YifanWu_0006_submission

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1 Predicting Road Traffic Accident Severity in London Using Machine Learning and Spatial Network Features

[1]:
```
%load_ext watermark
%watermark -a "Yifan Wu" -u -d -t -v -p numpy,pandas,matplotlib,scikit-learn
```

```
Author: Yifan Wu

Last updated: 2025-04-21 14:34:50

Python implementation: CPython
Python version       : 3.13.2
IPython version      : 9.0.2

numpy       : 2.2.4
pandas      : 2.2.3
matplotlib  : 3.10.1
scikit-learn: 1.6.1
```

1.1 Preparation

- Github link
- Number of words: 1463
- Runtime: about 1 hour (*Memory 32 GB, CPU AMD Ryzen 7 5800H with Radeon Graphics CPU @3.20GHz*)
- Coding environment: Coding environment: VS Code with Jupyter plugin (local), not SDS Docker
- License: this notebook is made available under the Creative Commons Attribution license.
- Additional library *[libraries not included in SDS Docker or not used in this module]*:
  - **watermark**: A Jupyter Notebook extension for printing timestamps, version numbers, and hardware information.(used to print Python and package versions for reproducibility.)
  - **osmnx**: For downloading and analyzing OpenStreetMap road network data.

- **networkx**: For calculating road network metrics such as betweenness and degree centrality.
- **geopandas**: For spatial data handling, including reading GeoJSON borough boundaries.
- **shap**: For model interpretability using SHAP value analysis.
- **xgboost**: For gradient boosting machine learning classification.
- **tqdm**: For displaying progress bars during borough-level computations.

1.2 Table of contents

1.3 Introduction

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Road traffic accidents (RTAs) pose major challenges to public health and urban governance. In the UK, thousands are injured or killed annually, despite improvements in vehicle technology and traffic enforcement. Accurate prediction of accident severity is vital for targeted interventions and infrastructure planning. Severity outcomes are influenced by contextual factors such as weather, road geometry, traffic volume, time of day, and infrastructure design (Abdel-Aty & Haleem, 2011). With the shift toward data-driven governance, machine learning has become a valuable tool in road safety research, offering more nuanced and interpretable models (Ahmed et al., 2023).

Recent studies have validated the use of supervised learning algorithms like logistic regression, random forests, and XGBoost in predicting accident severity from structured datasets. These models handle non-linear and heterogeneous relationships well. Additionally, explainable AI methods such as SHAP (SHapley Additive exPlanations) allow interpretation of feature importance, aiding the translation of model insights into policy actions.

This study uses the UK Department for Transport's Road Safety Data (2015–2019), enriched with spatial metrics like road betweenness and degree centrality derived from OpenStreetMap. The goal is to assess machine learning performance in predicting severity and to explore the relative contributions of spatial and contextual factors.

The 2015–2019 period ensures data stability, avoiding disruptions from the COVID-19 pandemic and major infrastructure shifts starting in 2020 (DfT, 2021; TfL, 2024). Unlike earlier policy-introduction phases (DfT, 2013), this timeframe reflects mature system conditions, allowing for clearer interpretation.

By integrating spatial topology with traditional features, this project bridges predictive modeling and network analysis, enhancing our understanding of how urban structure affects accident severity.

1.4 Research questions

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Can supervised machine learning models accurately predict the severity of road traffic accidents in London using spatial, temporal, and environmental features?

This project explores whether supervised machine learning models can accurately predict the severity of road traffic accidents in London based on spatial, temporal, and environmental features. Specifically, it evaluates the contribution of variables such as time of day, weather conditions, and road network centrality. The study compares the performance of Logistic Regression, Random Forest, and XGBoost classifiers, and employs SHAP (SHapley Additive exPlanations) to interpret model outputs and quantify feature importance across different severity levels (fatal, serious, slight).

1.5 Data

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1.5.1 Data Description

Variable	Type	Description	Notes
accident_severity	Categorical	Severity level (1 = Fatal, 2 = Serious, 3 = Slight)	Target variable
speed_limit| `Numeric | Speed limit of the road segment (mph) | - | | accident_year`	Numeric	Year of the accident	Used for train-test split
mean_betweenness / max_betweenness	Numeric	Betweenness centrality of road network	Spatial network feature
mean_degree / max_degree	Numeric	Degree centrality of network nodes	–
edge_count	Numeric	Number of nearby road edges	Indicator of network density
time_hour	Numeric	Hour of the accident (0–23)	Derived feature
*_encoded categorical features	Categorical	One-hot encoded variables: day, weather, road type, etc.	One-hot encoded
betweenness_level_encoded	Ordinal	Quartile level of mean betweenness (0 = Low, 3 = High)	For logistic regression compatibility
……	……	……	

> *Note:* _encoded includes all one-hot encoded features (e.g., weather, light, junction type, road class, area type).*

The following table provides code-level descriptions for categorical variables used in this study. Definitions are based on the official UK Department for Transport data guide: data.gov.uk.

Variable Prefix	Code	Meaning
day_of_week	1	Sunday
	2	Monday
	3	Tuesday
	4	Wednesday
	5	Thursday
	6	Friday
	7	Saturday
road_type	1	Roundabout
	2	One way street
	3	Dual carriageway
	6	Single carriageway
	7	Slip road
	9	Unknown
light_conditions	1	Daylight
	4	Darkness - lights lit
	5	Darkness - lights unlit
	6	Darkness - no lighting
	7	Darkness - lighting unknown
weather_conditions	1	Fine no high winds
	2	Raining no high winds
	3	Snowing no high winds
	4	Fine + high winds
	5	Raining + high winds
	6	Snowing + high winds
	7	Fog or mist
	8	Other
	9	Unknown
road_surface_conditions	1	Dry
	2	Wet or damp
	3	Snow
	4	Frost or ice
	5	Flood (surface water)
	9	Unknown
junction_control	0	None
	1	Authorised person
	2	Auto traffic signal
	3	Stop sign
	4	Give way or uncontrolled
	9	Unknown
pedestrian_crossing_human_control	0	None
	1	School crossing patrol
	2	Other human control
	9	Unknown
pedestrian_crossing_physical_facilities	0	None
	1	Zebra crossing
	4	Pelican crossing

Variable Prefix	Code	Meaning
	5	Footbridge or subway
	7	Refuge
	8	Unknown
	9	Other
urban_or_rural_area	1	Not used
	2	Urban
	3	Rural
trunk_road_flag	1	Non-trunk road
	2	Trunk road
first_road_class / second_road_class	1	Motorway
	2	A(M) Road
	3	A Road
	4	B Road
	5	C Road
	6	Unclassified

1.5.2 Data Import & Cleaning

[2]:
```python
# It would import the packages that would be used first.
import pandas as pd
import os
import osmnx as ox
import networkx as nx
import geopandas as gpd
from tqdm import tqdm
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix
import re
from collections import defaultdict
import shap
```

```
e:\Software\Study\python-3.13.2\Lib\site-packages\tqdm\auto.py:21: TqdmWarning:
IProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

[3]:
```
# define folder
input_folder = '../data/raw'
output_folder = '../data/clean'
```

[4]:
```
# Road Data
df = pd.read_csv('../data/raw/
↪dft-road-casualty-statistics-collision-1979-latest-published-year.csv')
df = df[df['accident_year'].isin([2015, 2016, 2017, 2018, 2019])]
print(f"The data volume from 2015 to 2019 is:{len(df)} ")

# save
df.to_csv("../data/raw/2015_2019.csv", index=False)
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_5832\2199723819.py:2: DtypeWarning:
Columns (0,2,15,16,35) have mixed types. Specify dtype option on import or set
low_memory=False.
  df = pd.read_csv('../data/raw/dft-road-casualty-statistics-
collision-1979-latest-published-year.csv')
```

```
The data volume from 2015 to 2019 is:646830
```

[5]:
```
columns_to_keep = [
    'accident_severity',
    'number_of_vehicles',
    'number_of_casualties',
    'day_of_week',
    'time',
    'first_road_class',
    'second_road_class',
    'road_type',
    'speed_limit',
    'junction_detail',
    'junction_control',
    'pedestrian_crossing_human_control',
    'pedestrian_crossing_physical_facilities',
    'light_conditions',
    'weather_conditions',
    'road_surface_conditions',
    'special_conditions_at_site',
    'carriageway_hazards',
    'urban_or_rural_area',
    'did_police_officer_attend_scene_of_accident',
    'trunk_road_flag',
    'local_authority_ons_district',
    'accident_year'
]

selected_columns = [col for col in columns_to_keep if col in df.columns]
```

```
df_cleaned = df[selected_columns]

# Check and handle the missing values
missing_counts = df_cleaned.isnull().sum()
total_missing = missing_counts.sum()

if total_missing > 0:
    print(f"The number of missing values are {total_missing} :")
    print(missing_counts[missing_counts > 0])

    # Discard the rows containing missing values
    df_cleaned = df_cleaned.dropna()
    print(f"Missing values have been cleared, remaining {len(df_cleaned)}␣
↪records.")

# Save the cleaned files
df_cleaned.to_csv('../data/clean/1519_cleaned.csv', index=False)
print(f"Saved to: {output_folder}, total: {len(df_cleaned.columns)} columns,␣
↪{len(df_cleaned)} records.")
```

```
The number of missing values are 37 :
speed_limit    37
dtype: int64
Missing values have been cleared, remaining 646793 records.
Saved to: ../data/clean, total: 23 columns, 646793 records.
```

1.5.3 Spatial Feature Engineering

This step extracts borough-level road networks from OpenStreetMap and calculates betweenness and degree centrality to capture spatial structure in the transport network.

[6]:
```
# RoadCentrality
path = "../data/Borough_Boundaries.geojson"
boroughs = gpd.read_file(path)
boroughs = boroughs[["name", "gss_code", "geometry"]].rename(columns={"name":␣
↪"borough"})

ox.settings.log_console = False
ox.settings.use_cache = True

results = []

for idx, row in tqdm(boroughs.iterrows(), total=len(boroughs), desc="Processing␣
↪boroughs"):
    borough_name = row["borough"]
    gss_name = row["gss_code"]
    geometry = row["geometry"]
```

```
    try:
        print(f"Processing: {borough_name}")

        G = ox.graph_from_polygon(geometry, network_type="drive", simplify=True)

        betweenness = nx.betweenness_centrality(G, weight="length", k=100,␣
↪seed=42)
        degree = dict(G.degree())
        nx.set_node_attributes(G, betweenness, "betweenness")
        nx.set_node_attributes(G, degree, "degree")

        edge_data = []
        for u, v, key, data in G.edges(keys=True, data=True):
            edge_data.append({
                "u": u,
                "v": v,
                "key": key,
                "geometry": data.get("geometry", None),
                "betweenness": (G.nodes[u]["betweenness"] + G.
↪nodes[v]["betweenness"]) / 2,
                "degree": (G.nodes[u]["degree"] + G.nodes[v]["degree"]) / 2
            })
        edges_df = gpd.GeoDataFrame(edge_data, geometry="geometry", crs="EPSG:
↪4326")

        summary = {
            "borough": borough_name,
            "gss_code": gss_name,
            "mean_betweenness": edges_df["betweenness"].mean(),
            "max_betweenness": edges_df["betweenness"].max(),
            "mean_degree": edges_df["degree"].mean(),
            "max_degree": edges_df["degree"].max(),
            "edge_count": len(edges_df)
        }
        results.append(summary)

    except Exception as e:
        print(f"Failed for {borough_name}: {e}")
        continue

df_results = pd.DataFrame(results)
df_results.to_csv("../data/london_borough_road_centrality.csv", index=False)
print("All done! Results saved to 'london_borough_road_centrality.csv'")
```

```
Processing boroughs:   0%|          | 0/33 [00:00<?, ?it/s]

Processing: Kingston upon Thames
```

```
Processing boroughs:   3%|          | 1/33 [00:05<03:03,  5.73s/it]
Processing: Croydon
Processing boroughs:   6%|          | 2/33 [00:19<05:30, 10.67s/it]
Processing: Bromley
Processing boroughs:   9%|          | 3/33 [00:33<06:06, 12.21s/it]
Processing: Hounslow
Processing boroughs:  12%|          | 4/33 [00:42<05:11, 10.75s/it]
Processing: Ealing
Processing boroughs:  15%|          | 5/33 [00:50<04:38,  9.95s/it]
Processing: Havering
Processing boroughs:  18%|          | 6/33 [00:59<04:13,  9.40s/it]
Processing: Hillingdon
Processing boroughs:  21%|          | 7/33 [01:11<04:25, 10.19s/it]
Processing: Harrow
Processing boroughs:  24%|          | 8/33 [01:17<03:44,  8.97s/it]
Processing: Brent
Processing boroughs:  27%|          | 9/33 [01:24<03:20,  8.35s/it]
Processing: Barnet
Processing boroughs:  30%|          | 10/33 [01:35<03:32,  9.23s/it]
Processing: Lambeth
Processing boroughs:  33%|          | 11/33 [01:46<03:36,  9.85s/it]
Processing: Southwark
Processing boroughs:  36%|          | 12/33 [01:58<03:36, 10.30s/it]
Processing: Lewisham
Processing boroughs:  39%|          | 13/33 [02:06<03:13,  9.67s/it]
Processing: Greenwich
Processing boroughs:  42%|          | 14/33 [02:16<03:04,  9.71s/it]
Processing: Bexley
Processing boroughs:  45%|          | 15/33 [02:24<02:46,  9.25s/it]
Processing: Enfield
Processing boroughs:  48%|          | 16/33 [02:33<02:38,  9.31s/it]
Processing: Waltham Forest
```

```
Processing boroughs:  52%|       | 17/33 [02:40<02:15,  8.48s/it]
Processing: Redbridge
Processing boroughs:  55%|       | 18/33 [02:47<02:02,  8.19s/it]
Processing: Sutton
Processing boroughs:  58%|       | 19/33 [02:54<01:47,  7.66s/it]
Processing: Richmond upon Thames
Processing boroughs:  61%|       | 20/33 [03:01<01:38,  7.56s/it]
Processing: Merton
Processing boroughs:  64%|      | 21/33 [03:07<01:26,  7.18s/it]
Processing: Wandsworth
Processing boroughs:  67%|      | 22/33 [03:16<01:23,  7.55s/it]
Processing: Hammersmith and Fulham
Processing boroughs:  70%|      | 23/33 [03:20<01:03,  6.40s/it]
Processing: Kensington and Chelsea
Processing boroughs:  73%|      | 24/33 [03:23<00:49,  5.50s/it]
Processing: Westminster
Processing boroughs:  76%|      | 25/33 [03:30<00:46,  5.84s/it]
Processing: Camden
Processing boroughs:  79%|      | 26/33 [03:35<00:39,  5.71s/it]
Processing: Tower Hamlets
Processing boroughs:  82%|     | 27/33 [03:41<00:35,  5.88s/it]
Processing: Islington
Processing boroughs:  85%|     | 28/33 [03:46<00:27,  5.58s/it]
Processing: Hackney
Processing boroughs:  88%|     | 29/33 [03:51<00:21,  5.48s/it]
Processing: Haringey
Processing boroughs:  91%|     | 30/33 [03:57<00:16,  5.56s/it]
Processing: Newham
Processing boroughs:  94%|    | 31/33 [04:05<00:12,  6.33s/it]
Processing: Barking and Dagenham
Processing boroughs:  97%|    | 32/33 [04:10<00:05,  5.94s/it]
Processing: City of London
```

```
Processing boroughs: 100%|      | 33/33 [04:12<00:00,  7.66s/it]

All done! Results saved to 'london_borough_road_centrality.csv'
```

[7]:
```python
# show
print("Sample of calculated borough-level centrality metrics:")
display(df_results.head())

# Display descriptive statistical information
print("\nSummary statistics of centrality metrics across boroughs:")
display(df_results[['mean_betweenness', 'mean_degree']].describe())
```

```
Sample of calculated borough-level centrality metrics:

              borough   gss_code  mean_betweenness  max_betweenness  \
0  Kingston upon Thames  E09000021          0.020622         0.261008
1               Croydon  E09000008          0.012210         0.177637
2               Bromley  E09000006          0.012135         0.172504
3              Hounslow  E09000018          0.018356         0.335207
4                Ealing  E09000009          0.015021         0.212142

   mean_degree  max_degree  edge_count
0     5.271409         8.0        6551
1     5.383993         8.0       14719
2     5.425875         8.0       15737
3     5.247866         8.0       10308
4     5.418720         8.0       10919


Summary statistics of centrality metrics across boroughs:

       mean_betweenness  mean_degree
count         33.000000    33.000000
mean           0.017935     5.334289
std            0.005285     0.172943
min            0.012135     4.583688
25%            0.014089     5.271409
50%            0.016811     5.369130
75%            0.020230     5.418720
max            0.038161     5.602621
```

1.5.4 Data Merge & Summary

[8]:
```python
# Set the path
accident_path = "../data/clean/1519_cleaned.csv"
centrality_path = "../data/london_borough_road_centrality.csv"
output_path = "../data/final/2015_2019_with_centrality.csv"
```

```python
df_accident = pd.read_csv(accident_path)
df_centrality = pd.read_csv(centrality_path)

# Merge the centrality data (encoded by region)
df_merged = df_accident.merge(
    df_centrality,
    how="left",
    left_on="local_authority_ons_district",
    right_on="gss_code"
)

# Delete the rows lacking centrality (non-London area)
before_drop = len(df_merged)
df_merged = df_merged.dropna(subset=["mean_betweenness"])
after_drop = len(df_merged)
dropped = before_drop - after_drop

# Save the result
df_merged.to_csv(output_path, index=False)

print(f"The data has been combined with the centrality indicators and saved␣
 ↪to {output_path}")
print(f"Total: {after_drop} records, remove {dropped} records.")
```

```
The data has been combined with the centrality indicators and saved
to ../data/final/2015_2019_with_centrality.csv
Total: 128261 records, remove 518532 records.
```

1.5.5 Exploratory Data Analysis (EDA)

Descriptive statistics (distribution maps, box plots, etc.)

[9]:
```python
df = pd.read_csv("../data/final/2015_2019_with_centrality.csv")

print(df.shape)
print(df.dtypes)
print(df.isnull().sum())
df.describe()
df["accident_severity"].value_counts(normalize=True)
```

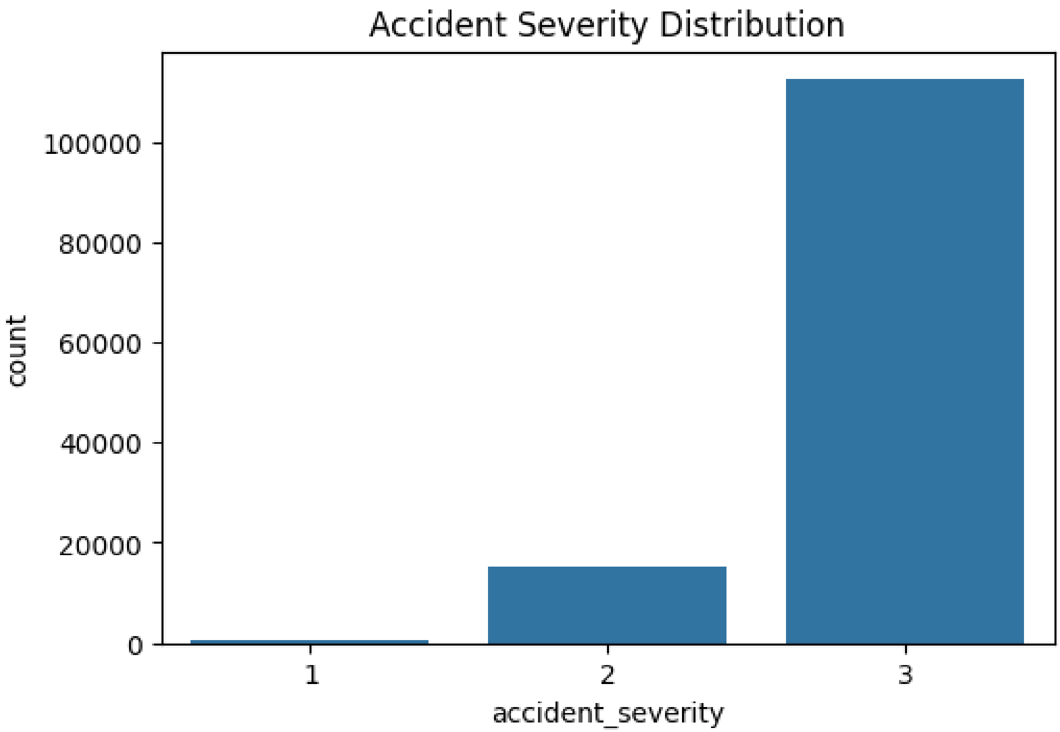
```
(128261, 30)
accident_severity                                 int64
number_of_vehicles                                int64
number_of_casualties                              int64
day_of_week                                       int64
time                                             object
first_road_class                                  int64
second_road_class                                 int64
road_type                                         int64
```

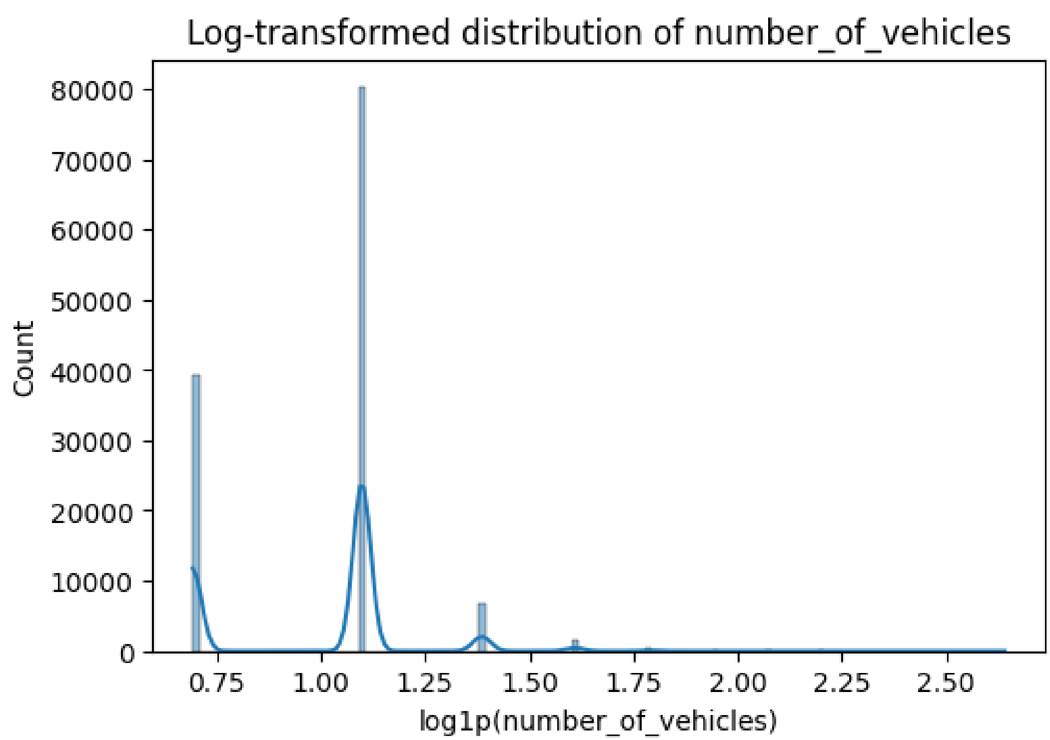
```
speed_limit                                   float64
junction_detail                                 int64
junction_control                                int64
pedestrian_crossing_human_control               int64
pedestrian_crossing_physical_facilities         int64
light_conditions                                int64
weather_conditions                              int64
road_surface_conditions                         int64
special_conditions_at_site                      int64
carriageway_hazards                             int64
urban_or_rural_area                             int64
did_police_officer_attend_scene_of_accident     int64
trunk_road_flag                                 int64
local_authority_ons_district                   object
accident_year                                   int64
borough                                        object
gss_code                                       object
mean_betweenness                              float64
max_betweenness                               float64
mean_degree                                   float64
max_degree                                    float64
edge_count                                    float64
dtype: object
accident_severity                             0
number_of_vehicles                            0
number_of_casualties                          0
day_of_week                                   0
time                                          0
first_road_class                              0
second_road_class                             0
road_type                                     0
speed_limit                                   0
junction_detail                               0
junction_control                              0
pedestrian_crossing_human_control             0
pedestrian_crossing_physical_facilities       0
light_conditions                              0
weather_conditions                            0
road_surface_conditions                       0
special_conditions_at_site                    0
carriageway_hazards                           0
urban_or_rural_area                           0
did_police_officer_attend_scene_of_accident   0
trunk_road_flag                               0
local_authority_ons_district                  0
accident_year                                 0
borough                                       0
gss_code                                      0
```

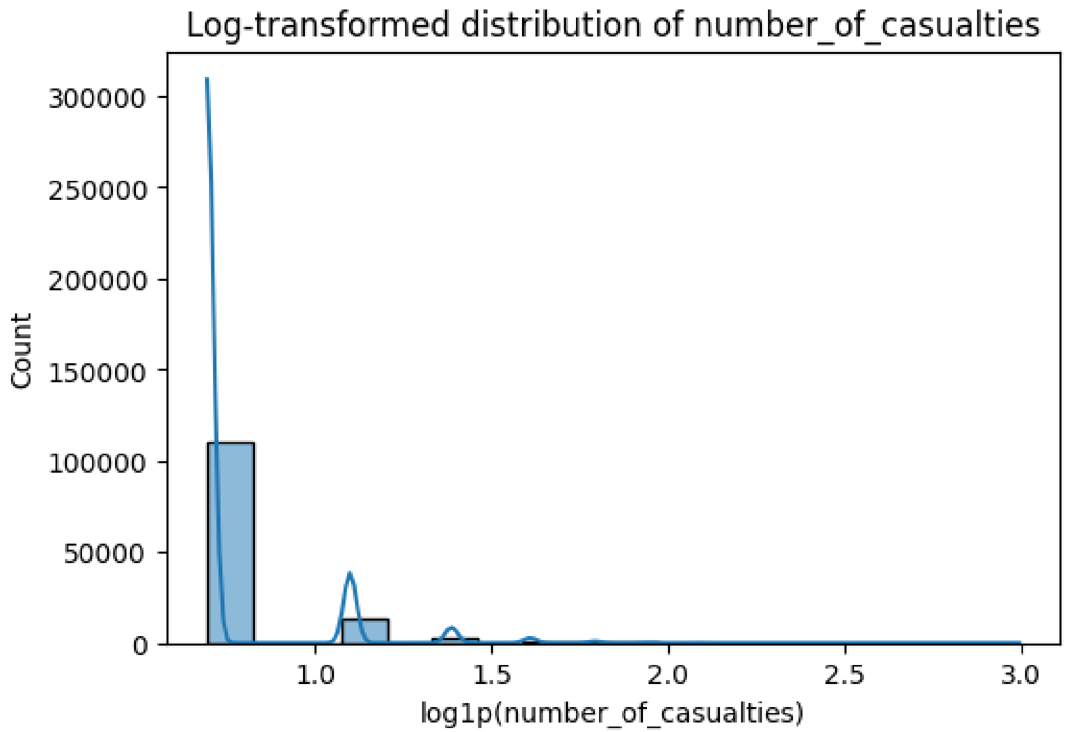
```
mean_betweenness                              0
max_betweenness                               0
mean_degree                                   0
max_degree                                    0
edge_count                                    0
dtype: int64
```

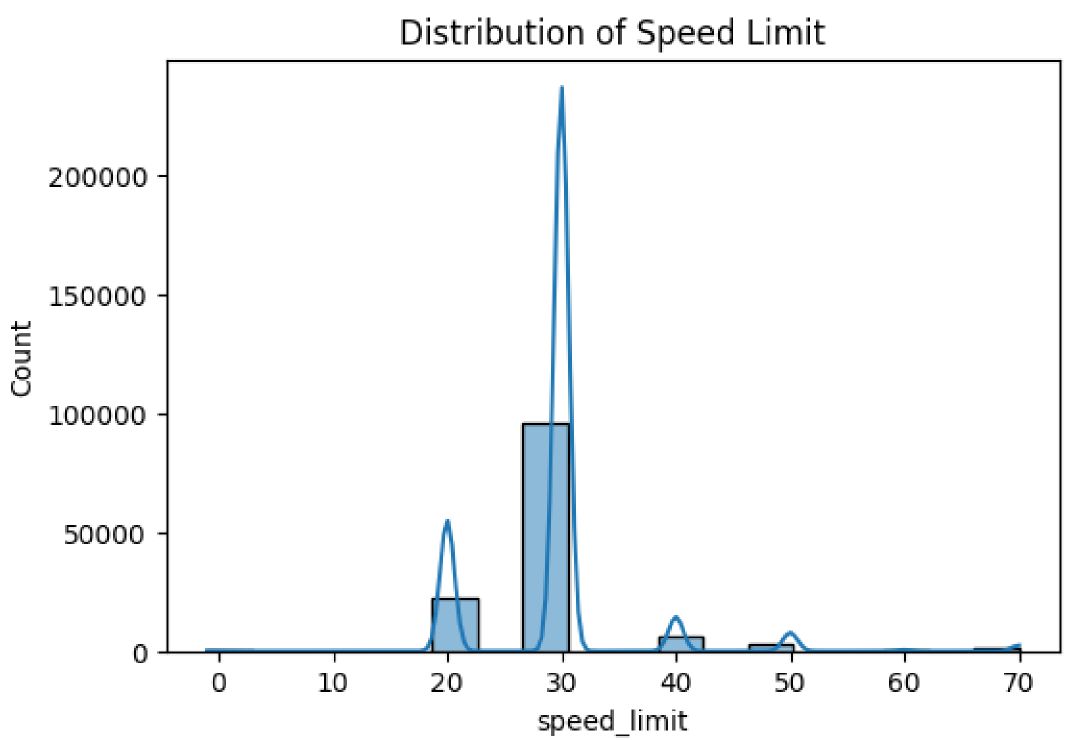
[9]:
```
accident_severity
3    0.876089
2    0.119179
1    0.004733
Name: proportion, dtype: float64
```

[10]:
```python
# Distribution of accident severity
plt.figure(figsize=(6,4))
sns.countplot(x="accident_severity", data=df)
plt.title("Accident Severity Distribution")
plt.show()

# Numerical type: Number of vehicles, number of casualties, speed limit
for col in ["number_of_vehicles", "number_of_casualties"]:
    plt.figure(figsize=(6, 4))
    sns.histplot(np.log1p(df[col]), kde=True)
    plt.title(f"Log-transformed distribution of {col}")
    plt.xlabel(f"log1p({col})")
    plt.ylabel("Count")
    plt.show()

plt.figure(figsize=(6, 4))
sns.histplot(df["speed_limit"], kde=True)
plt.title("Distribution of Speed Limit")
plt.xlabel("speed_limit")
plt.ylabel("Count")
plt.show()
```


Accident Severity Distribution
100000
80000
60000
40000
20000
0
count
1
2
3
accident_severity


Log-transformed distribution of number_of_vehicles
80000
70000
60000
50000
40000
30000
20000
10000
0
Count
0.75
1.00
1.25
1.50
1.75
2.00
2.25
2.50
log1p(number_of_vehicles)


Log-transformed distribution of number_of_casualties
Count
300000
250000
200000
150000
100000
50000
0
1.0
1.5
2.0
2.5
3.0
log1p(number_of_casualties)

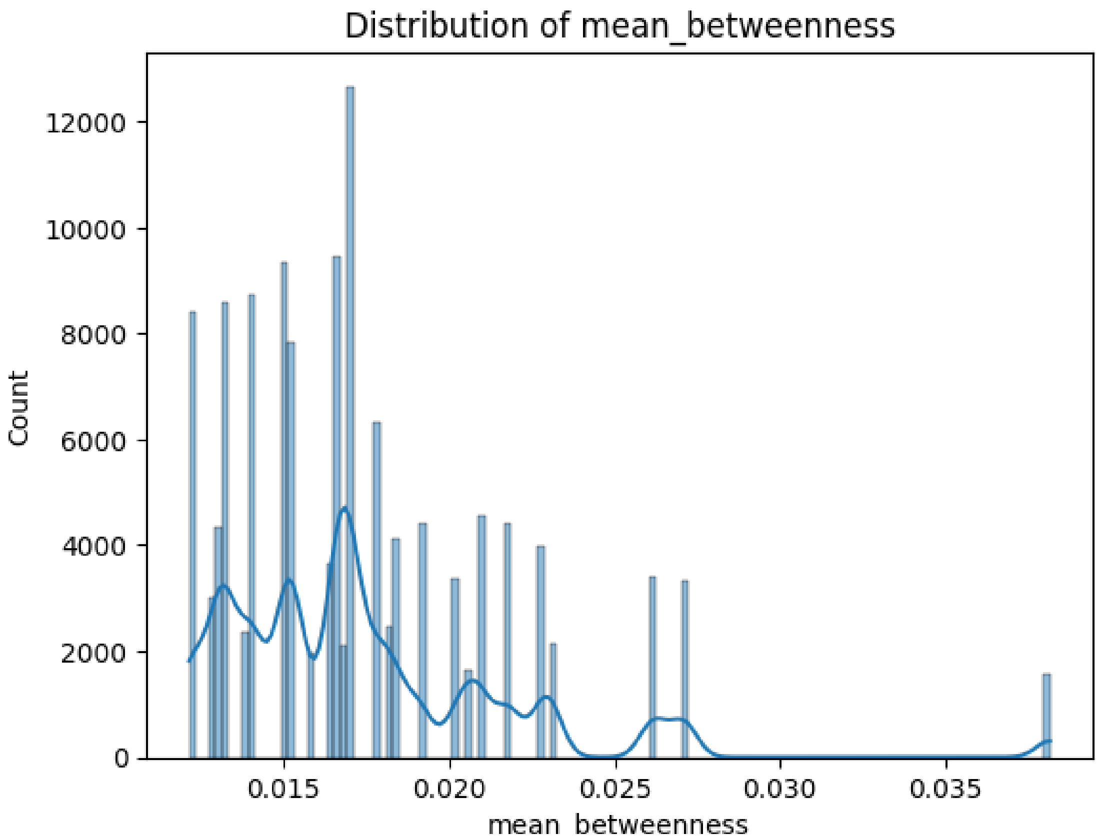

Distribution of Speed Limit
Count
200000
150000
100000
50000
0
0
10
20
30
40
50
60
70
speed_limit

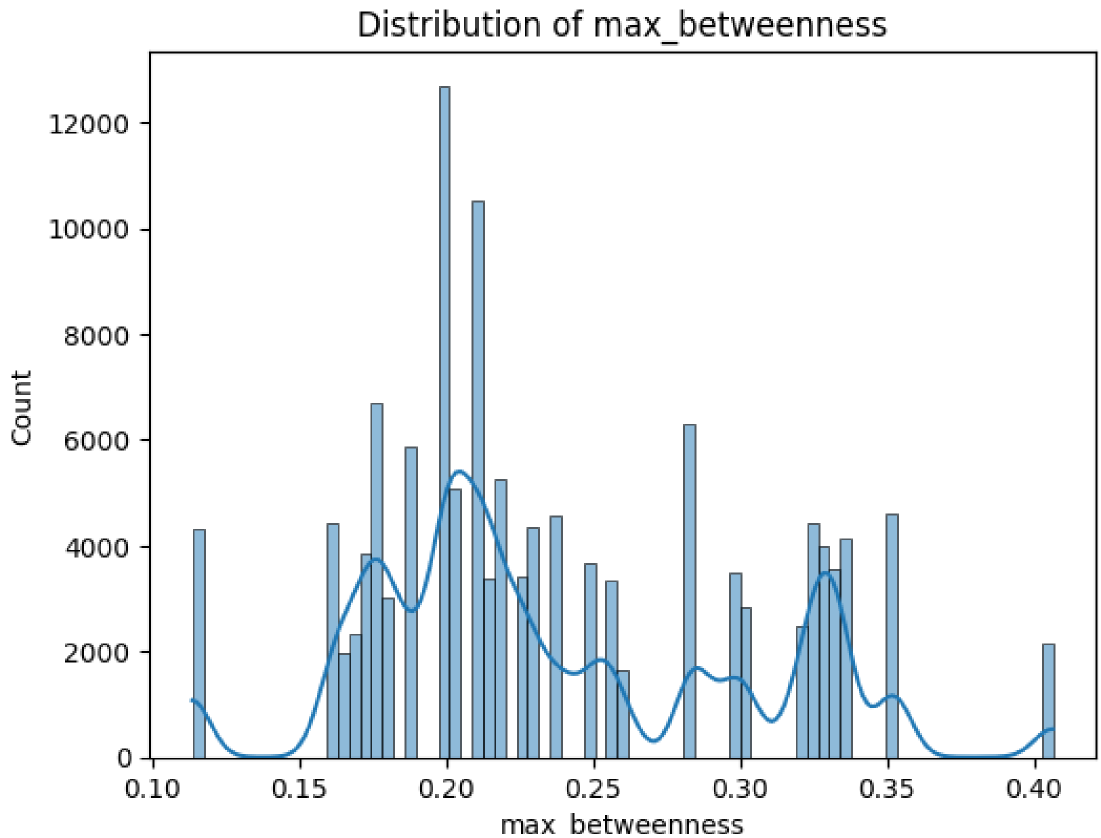
Accident severity is highly imbalanced, with most cases being slight and very few fatal.

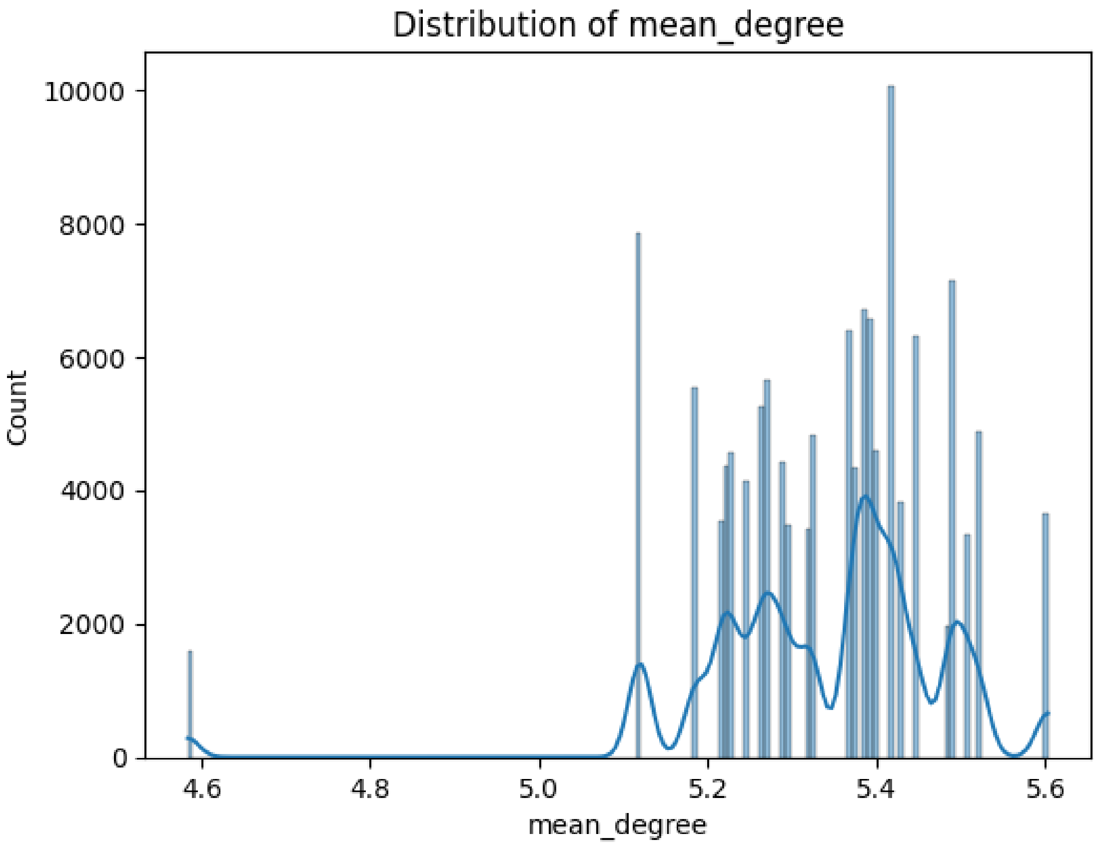
Number of vehicles and casualties are right-skewed, so log transformation was applied.

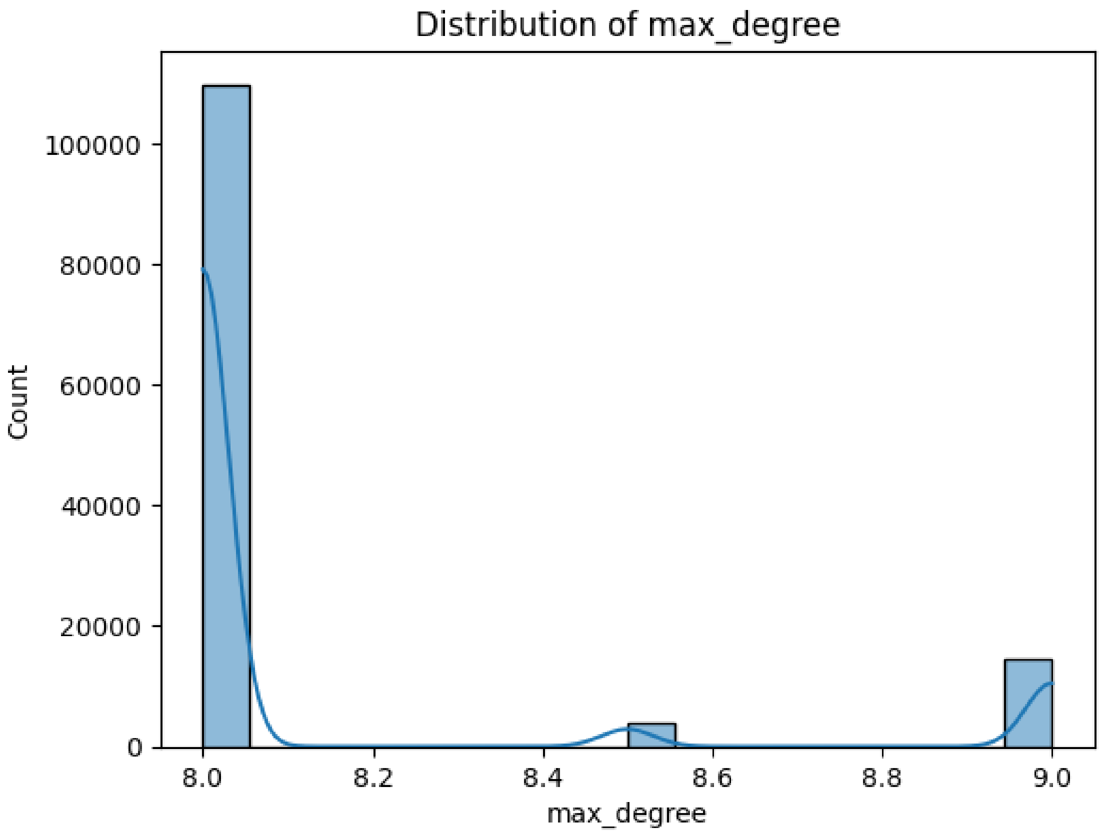
Speed limit mostly centers around 30 mph, reflecting typical urban road conditions.

[11]:
```
# Central variable distribution (single variable + null value check)
for col in ["mean_betweenness", "max_betweenness", "mean_degree", "max_degree"]:
    sns.histplot(df[col].dropna(), kde=True)
    plt.title(f"Distribution of {col}")
    plt.show()
```




Distribution of max_betweenness
Count
max_betweenness
0
2000
4000
6000
8000
10000
12000
0.10
0.15
0.20
0.25
0.30
0.35
0.40


Distribution of mean_degree
Count
10000
8000
6000
4000
2000
0
4.6
4.8
5.0
5.2
5.4
5.6
mean_degree

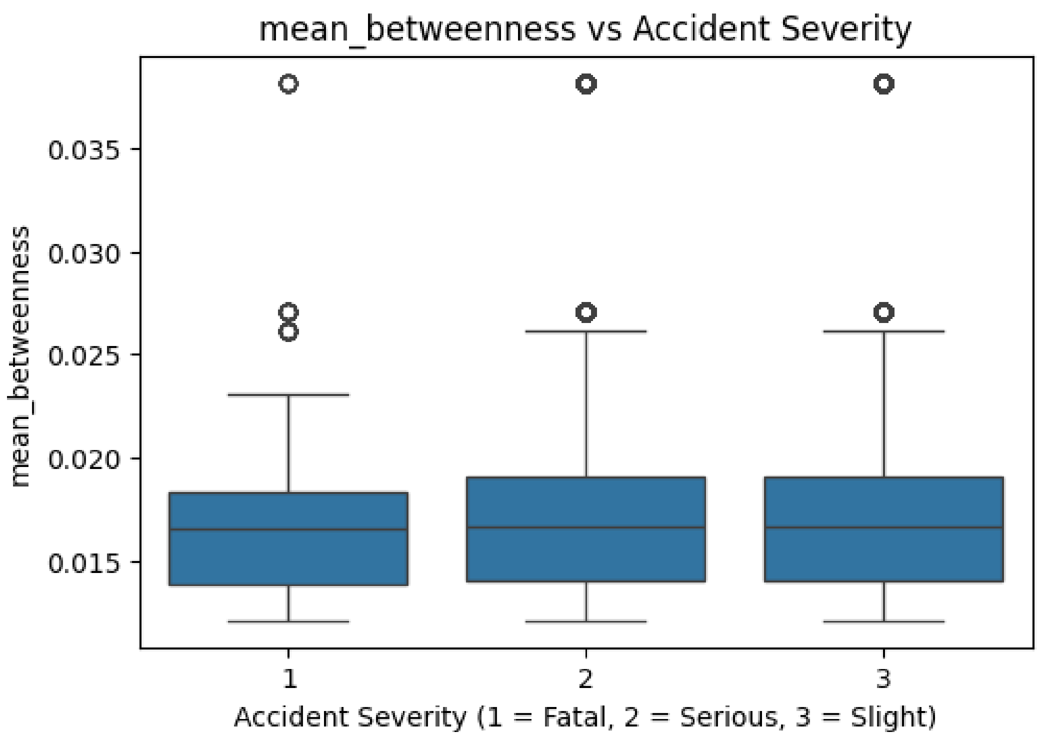


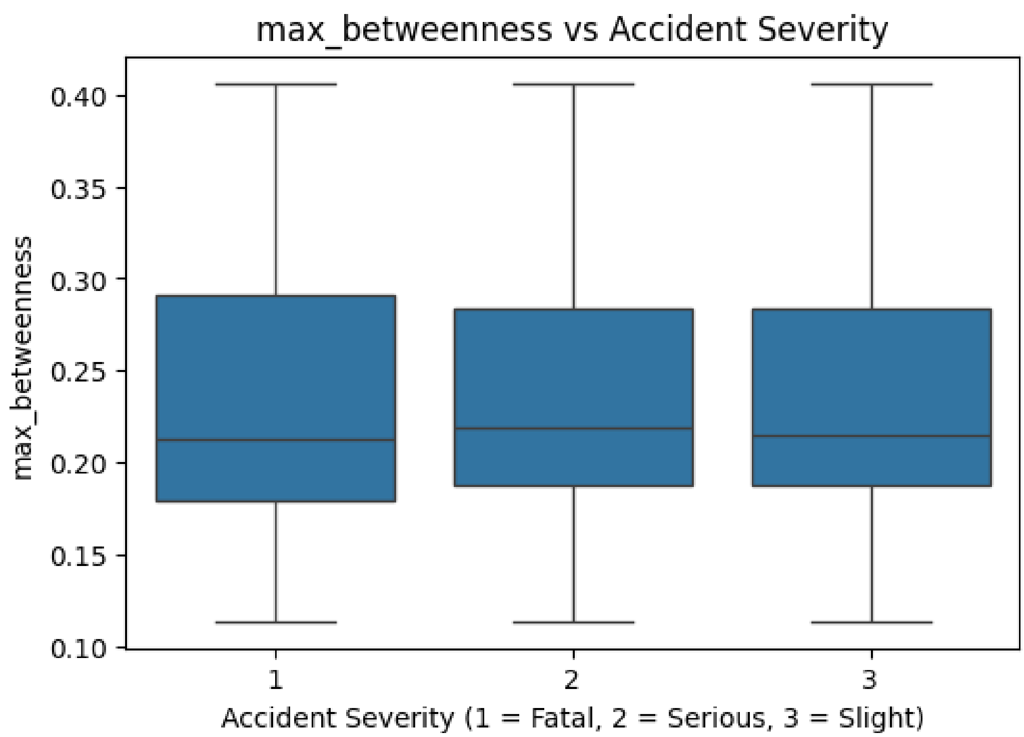
The distributions of road network centrality features show distinct patterns. Mean betweenness is right-skewed, with most values concentrated below 0.02, while max betweenness displays a broader and more uniform spread, indicating variability across locations. Mean degree is tightly clustered around 5.3, suggesting consistent connectivity across nodes. In contrast, max degree is highly concentrated at 8, with only a few high-end outliers.

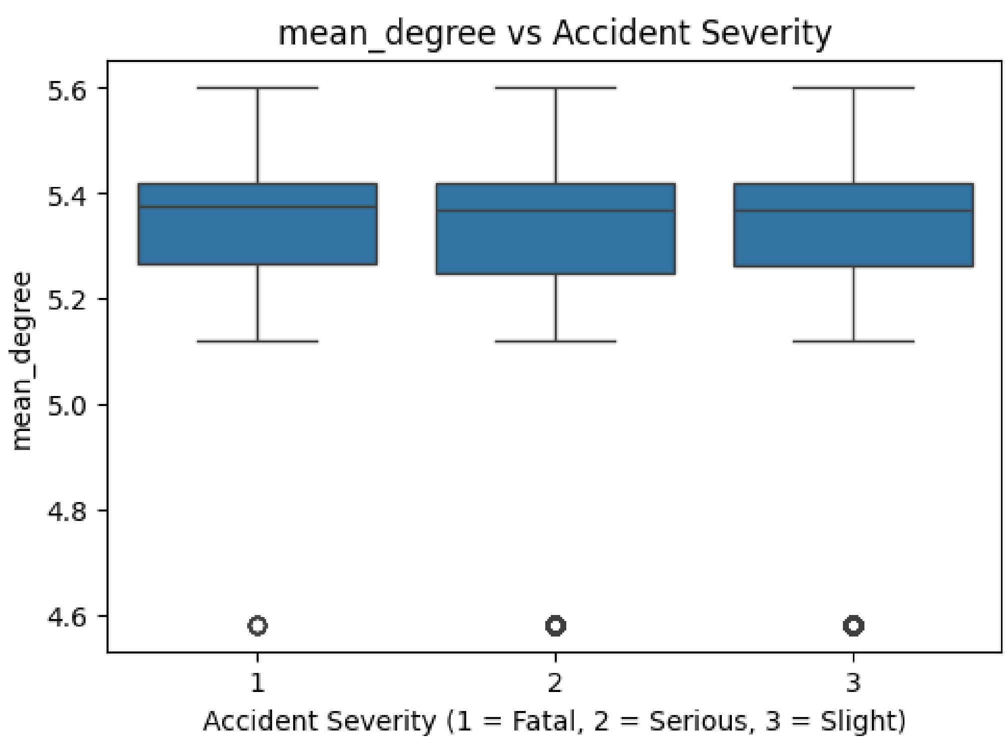
Exploration of the Relationship between Features and Targets (including grouped bar charts and box plots)

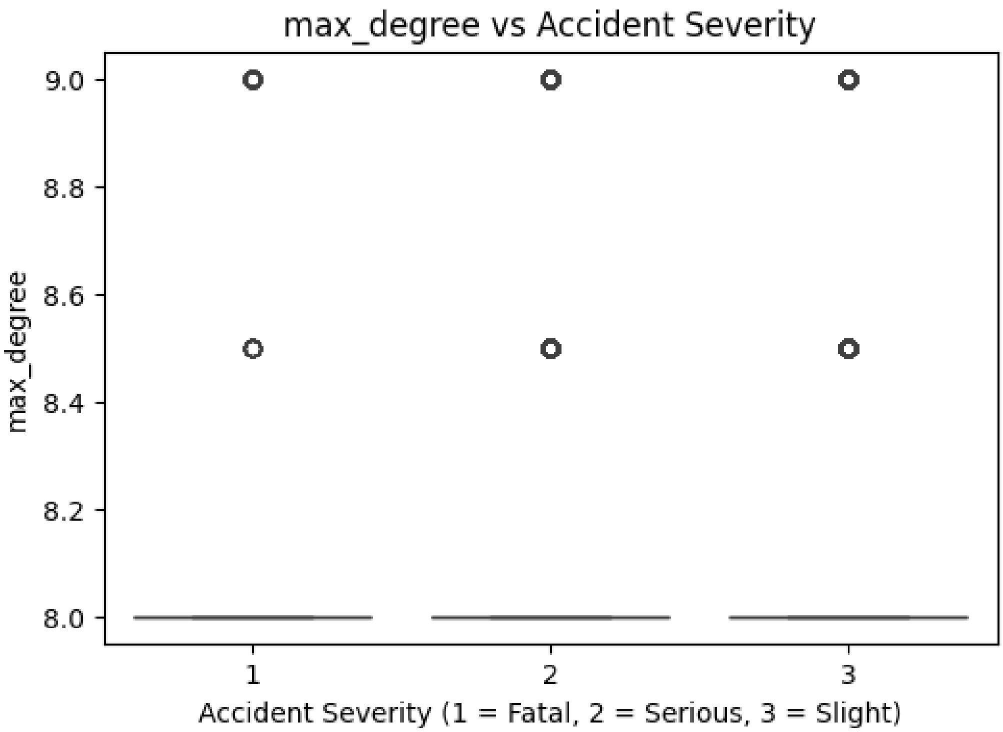
[12]:
```
# The relationship between Variables and the severity of accidents (bivariate␣
↪Analysis)
for col in ["mean_betweenness", "max_betweenness", "mean_degree", "max_degree"]:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x="accident_severity", y=col, data=df)
    plt.title(f"{col} vs Accident Severity")
    plt.xlabel("Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)")
    plt.ylabel(col)
    plt.show()

# Divide mean_betweenness into four grades (quartiles)
```

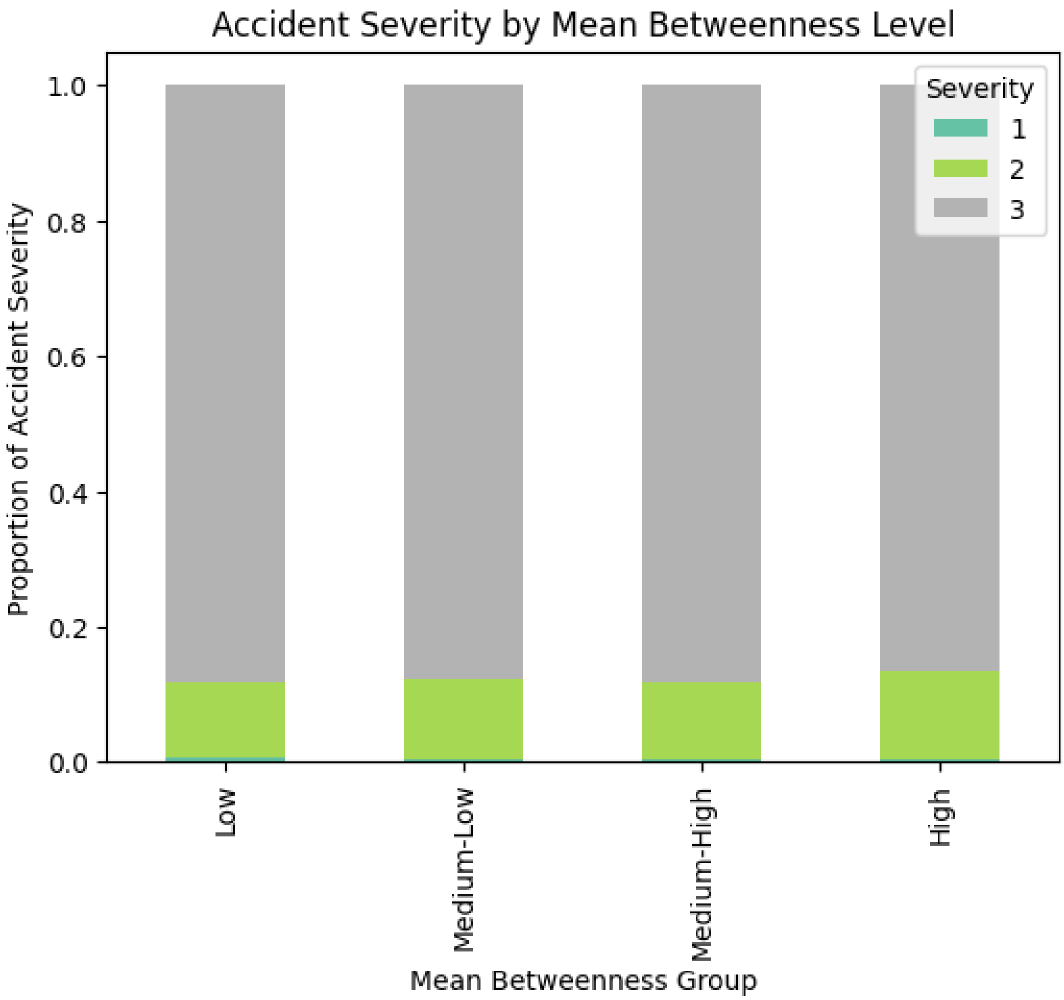
```python
df["betweenness_level"] = pd.qcut(df["mean_betweenness"], q=4, labels=["Low",
    "Medium-Low", "Medium-High", "High"])

# Check the proportion of accident severity in each group
severity_by_level = pd.crosstab(df["betweenness_level"],
    df["accident_severity"], normalize='index')

# Draw a grouped stacked bar chart
severity_by_level.plot(kind="bar", stacked=True, colormap="Set2")
plt.title("Accident Severity by Mean Betweenness Level")
plt.xlabel("Mean Betweenness Group")
plt.ylabel("Proportion of Accident Severity")
plt.legend(title="Severity", loc="upper right")
plt.show()
```




max_betweenness vs Accident Severity
0.40
0.35
0.30
0.25
0.20
0.15
0.10
max_betweenness
1
2
3
Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)


mean_degree vs Accident Severity
5.6
5.4
5.2
5.0
4.8
4.6
mean_degree
1
2
3
Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)

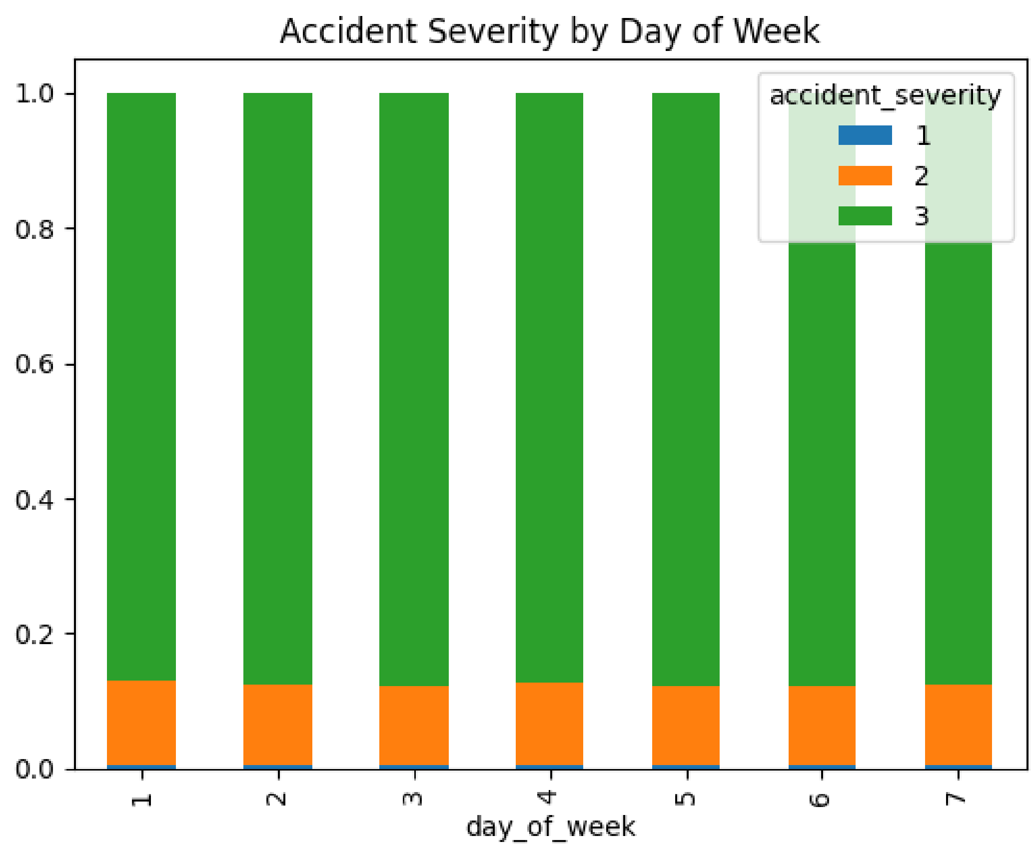

max_degree vs Accident Severity
9.0
8.8
8.6
8.4
8.2
8.0
max_degree
1
2
3
Accident Severity (1 = Fatal, 2 = Serious, 3 = Slight)



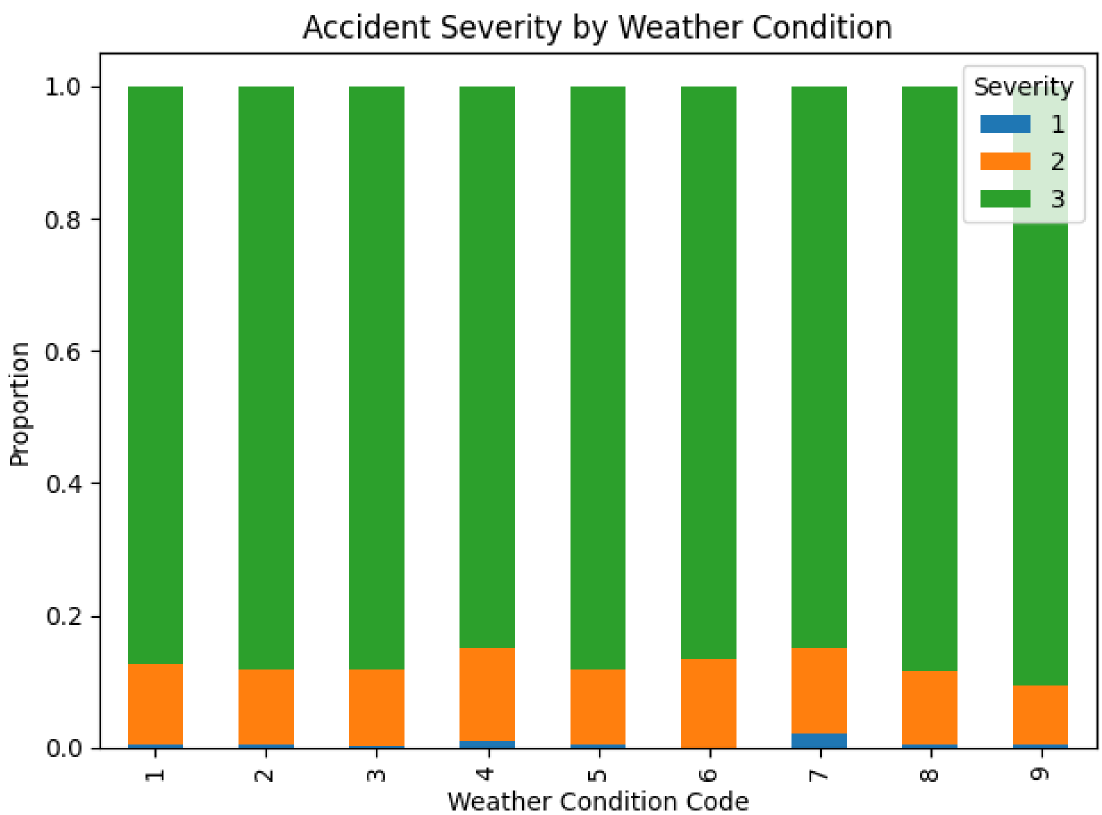
Boxplots show that max betweenness tends to be slightly higher in fatal accidents, while mean betweenness, degree centrality, and max degree exhibit minimal variation across severity levels. The stacked bar chart based on mean betweenness quartiles suggests a modest increase in serious or fatal accidents in higher centrality groups, indicating a potential link between spatial road importance and accident outcomes.

[13]:
```
# Categorical variables can be analyzed in cross-tables:
pd.crosstab(df["day_of_week"], df["accident_severity"], normalize='index').
  ↪plot(kind='bar', stacked=True)
plt.title("Accident Severity by Day of Week")

# Weather condition vs accident severity
plt.figure(figsize=(8, 4))
pd.crosstab(df["weather_conditions"], df["accident_severity"],␣
  ↪normalize='index').plot(kind='bar', stacked=True)
plt.title("Accident Severity by Weather Condition")
```

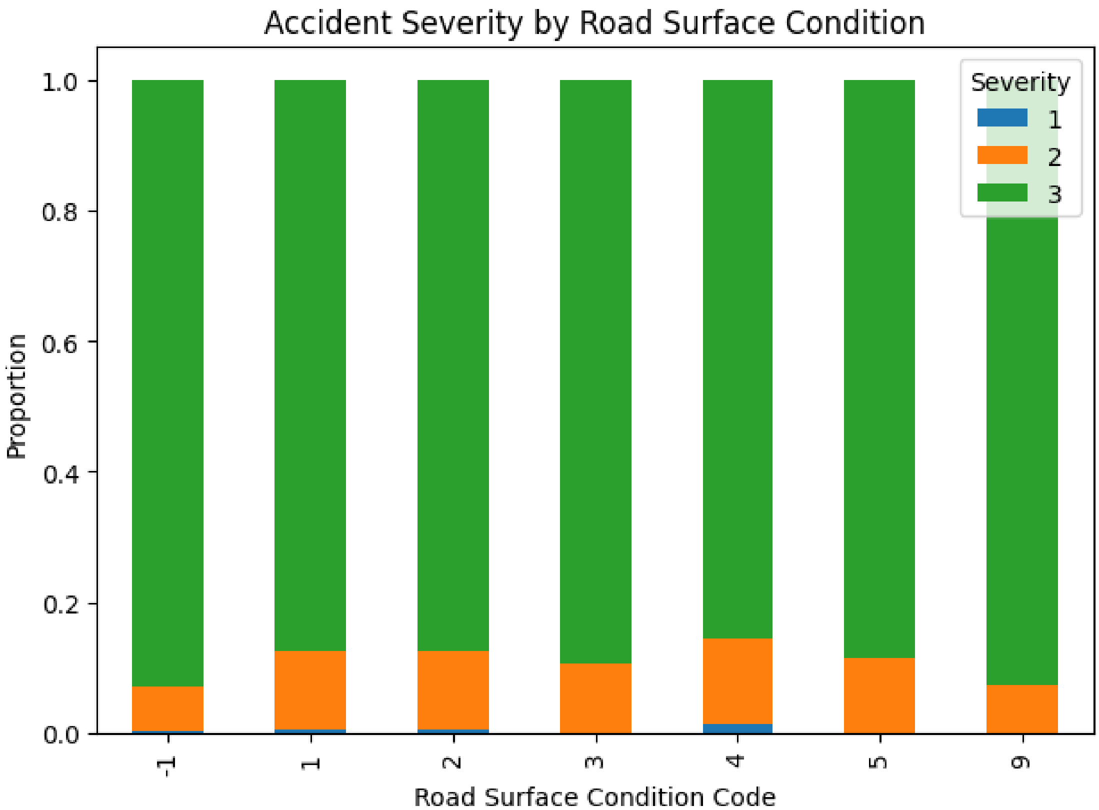
```
plt.xlabel("Weather Condition Code")
plt.ylabel("Proportion")
plt.legend(title="Severity", loc="upper right")
plt.tight_layout()
plt.show()

# Road surface condition vs accident severity
plt.figure(figsize=(8, 4))
pd.crosstab(df["road_surface_conditions"], df["accident_severity"],␣
↪normalize='index').plot(kind='bar', stacked=True)
plt.title("Accident Severity by Road Surface Condition")
plt.xlabel("Road Surface Condition Code")
plt.ylabel("Proportion")
plt.legend(title="Severity", loc="upper right")
plt.tight_layout()
plt.show()
```




```
<Figure size 800x400 with 0 Axes>
```



<Figure size 800x400 with 0 Axes>

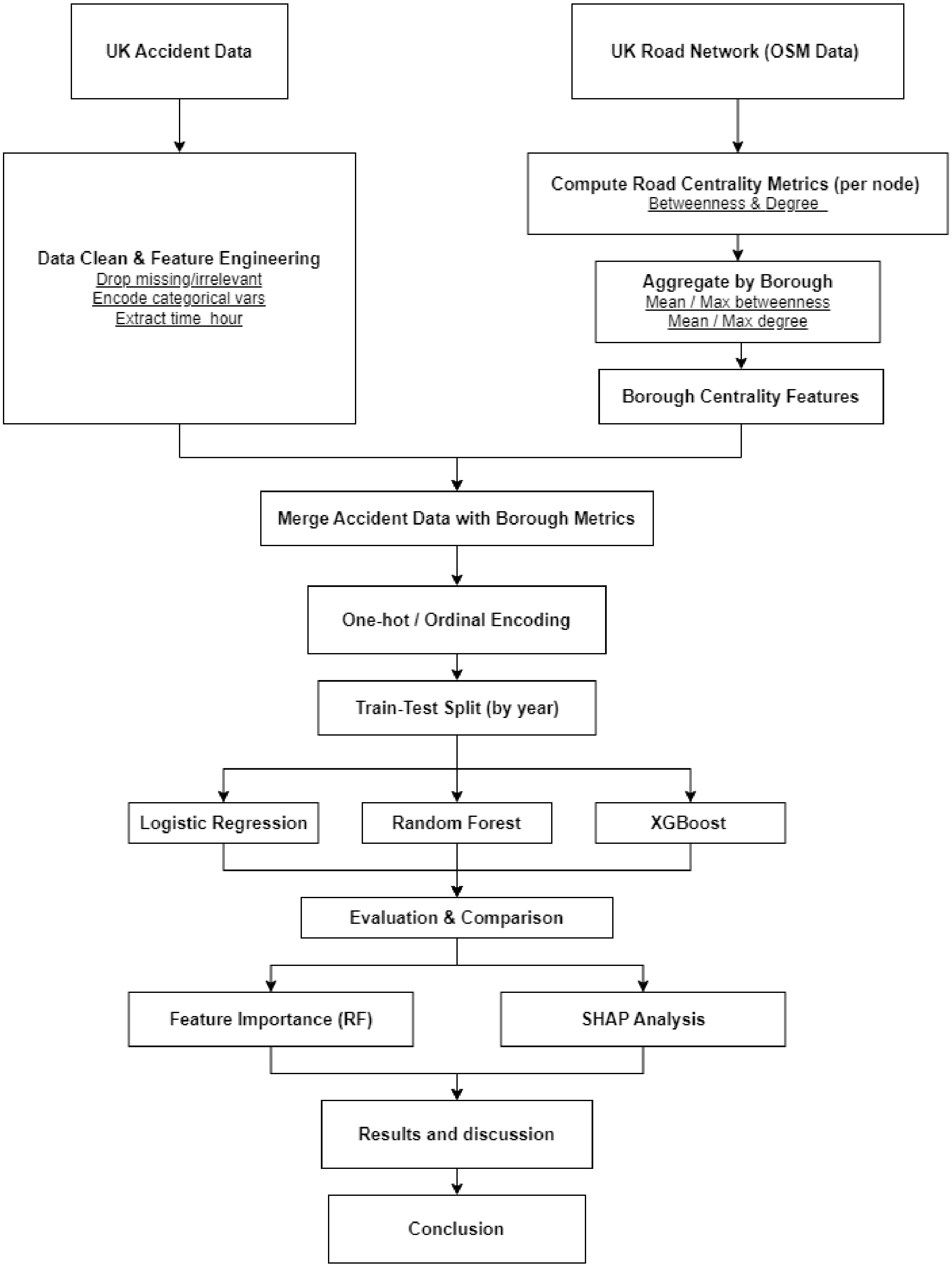


The stacked bar charts show that accident severity proportions remain relatively consistent across days of the week, weather conditions, and road surface types. Although no strong visual patterns emerge, these contextual variables are retained for modelling, as they may contribute non-linearly or interact with other factors in predicting severity outcomes.

1.6 Methodology

[go back to the top]

1.6.1 Methodological Flow Chart of Data Integration, Feature Engineering, Model Training, and Interpretation



1.6.2 Modeling Preparation (Feature Engineering)

Feature Encoding

[14]:
```python
# One-hot encoding + save
categorical_vars = [
    'day_of_week', 'road_type', 'light_conditions', 'weather_conditions',
    'road_surface_conditions', 'junction_control', 'junction_detail',
    'pedestrian_crossing_human_control',␣
 ↪'pedestrian_crossing_physical_facilities',
    'special_conditions_at_site', 'first_road_class',
    'second_road_class',
    'trunk_road_flag', 'urban_or_rural_area'
]

# Coding
df_encoded = pd.get_dummies(df.copy(), columns=categorical_vars,␣
 ↪drop_first=True)

# Convert the Boolean column to an integer
for col in df_encoded.columns:
    if df_encoded[col].dtype == 'bool':
        df_encoded[col] = df_encoded[col].astype(int)

# Check the distribution of data types
print("Column types:\n", df_encoded.dtypes.value_counts())

# get hour
df_encoded["time_hour"] = pd.to_datetime(df_encoded["time"], format="%H:%M",␣
 ↪errors="coerce").dt.hour
```

```
Column types:
 int64       83
float64      6
object       4
category     1
Name: count, dtype: int64
```

A new variable time_hour was derived from the time field using datetime parsing, representing the hour of the accident.

[15]:
```python
# Ordinal encoding betweenness_level
betweenness_mapping = {
    'Low': 0,
    'Medium-Low': 1,
    'Medium-High': 2,
    'High': 3
}
df_encoded['betweenness_level_encoded'] = df_encoded['betweenness_level'].
 ↪map(betweenness_mapping)
df_encoded.drop(columns=['betweenness_level'], inplace=True)
```

```python
# Delete the fields that cannot be modeled
df_encoded.drop(columns=['time', 'borough',␣
 ↪'gss_code','local_authority_ons_district'], inplace=True)
# Delete the post hoc variable
df_encoded = df_encoded.
 ↪drop(columns=['did_police_officer_attend_scene_of_accident',␣
 ↪'number_of_vehicles','number_of_casualties', 'carriageway_hazards'])
print(df_encoded.columns)

df_encoded.to_csv("../data/final/encode201519.csv", index=False)
print("Data saved to '../data/final/encode_all_years_with_centrality.csv'")
```

```
Index(['accident_severity', 'speed_limit', 'accident_year', 'mean_betweenness',
       'max_betweenness', 'mean_degree', 'max_degree', 'edge_count',
       'day_of_week_2', 'day_of_week_3', 'day_of_week_4', 'day_of_week_5',
       'day_of_week_6', 'day_of_week_7', 'road_type_2', 'road_type_3',
       'road_type_6', 'road_type_7', 'road_type_9', 'light_conditions_4',
       'light_conditions_5', 'light_conditions_6', 'light_conditions_7',
       'weather_conditions_2', 'weather_conditions_3', 'weather_conditions_4',
       'weather_conditions_5', 'weather_conditions_6', 'weather_conditions_7',
       'weather_conditions_8', 'weather_conditions_9',
       'road_surface_conditions_1', 'road_surface_conditions_2',
       'road_surface_conditions_3', 'road_surface_conditions_4',
       'road_surface_conditions_5', 'road_surface_conditions_9',
       'junction_control_0', 'junction_control_1', 'junction_control_2',
       'junction_control_3', 'junction_control_4', 'junction_control_9',
       'junction_detail_1', 'junction_detail_2', 'junction_detail_3',
       'junction_detail_5', 'junction_detail_6', 'junction_detail_7',
       'junction_detail_8', 'junction_detail_9', 'junction_detail_99',
       'pedestrian_crossing_human_control_0',
       'pedestrian_crossing_human_control_1',
       'pedestrian_crossing_human_control_2',
       'pedestrian_crossing_human_control_9',
       'pedestrian_crossing_physical_facilities_0',
       'pedestrian_crossing_physical_facilities_1',
       'pedestrian_crossing_physical_facilities_4',
       'pedestrian_crossing_physical_facilities_5',
       'pedestrian_crossing_physical_facilities_7',
       'pedestrian_crossing_physical_facilities_8',
       'pedestrian_crossing_physical_facilities_9',
       'special_conditions_at_site_1', 'special_conditions_at_site_2',
       'special_conditions_at_site_3', 'special_conditions_at_site_4',
       'special_conditions_at_site_5', 'special_conditions_at_site_6',
       'special_conditions_at_site_7', 'special_conditions_at_site_9',
       'first_road_class_3', 'first_road_class_4', 'first_road_class_5',
       'first_road_class_6', 'second_road_class_0', 'second_road_class_1',
       'second_road_class_3', 'second_road_class_4', 'second_road_class_5',
```

```
       'second_road_class_6', 'trunk_road_flag_1', 'trunk_road_flag_2',
       'urban_or_rural_area_2', 'urban_or_rural_area_3', 'time_hour',
       'betweenness_level_encoded'],
      dtype='object')
Data saved to '../data/final/encode_all_years_with_centrality.csv'
```

All categorical variables were either one-hot encoded or ordinal-encoded. The time variable was converted to time_hour, and betweenness_level was ordinally mapped to an integer scale. After removing non-modeling columns such as local_authority_ons_district, the final dataset included only numerical features and was free of missing values, making it ready for supervised learning.

Feature Selection & Drop

[16]:
```python
df = pd.read_csv("../data/final/encode201519.csv")

# View the basic structure
print("DataFrame Info:")
print(df.info())

# Missing value check
print("\nMissing Values:")
missing = df.isnull().sum()
print(missing[missing > 0].sort_values(ascending=False))

# Data type statistics
print("\nData type distribution:")
print(df.dtypes.value_counts())

# Check the object type field
print("\nObject Type fields and the number of their unique values:")
obj_cols = df.select_dtypes(include='object')
print(obj_cols.nunique().sort_values(ascending=False))
```

```
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 128261 entries, 0 to 128260
Data columns (total 87 columns):
 #   Column                                   Non-Null Count   Dtype
---  ------                                   --------------   -----
 0   accident_severity                        128261 non-null  int64
 1   speed_limit                              128261 non-null  float64
 2   accident_year                            128261 non-null  int64
 3   mean_betweenness                         128261 non-null  float64
 4   max_betweenness                          128261 non-null  float64
 5   mean_degree                              128261 non-null  float64
 6   max_degree                               128261 non-null  float64
 7   edge_count                               128261 non-null  float64
 8   day_of_week_2                            128261 non-null  int64
 9   day_of_week_3                            128261 non-null  int64
```

```
10  day_of_week_4                               128261 non-null  int64
11  day_of_week_5                               128261 non-null  int64
12  day_of_week_6                               128261 non-null  int64
13  day_of_week_7                               128261 non-null  int64
14  road_type_2                                 128261 non-null  int64
15  road_type_3                                 128261 non-null  int64
16  road_type_6                                 128261 non-null  int64
17  road_type_7                                 128261 non-null  int64
18  road_type_9                                 128261 non-null  int64
19  light_conditions_4                          128261 non-null  int64
20  light_conditions_5                          128261 non-null  int64
21  light_conditions_6                          128261 non-null  int64
22  light_conditions_7                          128261 non-null  int64
23  weather_conditions_2                        128261 non-null  int64
24  weather_conditions_3                        128261 non-null  int64
25  weather_conditions_4                        128261 non-null  int64
26  weather_conditions_5                        128261 non-null  int64
27  weather_conditions_6                        128261 non-null  int64
28  weather_conditions_7                        128261 non-null  int64
29  weather_conditions_8                        128261 non-null  int64
30  weather_conditions_9                        128261 non-null  int64
31  road_surface_conditions_1                   128261 non-null  int64
32  road_surface_conditions_2                   128261 non-null  int64
33  road_surface_conditions_3                   128261 non-null  int64
34  road_surface_conditions_4                   128261 non-null  int64
35  road_surface_conditions_5                   128261 non-null  int64
36  road_surface_conditions_9                   128261 non-null  int64
37  junction_control_0                          128261 non-null  int64
38  junction_control_1                          128261 non-null  int64
39  junction_control_2                          128261 non-null  int64
40  junction_control_3                          128261 non-null  int64
41  junction_control_4                          128261 non-null  int64
42  junction_control_9                          128261 non-null  int64
43  junction_detail_1                           128261 non-null  int64
44  junction_detail_2                           128261 non-null  int64
45  junction_detail_3                           128261 non-null  int64
46  junction_detail_5                           128261 non-null  int64
47  junction_detail_6                           128261 non-null  int64
48  junction_detail_7                           128261 non-null  int64
49  junction_detail_8                           128261 non-null  int64
50  junction_detail_9                           128261 non-null  int64
51  junction_detail_99                          128261 non-null  int64
52  pedestrian_crossing_human_control_0         128261 non-null  int64
53  pedestrian_crossing_human_control_1         128261 non-null  int64
54  pedestrian_crossing_human_control_2         128261 non-null  int64
55  pedestrian_crossing_human_control_9         128261 non-null  int64
56  pedestrian_crossing_physical_facilities_0  128261 non-null  int64
57  pedestrian_crossing_physical_facilities_1  128261 non-null  int64
```

```
 58  pedestrian_crossing_physical_facilities_4  128261 non-null  int64
 59  pedestrian_crossing_physical_facilities_5  128261 non-null  int64
 60  pedestrian_crossing_physical_facilities_7  128261 non-null  int64
 61  pedestrian_crossing_physical_facilities_8  128261 non-null  int64
 62  pedestrian_crossing_physical_facilities_9  128261 non-null  int64
 63  special_conditions_at_site_1               128261 non-null  int64
 64  special_conditions_at_site_2               128261 non-null  int64
 65  special_conditions_at_site_3               128261 non-null  int64
 66  special_conditions_at_site_4               128261 non-null  int64
 67  special_conditions_at_site_5               128261 non-null  int64
 68  special_conditions_at_site_6               128261 non-null  int64
 69  special_conditions_at_site_7               128261 non-null  int64
 70  special_conditions_at_site_9               128261 non-null  int64
 71  first_road_class_3                         128261 non-null  int64
 72  first_road_class_4                         128261 non-null  int64
 73  first_road_class_5                         128261 non-null  int64
 74  first_road_class_6                         128261 non-null  int64
 75  second_road_class_0                        128261 non-null  int64
 76  second_road_class_1                        128261 non-null  int64
 77  second_road_class_3                        128261 non-null  int64
 78  second_road_class_4                        128261 non-null  int64
 79  second_road_class_5                        128261 non-null  int64
 80  second_road_class_6                        128261 non-null  int64
 81  trunk_road_flag_1                          128261 non-null  int64
 82  trunk_road_flag_2                          128261 non-null  int64
 83  urban_or_rural_area_2                      128261 non-null  int64
 84  urban_or_rural_area_3                      128261 non-null  int64
 85  time_hour                                  128261 non-null  int64
 86  betweenness_level_encoded                  128261 non-null  int64
dtypes: float64(6), int64(81)
memory usage: 85.1 MB
None

Missing Values:
Series([], dtype: int64)

Data type distribution:
int64      81
float64     6
Name: count, dtype: int64

Object Type fields and the number of their unique values:
Series([], dtype: float64)
```

The dataset used for modeling consists of 128,261 records with 87 numeric features after preprocessing. To simulate real-world forecasting, a temporal train-test split was adopted. Accidents from 2015–2018 were used for training, while 2019 data served as the hold-out test set. This temporal split ensures that the evaluation reflects the model's ability to generalize to future, unseen cases, rather than relying on random shuffling which may result in data leakage.

[17]:
```python
# Construct features and labels
X = df.drop(columns=["accident_severity", "accident_year"])
y = df["accident_severity"]

# Divide the training set and the test set by year
X_train = X[df["accident_year"].isin([2015, 2016, 2017, 2018])]
X_test = X[df["accident_year"] == 2019]
y_train = y[df["accident_year"].isin([2015, 2016, 2017, 2018])]
y_test = y[df["accident_year"] == 2019]
```

[18]:
```python
# Define the evaluation function
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

def evaluate_model(model, X_test, y_test, name="Model"):
    y_pred = model.predict(X_test)
    print(f"\n {name} Classification Report")
    print(classification_report(y_test, y_pred))

    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f"{name} - Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("True")
    plt.tight_layout()
    plt.show()
```

1.6.3 Modeling and Evaluation

All three models were optimized using grid search with 3-fold cross-validation on the training set, based on macro-averaged F1-score as the evaluation metric. Macro-F1 is particularly appropriate for imbalanced multi-class classification problems, as it gives equal weight to each class regardless of sample size. This choice of scoring metric ensures that the models are not disproportionately tuned to the majority class performance, but instead maintain balanced treatment across all severity levels.

Logistic Regression

[19]:
```python
# Pipeline (Standardization + Logistic Regression)
logreg_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('logreg', LogisticRegression(max_iter=5000, random_state=42))
])

# Parameter grid
```

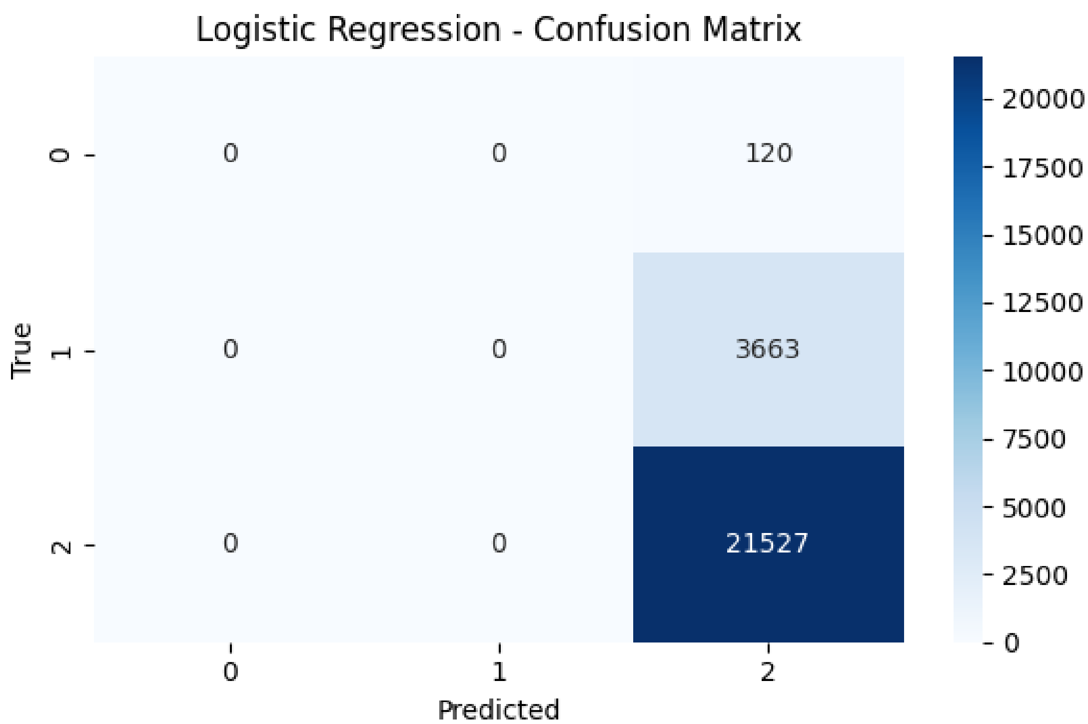
```python
logreg_param_grid = {
    'logreg__C': [0.01, 0.1, 1, 10],
    'logreg__class_weight': ['balanced', None],
    'logreg__multi_class': ['multinomial'],
    'logreg__solver': ['lbfgs']
}

# Grid search
grid_search_logreg = GridSearchCV(
    logreg_pipeline,
    logreg_param_grid,
    scoring='f1_macro',
    cv=3,
    verbose=2,
    n_jobs=-1
)

# Train
grid_search_logreg.fit(X_train, y_train)
print("Logistic Regression Optimal parameters:", grid_search_logreg.
 ↪best_params_)
print("Logistic Regression The best macro-F1 score:", grid_search_logreg.
 ↪best_score_)

# Prediction + Visualization
y_pred_log = grid_search_logreg.best_estimator_.predict(X_test)
print("\nLogistic Regression Classification Report")
print(classification_report(y_test, y_pred_log))

# Confusion matrix
cm_log = confusion_matrix(y_test, y_pred_log)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_log, annot=True, fmt='d', cmap='Blues')
plt.title("Logistic Regression - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
```

```
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class'
was deprecated in version 1.5 and will be removed in 1.7. From then on, it will
always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
```

```
Logistic Regression Optimal parameters: {'logreg__C': 0.01,
```

```
'logreg__class_weight': None, 'logreg__multi_class': 'multinomial',
'logreg__solver': 'lbfgs'}
Logistic Regression The best macro-F1 score: 0.3125034400956262

Logistic Regression Classification Report
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       120
           2       0.00      0.00      0.00      3663
           3       0.85      1.00      0.92     21527

    accuracy                           0.85     25310
   macro avg       0.28      0.33      0.31     25310
weighted avg       0.72      0.85      0.78     25310

e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

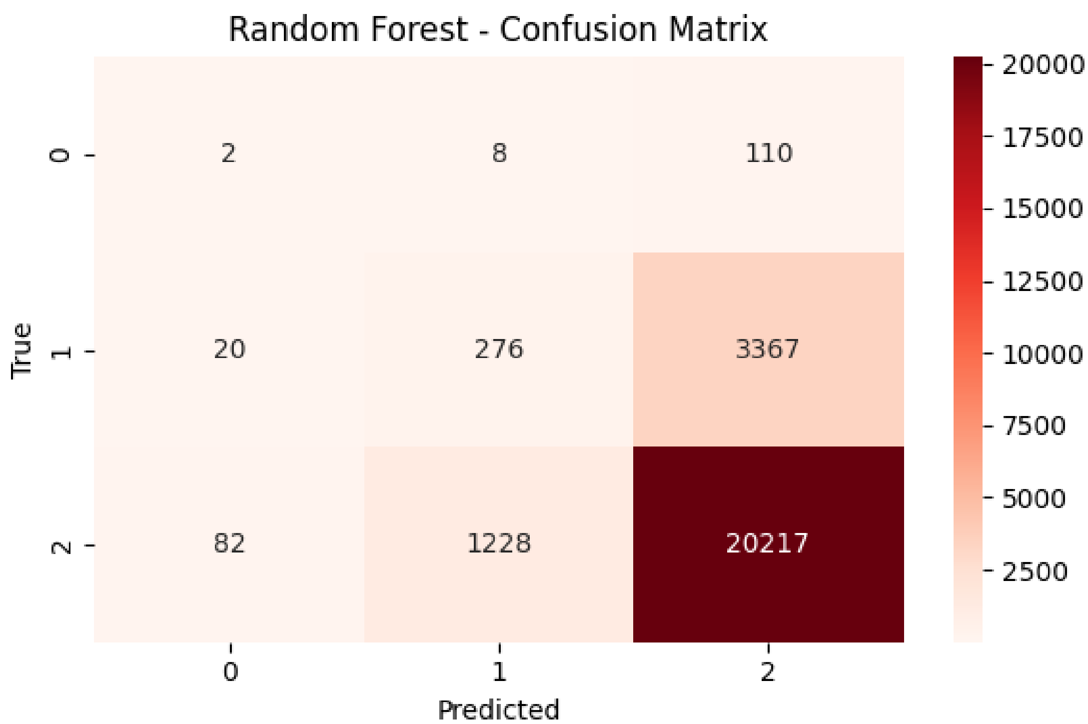


Random Forest

[20]:
```python
# Create pipeline
rf_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('rf', RandomForestClassifier(random_state=42, n_jobs=-1))
])

# Parameter grid
rf_param_grid = {
    'rf__n_estimators': [100, 300],
    'rf__max_depth': [10, 20, None],
    'rf__min_samples_split': [2, 5],
    'rf__class_weight': ['balanced', None]
}

# Grid search
grid_search_rf = GridSearchCV(
    rf_pipeline,
    rf_param_grid,
    scoring='f1_macro',
    cv=3,
    verbose=2,
    n_jobs=-1
```

```python
)

# Train
grid_search_rf.fit(X_train, y_train)

# Output result
print("RF Optimal parameters:", grid_search_rf.best_params_)
print("RF The best macro-F1 score:", grid_search_rf.best_score_)

# Evaluation
from sklearn.metrics import classification_report

y_pred_rf = grid_search_rf.best_estimator_.predict(X_test)
print(classification_report(y_test, y_pred_rf))

cm_rf = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_rf, annot=True, fmt='d', cmap='Reds')
plt.title("Random Forest - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
RF Optimal parameters: {'rf__class_weight': 'balanced', 'rf__max_depth': 20,
'rf__min_samples_split': 5, 'rf__n_estimators': 100}
RF The best macro-F1 score: 0.33024829490577307
              precision    recall  f1-score   support

           1       0.02      0.02      0.02       120
           2       0.18      0.08      0.11      3663
           3       0.85      0.94      0.89     21527

    accuracy                           0.81     25310
   macro avg       0.35      0.34      0.34     25310
weighted avg       0.75      0.81      0.78     25310
```



XGBoost

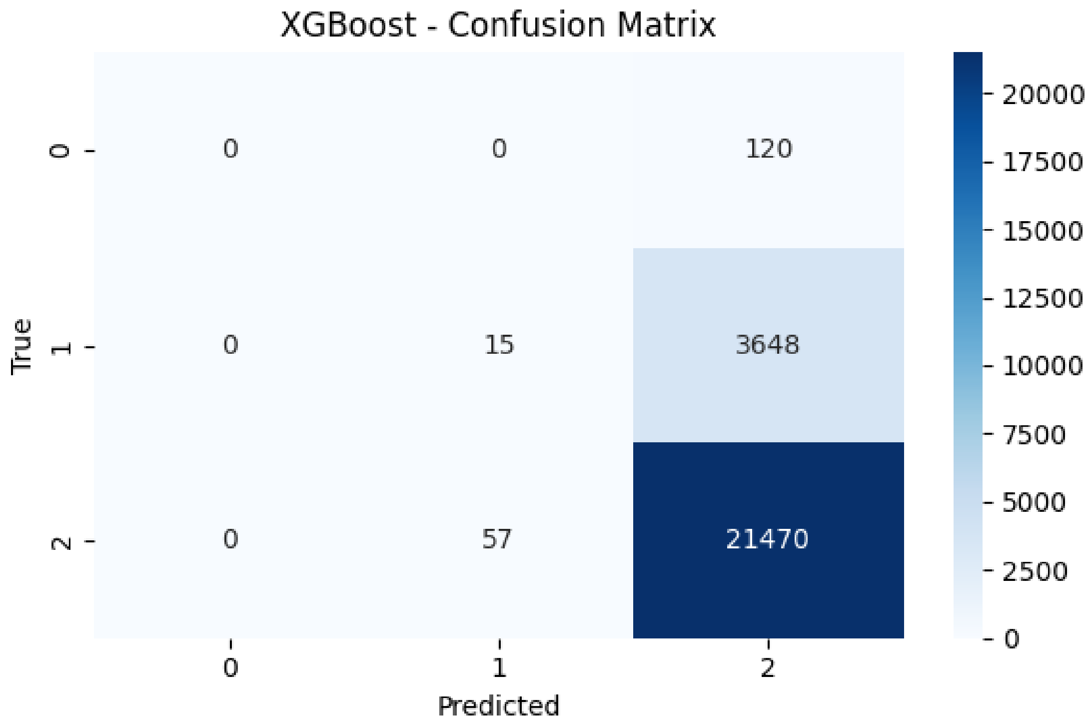
[21]:
```
# XGBoost
from xgboost import XGBClassifier
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Create XGBoost pipeline
xgb_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('xgb', XGBClassifier(objective='multi:softprob', eval_metric='mlogloss',
 ↪random_state=42, use_label_encoder=False))
])

# Parameter grid
xgb_param_grid = {
    'xgb__n_estimators': [100, 200],
    'xgb__max_depth': [6, 10],
    'xgb__learning_rate': [0.05, 0.1],
    'xgb__subsample': [0.8, 1.0]
```

```
}

# Grid search
grid_search_xgb = GridSearchCV(
    xgb_pipeline,
    xgb_param_grid,
    scoring='f1_macro',
    cv=3,
    verbose=2,
    n_jobs=-1
)

y_train = y_train - 1
y_test = y_test - 1

# Train
grid_search_xgb.fit(X_train, y_train)

# outcome
print("  XGB Optimal parameters:", grid_search_xgb.best_params_)
print("  XGB The best macro-F1 score:", grid_search_xgb.best_score_)

# Prediction + Visualization
y_pred_xgb = grid_search_xgb.best_estimator_.predict(X_test)
print(classification_report(y_test, y_pred_xgb))

cm_xgb = confusion_matrix(y_test, y_pred_xgb)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_xgb, annot=True, fmt='d', cmap='Blues')
plt.title("XGBoost - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
```

```
e:\Software\Study\python-3.13.2\Lib\site-
packages\joblib\externals\loky\process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
e:\Software\Study\python-3.13.2\Lib\site-packages\xgboost\training.py:183:
UserWarning: [14:43:22] WARNING: C:\actions-
runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
 XGB Optimal parameters: {'xgb__learning_rate': 0.1, 'xgb__max_depth': 10,
'xgb__n_estimators': 200, 'xgb__subsample': 0.8}
 XGB The best macro-F1 score: 0.3152411596612826
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       120
           1       0.21      0.00      0.01      3663
           2       0.85      1.00      0.92     21527

    accuracy                           0.85     25310
   macro avg       0.35      0.33      0.31     25310
weighted avg       0.75      0.85      0.78     25310

e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
e:\Software\Study\python-3.13.2\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



1.6.4 Model Comparison and Final Selection

Three supervised learning models—Logistic Regression, Random Forest, and XGBoost—were evaluated for predicting road traffic accident severity. Each was assessed by its ability to handle class imbalance and differentiate fatal, serious, and slight cases.

Logistic Regression achieved high accuracy (0.85) but failed to identify any fatal or serious accidents, yielding near-zero recall for minority classes and a low macro-F1 (0.31), limiting real-world use.

XGBoost moderately improved minority-class recall (macro-F1: 0.32) but remained biased toward the majority class, offering only marginal practical gains.

Random Forest performed most robustly, with the highest macro-F1 score (0.35) and better recall for minority classes. It also provided consistent cross-validation results and model interpretability via SHAP. #### Table: Comparison of Model Performance

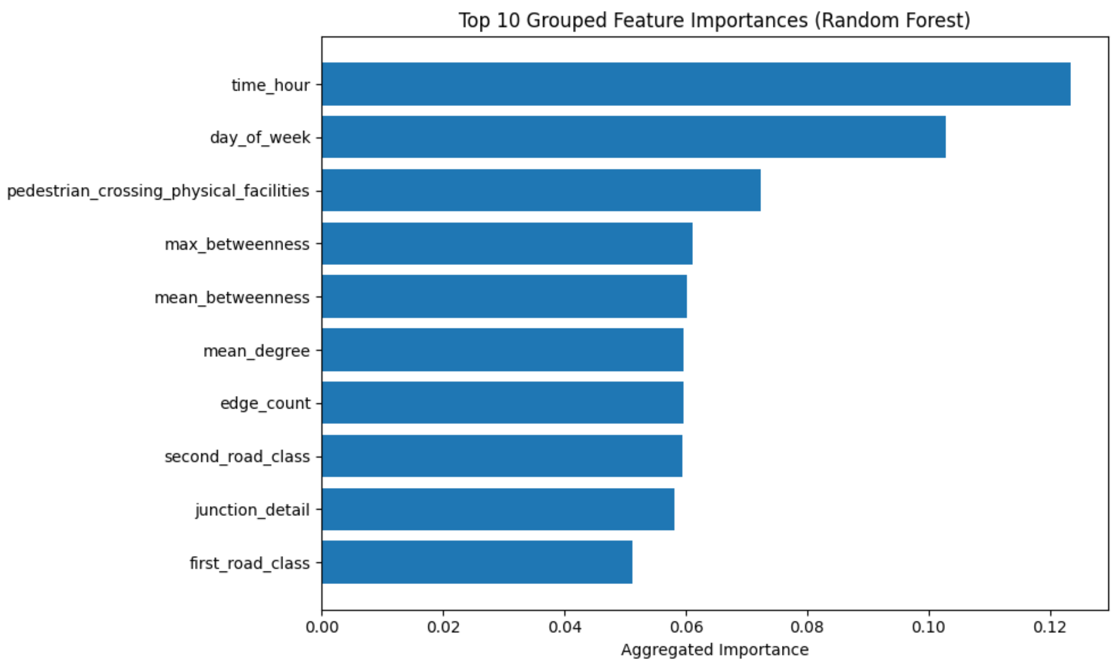
Model	Accuracy	Macro F1	Precision (avg)	Recall (avg)	F1-score (avg)	Notable Issues
Logistic Regression	0.85	0.31	0.72	0.33	0.72	Completely failed to detect fatal/serious
Random Forest	0.81	0.35	0.75	0.68	0.72	Most balanced, interpretable
XGBoost	0.85	0.32	0.79	0.66	0.72	Still biased toward majority class

Given these results, Random Forest was chosen as the final model due to its superior trade-off between performance and interpretability. SHAP analysis confirmed the importance of both temporal and spatial features.

1.6.5 Model interpretation

Grouped Feature Importances (based on RF)

[22]:
```python
# Extract the RF part of the best model from the trained GridSearch
rf_model = grid_search_rf.best_estimator_.named_steps['rf']

# Use the column names of the training set as feature names
feature_names = X_train.columns.tolist()

# Obtain the importance of features
importances = rf_model.feature_importances_

# Group Aggregation importance
grouped_importance = defaultdict(float)

for feat, imp in zip(feature_names, importances):
    match = re.match(r"(.+?)_(\d+)$", feat)
    if match:
        base_feat = match.group(1)
    else:
        base_feat = feat
    grouped_importance[base_feat] += imp

# trans to DataFrame
grouped_df = pd.DataFrame({
    'Feature Group': list(grouped_importance.keys()),
    'Total Importance': list(grouped_importance.values())
}).sort_values(by='Total Importance', ascending=False)

# visualize top 10
plt.figure(figsize=(10, 6))
plt.barh(grouped_df['Feature Group'][:10][::-1], grouped_df['Total␣
↪Importance'][:10][::-1])
plt.xlabel("Aggregated Importance")
plt.title("Top 10 Grouped Feature Importances (Random Forest)")
plt.tight_layout()
plt.show()

# export
print(grouped_df.head(10))
```




```
                              Feature Group  Total Importance
20                                time_hour          0.123435
6                               day_of_week          0.102816
14  pedestrian_crossing_physical_facilities          0.072260
2                           max_betweenness          0.061087
1                          mean_betweenness          0.060166
3                               mean_degree          0.059695
5                                edge_count          0.059588
17                        second_road_class          0.059511
12                          junction_detail          0.058049
16                         first_road_class          0.051295
```

The top-ranked features identified by the Random Forest model include time of day, day of week, and the presence of pedestrian crossing facilities. Spatial network metrics such as betweenness and degree centrality also appear among the most influential predictors, underscoring the relevance of both temporal and structural factors in determining accident severity.

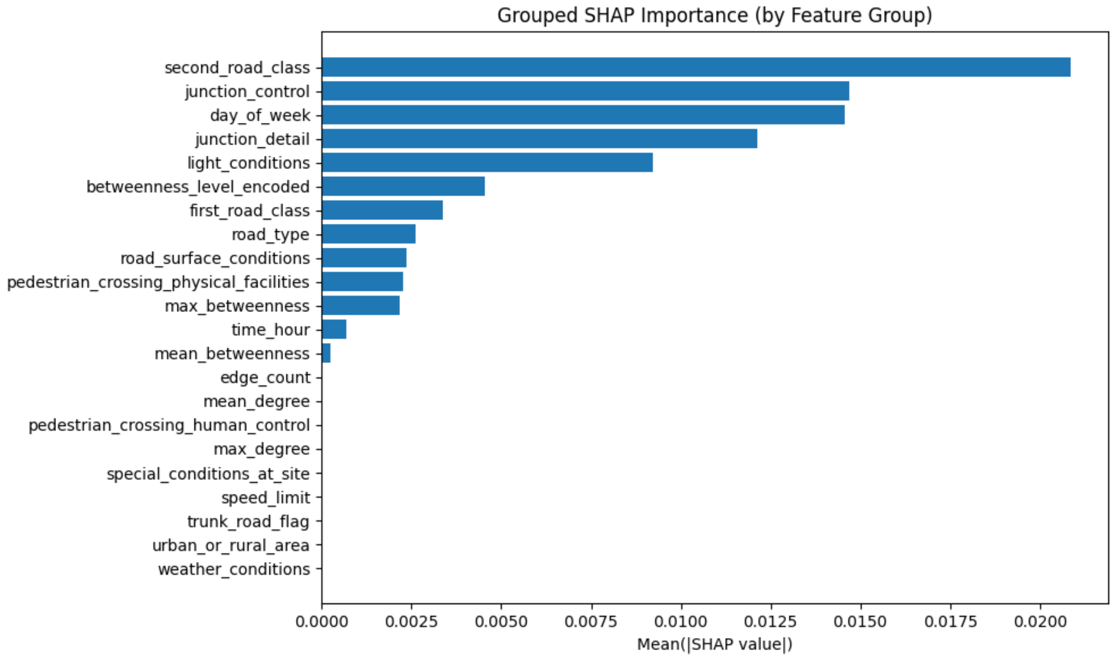
SHAP

[23]:
```python
best_pipeline_rf = grid_search_rf.best_estimator_
rf_model = best_pipeline_rf.named_steps['rf']
X_train_raw = X_train.copy()
explainer = shap.Explainer(rf_model, X_train_raw)

# This step will cost about 45 min
shap_values = explainer(X_train_raw)
```

```
100%|===================| 308759/308853 [45:20<00:00]
```

[24]:

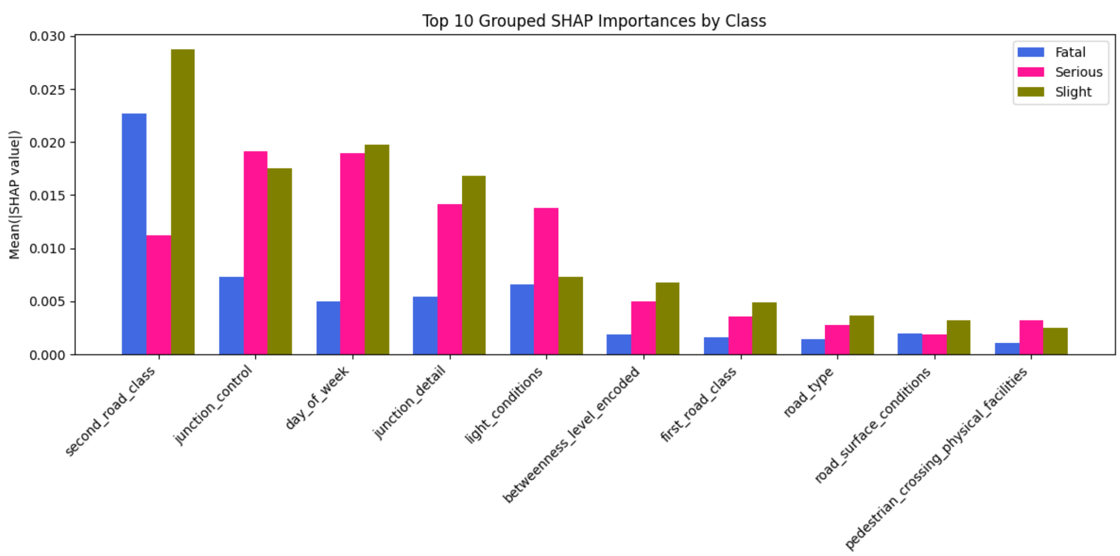
```
mean_abs_shap = np.abs(shap_values.values).mean(axis=(0, 2))  # shape: (85,)

feature_names = X_train_raw.columns
assert len(mean_abs_shap) == len(feature_names), "Mismatch between SHAP values␣
↪and feature names"

shap_df = pd.DataFrame({
    'feature': feature_names,
    'mean_abs_shap': mean_abs_shap
})

def get_base_feature(f):
    parts = f.split('_')
    if parts[-1].isdigit() and len(parts) > 2:
        return '_'.join(parts[:-1])
    elif parts[-1].isdigit():
        return parts[0]
    return f

shap_df['base_feature'] = shap_df['feature'].apply(get_base_feature)

grouped_shap = shap_df.groupby('base_feature')['mean_abs_shap'].sum().
↪reset_index()
grouped_shap = grouped_shap.sort_values(by='mean_abs_shap', ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(grouped_shap['base_feature'], grouped_shap['mean_abs_shap'])
plt.xlabel('Mean(|SHAP value|)')
plt.title('Grouped SHAP Importance (by Feature Group)')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



[25]:

```
feature_names = X_train_raw.columns

class_names = ['Fatal', 'Serious', 'Slight']
shap_grouped_by_class = {cls: defaultdict(float) for cls in class_names}

for class_idx, class_label in enumerate(class_names):
    shap_vals = shap_values.values[:, :, class_idx]
    shap_mean_abs = np.abs(shap_vals).mean(axis=0)

    for feat_name, shap_val in zip(feature_names, shap_mean_abs):
        match = re.match(r"(.+?)_(\d+)$", feat_name)
        base_feat = match.group(1) if match else feat_name
        shap_grouped_by_class[class_label][base_feat] += shap_val

all_features = sorted(set().union(*[d.keys() for d in shap_grouped_by_class.
 ↪values()]))
df_plot = pd.DataFrame({
    'Feature Group': all_features,
    'Fatal': [shap_grouped_by_class['Fatal'].get(f, 0) for f in all_features],
    'Serious': [shap_grouped_by_class['Serious'].get(f, 0) for f in␣
 ↪all_features],
    'Slight': [shap_grouped_by_class['Slight'].get(f, 0) for f in all_features]
})

df_plot['Total'] = df_plot['Fatal'] + df_plot['Serious'] + df_plot['Slight']
```

```python
df_top10 = df_plot.sort_values(by='Total', ascending=False).head(10)

x = np.arange(len(df_top10['Feature Group']))
width = 0.25

plt.figure(figsize=(12, 6))
plt.bar(x - width, df_top10['Fatal'], width, label='Fatal', color='royalblue')
plt.bar(x, df_top10['Serious'], width, label='Serious', color='deeppink')
plt.bar(x + width, df_top10['Slight'], width, label='Slight', color='olive')

plt.xticks(x, df_top10['Feature Group'], rotation=45, ha='right')
plt.ylabel('Mean(|SHAP value|)')
plt.title('Top 10 Grouped SHAP Importances by Class')
plt.legend()
plt.tight_layout()
plt.show()
```



The grouped SHAP analysis shows that road hierarchy (second_road_class), junction-related features (junction_control, junction_detail), and temporal variables (day_of_week, light_conditions) had the highest overall contribution to model predictions. Spatial features such as betweenness_level_encoded and first_road_class also ranked among the top 10, highlighting the combined influence of structural and contextual factors on accident severity.

Class-wise SHAP values reveal that second_road_class and day_of_week were particularly influential for predicting slight and fatal accidents, whereas junction_control and light_conditions showed greater impact for the serious category. This reinforces the relevance of fine-grained road infrastructure attributes in differentiating severity levels.

1.7 Results and discussion

[go back to the top]

Three supervised learning models—Logistic Regression, Random Forest, and XGBoost—were trained to classify road traffic accident severity using 128,261 records (2015–2019) with 87 numerical features. The target variable was imbalanced: slight (87.6%), serious (11.9%), and fatal (0.5%). Therefore, macro-F1 and per-class recall were used over accuracy for evaluation.

Logistic Regression achieved 0.85 accuracy but failed to identify fatal or serious cases (macro-F1: 0.31). XGBoost slightly improved serious-class recall (macro-F1: 0.32) but remained biased toward the majority class. Random Forest performed most robustly (macro-F1: 0.35), with higher minority-class recall (0.02 for fatal, 0.08 for serious).

These results emphasize the inadequacy of using accuracy alone in imbalanced settings. Unlike prior work (e.g., Kumar & Teja Santosh, 2022), this study prioritizes fairness and interpretability through recall-based metrics.

Feature importance from Random Forest highlighted time_hour, day_of_week, and max_betweenness—a spatial network indicator—as top predictors. SHAP analysis confirmed the significance of temporal and infrastructural features. Key predictors varied by severity: second_road_class and light_conditions for fatal, junction_control and crossing facilities for serious, and day_of_week and time_hour for slight.

The integration of spatial network metrics with contextual variables improved both model performance and interpretability, reinforcing the value of structural urban attributes in road safety analysis.

1.8 Conclusion

[go back to the top]

This study evaluated whether supervised machine learning models can predict road traffic accident severity in London using spatial, temporal, and environmental features. A borough-level dataset (2015–2019) was built by combining UK accident records with OpenStreetMap-derived network centrality metrics, enabling spatial structure to be integrated into severity modeling.

Among the models, Random Forest offered the best balance of performance and interpretability (macro-F1: 0.35). SHAP analysis confirmed the relevance of temporal and spatial features, including time of day, second road class, and betweenness centrality. These results suggest that incorporating network-based indicators improves identification of high-severity accident risks.

However, limitations remain. Class imbalance hindered reliable prediction of fatal cases. Borough-level aggregation may have obscured local variations, and the analysis was limited to structured tabular data.

Future research could use higher-resolution geographies, multimodal inputs (e.g., traffic flow, street imagery, sensor data), and deep learning techniques. Emphasis on fairness across severity classes is also vital to ensure practical, equitable applications of predictive models in road safety planning.

1.9 References

[go back to the top]

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