_data['counts'] >= threshold).astype(int)
```

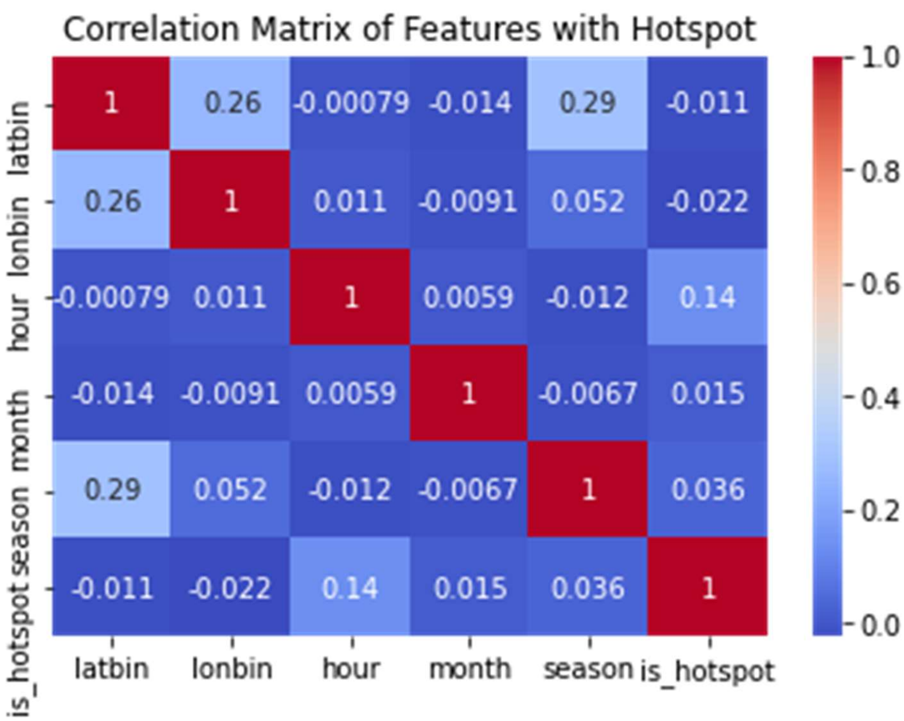
```python
# Count the number of hotspots and non-hotspots
hotspot_counts = aggregated_data['is_hotspot'].value_counts()

# Print the counts
print(hotspot_counts)
```

```
0    27325
1     1409
Name: is_hotspot, dtype: int64
```

Result: If an area (bin) has more than 9 accidents happening in a particular hour and month, this area will be featured as a hotspot. By utilizing this rule, we have 1409 hotspots and 27325 non-hotspots.

2. Feature selection: I implemented correlation matrix to identify the most relevant features to our hotspot.

```python
#adding a simple seasonality feature
aggregated_data['season'] = combined_data['month'].apply(lambda x: (x%12 + 3)//3)
# Correlation matrix
feature_cols = ['latbin', 'lonbin', 'hour', 'month', 'season']
corr_matrix = aggregated_data[feature_cols + ['is_hotspot']].corr()

# Plotting the correlation matrix
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix of Features with Hotspot')
plt.show()
```



Result: Because the corr values do not present a significant difference here, intuitively, I think the location (latbin, lonbin) and the time when the accidents happened should all matters to whether a certain area was a hotspot or not. Therefore, I select **all features** for our model development.

Modeling

Introduction of Models

In this project, I have considered three main machine learning models to predict accident hotspots:

1. **Logistic Regression**: A linear model used for binary classification tasks. It's useful for its interpretability and simplicity.
2. **Random Forest**: An ensemble learning method based on decision trees. This model is known for its robustness and ability to handle overfitting, making it excellent for handling complex datasets with mixed data types.
3. **Gradient Boosting Machine (GBM)**: Another ensemble model that builds trees in a sequential manner, where each new tree helps to correct errors made by previously built trees. GBM is effective for achieving high performance but can be sensitive to overfitting and requires careful tuning.

Implementation Details

Each model was implemented using scikit-learn. The data was first split into training and testing sets to ensure the model's ability to generalize to new data. Features included spatial (latitude and longitude bins) and temporal aspects (hour, day, month, season) of accident data.

```
# Define features and target
X = aggregated_data[['latbin', 'lonbin', 'hour','month','season']]
y = aggregated_data['is_hotspot']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize models
log_reg = LogisticRegression(max_iter=10000, random_state=42)
random_forest = RandomForestClassifier(n_estimators=100, random_state=42)
gbm = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=8, random_state=42)

# List of models
models = [log_reg, random_forest, gbm]
model_names = ['Logistic Regression', 'Random Forest', 'Gradient Boosting Machine']

# Train and evaluate models
for model, name in zip(models, model_names):
    model.fit(X_train, y_train)  # Train model
    y_pred = model.predict(X_test)  # Predict on test set

    print("Results from model: ", name)

    # Printing the classification report including metrics such as precision, recall, and F1-score
    print(classification_report(y_test, y_pred, target_names=['Non-Hotspot', 'Hotspot']))

    # Calculating additional classification metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted', zero_division=0)
    recall = recall_score(y_test, y_pred, average='weighted', zero_division=0)
    f1 = f1_score(y_test, y_pred, average='weighted', zero_division=0)

    # Printing calculated metrics
    print(f"Accuracy: {accuracy:.3f}")
    print(f"Precision: {precision:.3f}")
    print(f"Recall: {recall:.3f}")
    print(f"F1 Score: {f1:.3f}")

    # Calculate and display the confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Non-Hotspot', 'Hotspot'])

    # Display the confusion matrix
    disp.plot(cmap=plt.cm.Blues)
    plt.title(f'Confusion Matrix: {name}')
    plt.show()

    print("\n")
```

Cross-Validation and Hyperparameter Tuning

```
# Logistic Regression
log_reg = LogisticRegression(max_iter=10000, random_state=42)

# Random Forest
random_forest = RandomForestClassifier(n_estimators=100, random_state=42)

# Gradient Boosting Machine
gbm = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=8, random_state=42)
# Define features and target
X = aggregated_data[['latbin', 'lonbin', 'hour','month','season']]
y = aggregated_data['is_hotspot']

# Logistic Regression
log_reg_scores = cross_val_score(log_reg, X, y, cv=10, scoring='accuracy')
print("Logistic Regression - Accuracy for each fold:", log_reg_scores)
print("Logistic Regression - Mean accuracy: %0.2f (+/- %0.2f)" % (log_reg_scores.mean(), log_reg_scores.s

# Random Forest
rf_scores = cross_val_score(random_forest, X, y, cv=10, scoring='accuracy')
print("Random Forest - Accuracy for each fold:", rf_scores)
print("Random Forest - Mean accuracy: %0.2f (+/- %0.2f)" % (rf_scores.mean(), rf_scores.std() * 2))

# Gradient Boosting Machine
gbm_scores = cross_val_score(gbm, X, y, cv=10, scoring='accuracy')
print("Gradient Boosting Machine - Accuracy for each fold:", gbm_scores)
print("Gradient Boosting Machine - Mean accuracy: %0.2f (+/- %0.2f)" % (gbm_scores.mean(), gbm_scores.std
```

```
Logistic Regression - Accuracy for each fold: [0.95093946 0.95093946 0.95093946 0.95093946 0.95127045
0.95092238
 0.95092238 0.95092238 0.95092238 0.95092238]
Logistic Regression - Mean accuracy: 0.95 (+/- 0.00)
Random Forest - Accuracy for each fold: [0.95163535 0.70424495 0.75608907 0.65831594 0.63139575 0.695440
31
 0.35885834 0.69404803 0.77584407 0.95092238]
Random Forest - Mean accuracy: 0.72 (+/- 0.32)
Gradient Boosting Machine - Accuracy for each fold: [0.95163535 0.59464161 0.62386917 0.61551844 0.60946
746 0.73894883
 0.48172642 0.69161156 0.67490428 0.95092238]
Gradient Boosting Machine - Mean accuracy: 0.69 (+/- 0.29)
```

Methods Used for Validating Models and Tuning Hyperparameters

- **Cross-Validation**: We employed k-fold cross-validation, particularly useful in assessing the effectiveness and robustness of each model across different subsets of the data. This method helps in understanding how the model performs in various scenarios and reduces the variance of model performance estimation. Although logistic regression appears to be the best model here, it is not the case. Because if we refer to the confusion matrix later, it can predict none of the hotspots in the dataset.
- **Hyperparameter Tuning**: For tuning the models, especially the Random Forest and GBM, I manipulated the parameters such as learning_rate and max_depth to see the differences. This method did not give me guaranteed optimal performance, but it provided me with slightly better results by twisting the parameters.

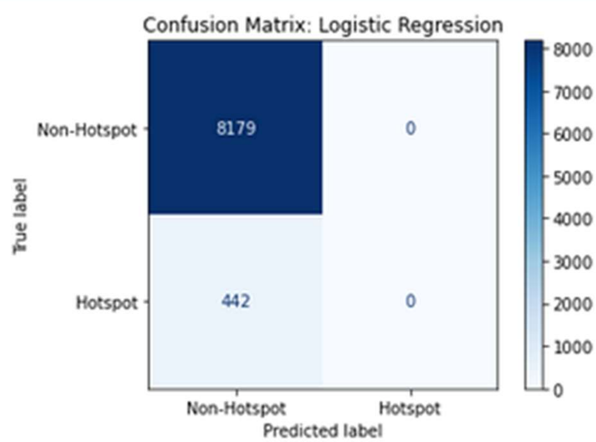
Model Evaluation

I implemented confusion matrix to see the performance of each model.

Summaries of each model:

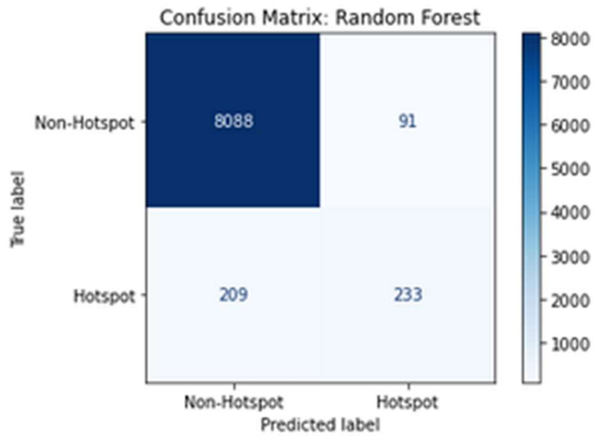
Logistic Regression

```
Results from model:  Logistic Regression
              precision    recall  f1-score   support

 Non-Hotspot       0.95      1.00      0.97      8179
     Hotspot       0.00      0.00      0.00       442

    accuracy                           0.95      8621
   macro avg       0.47      0.50      0.49      8621
weighted avg       0.90      0.95      0.92      8621

Accuracy: 0.949
Precision: 0.900
Recall: 0.949
F1 Score: 0.924
```



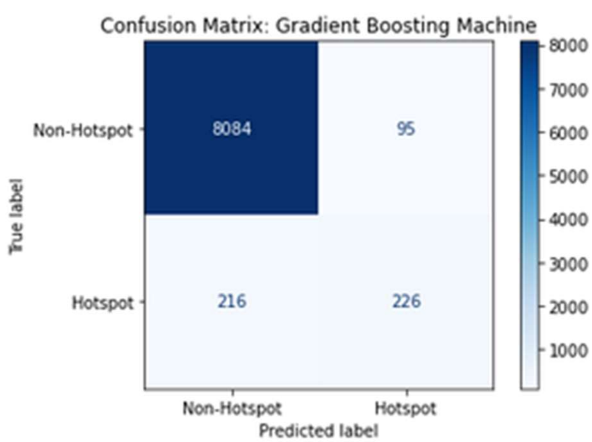
Random Forest

```
Results from model:  Random Forest
              precision    recall  f1-score   support

 Non-Hotspot       0.97      0.99      0.98      8179
     Hotspot       0.72      0.53      0.61       442

    accuracy                           0.97      8621
   macro avg       0.85      0.76      0.80      8621
weighted avg       0.96      0.97      0.96      8621

Accuracy: 0.965
Precision: 0.962
Recall: 0.965
F1 Score: 0.963
```



Gradient Boosting Machine

```
Results from model:  Gradient Boosting Machine
              precision    recall  f1-score   support

 Non-Hotspot       0.97      0.99      0.98      8179
     Hotspot       0.70      0.51      0.59       442

    accuracy                           0.96      8621
   macro avg       0.84      0.75      0.79      8621
weighted avg       0.96      0.96      0.96      8621

Accuracy: 0.964
Precision: 0.960
Recall: 0.964
F1 Score: 0.961
```



Model Recommendation:

After comparing the results of the Random Forest algorithm with other models, it has proven to be the most effective in predicting the hotspot status. It outperforms the other models, particularly in terms of overall accuracy and precision.

Accuracy: 96.5% overall accuracy indicates that the model is correctly predicting the hotspot status (either hotspot or not) for about 96.5% of the cases in the test set.

Class-Specific Performance:

Class 0 (non-hotspots):

Precision: 0.97 indicates that when the model predicts an area is not a hotspot, it is correct about 97% of the time.

Recall: 0.99 indicates that the model successfully identifies 99% of all actual non-hotspots.

F1-Score: 0.98 reflects balanced accuracy indicating excellent performance.

Class 1 (Hotspots):

Precision: 0.72 shows that when the model predicts an area as a hotspot, it is correct about 72% of the time.

Recall: 0.53 indicates that the model identifies 53% of all actual hotspots, suggesting areas for potential improvement.

F1-Score: 0.61 reflects fairly decent balanced accuracy concerning hotspot predictions.

Confusion Matrix Analysis

True Negatives (TN = 8088): Non-hotspots correctly identified.

False Positives (FP = 91): Non-hotspots incorrectly labeled as hotspots.

False Negatives (FN = 209): Hotspots missed by the model.

True Positives (TP = 233): Hotspots correctly identified.

The overall model's performance shows 96.5% accuracy, which indicates excellent overall performance, with particularly strong results in identifying non-hotspots. The performance metrics for hotspots, while lower, still provide a robust base for targeted improvements.

Conclusion

1. Data Preprocessing and Binning: Significant effort was devoted to preprocessing the data to render it suitable for analysis. This involved converting X and Y columns from UTM to WGS 84 latitude and longitude coordinates after extensive research. Additionally, I created spatial-temporal bins to reformat the raw accident data for machine learning

applications. Adjusting the sizes of these bins was crucial to accurately reflect the geographic density and distribution of accidents.

2. Feature Engineering: Beyond basic preprocessing, I enhanced the dataset with new features derived from the dtg_utc_diff datetime column. This enhancement was key in capturing more precise temporal patterns, which are essential for accurately predicting accident hotspots.

3. Exploratory Data Analysis (EDA): The exploratory analysis was geared towards understanding the distribution of accidents within the spatial-temporal bins. Determining the appropriate threshold for hotspot identification was the most significant for modeling building, as it shifted our approach from regression to binary classification. In this step, bins with accident counts surpassing this threshold were classified as hotspots.

4. Model Comparison and Evaluation: The performance of three predictive models—Logistic Regression, Random Forest, and Gradient Boosting Machine (GBM)—was evaluated. Logistic Regression served as a basic model, achieving moderate success and underscoring the potential of more complex models. The GBM excelled in capturing non-linear relationships and feature interactions. However, Random Forest emerged as the most effective, indicating a balance in detecting hotspot and non-hotspot classes and showing better performance metrics across precision, recall, F1-score, and accuracy.

Limitation and Recommendations for Future Work

1. Incorporate External Data (also the limitation): If resources are available, integrating additional data sources would potentially improve the overall model predictive power. These data sources include weather conditions, traffic volume, or holiday special events that can influence accident rates.

2. Spatial Features: Maybe we should consider more detailed geographic features such as proximity to schools, major intersections, or road work zones.

3. Model Enhancement: Experiment with deep learning approaches could potentially capture more complex patterns that those traditional models might miss.

4. Ensemble Techniques: Explore stacking or blending different models to leverage the strengths of each model. I tried DBSCAN for initial accidents clustering, but due to memory limitation it will not complete the task.

5. Real-time Testing: test the model in a real-time setting to validate its practical effectiveness in operational environments.

Recommendations for FPD Implementation

1. Strategic Resource Allocation: Use model predictions to dynamically allocate resources during high-risk times or in high-risk areas, ensuring that patrols and emergency response teams are more effectively distributed.
2. Preventive Measures: Implement preventive measures such as traffic lights, speed bumps, or signs in areas frequently predicted as hotspots.
3. Community Engagement: Launch community awareness campaigns about high-risk areas and times, educating the public on safe driving practices.
4. Infrastructure Adjustments: prioritized infrastructure upgrades in identified hotspots, such as improving road lighting, signage, and surface conditions.
5. Continuous Monitoring and Feedback: Feedback System: Establish a feedback loop with patrol officers and emergency responders to continually refine the hotspot predictions based on ground realities. Ongoing Evaluation: Regularly evaluate the impact of deployed measures and model-based deployments on accident rates and resource utilization.