In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler, OneHotEncoder
from sklearn.feature_selection import SelectKBest, chi2, f_classif
from sklearn.decomposition import PCA
from scipy.stats import chi2_contingency
from datetime import datetime, timedelta
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb
import lightgbm as lgb
import time
```

1. Data Exploration and Preprocessing for Parking Citations

In [2]:
```
# Load the dataset
citations_df = pd.read_csv('data/parking_citations_2025_part1_datasd.csv')
print(f"Dataset shape: {citations_df.shape}")
citations_df.head()
```

```
Dataset shape: (85533, 8)
```

Out[2]:

	citation_id	date_issue	date_creation	location	sector1	vio_code	vio_desc
0	101636493	2025-01-01	2025-02-10	2300 PARK BLVD	CSD (I) PARKING ENF	5204(A) CVC	CURRENT REGISTRATION NOT DISPLAYED
1	101680177	2025-01-01	2025-02-10	5400 RENAISSANCE AVE	CSD (I) PARKING ENF	86.0137(G) SDMC	VEHICLE NOT MOVED 1/10 MILE IN 72 HOURS
2	101636714	2025-01-01	2025-02-10	300 S VISTA AVE	CSD (I) PARKING ENF	5204(A) CVC	CURRENT REGISTRATION NOT DISPLAYED
3	101680179	2025-01-01	2025-02-10	4200 DECORO ST	CSD (I) PARKING ENF	4000(A)1 CVC	EXPIRED REGISTRATION
4	101495542	2025-01-01	2025-02-10	14129 OLD EL CAMINO REAL	CSD (I) PARKING ENF	22500(C) CVC	SIGNS, RED ZONES

In [3]:

```
citations_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85533 entries, 0 to 85532
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   citation_id    85533 non-null  int64  
 1   date_issue     85533 non-null  object 
 2   date_creation  85533 non-null  object 
 3   location       85525 non-null  object 
 4   sector1        85533 non-null  object 
 5   vio_code       85533 non-null  object 
 6   vio_desc       85533 non-null  object 
 7   vio_fine       85533 non-null  float64
dtypes: float64(1), int64(1), object(6)
memory usage: 5.2+ MB
```

In [4]:

```
citations_df.describe(include='all')
```

Out[4]:

	citation_id	date_issue	date_creation	location	sector1	vio_code	vio_desc
count	8.553300e+04	85533	85533	85525	85533	85533	8553
unique	NaN	59	58	32468	5	60	60
top	NaN	2025-02-05	2025-02-10	DE ANZA BOAT LAUNCH RAMP 3500 MISSION BAY DR	CSD (I) PARKING ENF	86.0112(E)S DMC	VIOLATION OF SIGNS-STREET SWEEPING
freq	NaN	2567	2965	387	66588	17935	17935
mean	6.180743e+07	NaN	NaN	NaN	NaN	NaN	NaN
std	4.324837e+06	NaN	NaN	NaN	NaN	NaN	NaN
min	5.994270e+07	NaN	NaN	NaN	NaN	NaN	NaN
25%	6.131920e+07	NaN	NaN	NaN	NaN	NaN	NaN
50%	6.134246e+07	NaN	NaN	NaN	NaN	NaN	NaN
75%	6.136813e+07	NaN	NaN	NaN	NaN	NaN	NaN
max	1.017586e+08	NaN	NaN	NaN	NaN	NaN	NaN

In [5]:

```
citations_df.isnull().sum()
```

Out[5]:

```
citation_id      0
date_issue       0
date_creation    0
location         8
sector1          0
vio_code         0
vio_desc         0
vio_fine         0
dtype: int64
```

1.1 Date and Time Analysis

In [6]:

```
# Convert date columns to datetime
citations_df['date_issue'] = pd.to_datetime(citations_df['date_issue'])
citations_df['date_creation'] = pd.to_datetime(citations_df['date_creation'])
```

In [7]:

```
# Extract date components
citations_df['issue_year'] = citations_df['date_issue'].dt.year
citations_df['issue_month'] = citations_df['date_issue'].dt.month
citations_df['issue_day'] = citations_df['date_issue'].dt.day
citations_df['issue_dayofweek'] = citations_df['date_issue'].dt.dayofweek
```

```
citations_df['issue_dayname'] = citations_df['date_issue'].dt.day_name()
citations_df['issue_weekend'] = citations_df['issue_dayofweek'].apply(lambda x: 1 i
```

In [8]:
```
# Create month name for better readability in visualizations
month_names = {
    1: 'January', 2: 'February', 3: 'March', 4: 'April',
    5: 'May', 6: 'June', 7: 'July', 8: 'August',
    9: 'September', 10: 'October', 11: 'November', 12: 'December'
}
citations_df['issue_monthname'] = citations_df['issue_month'].map(month_names)
```

In [9]:
```
# Display sample of data with new date features
citations_df[['date_issue', 'issue_year', 'issue_month', 'issue_day',
   'issue_dayofweek', 'issue_dayname', 'issue_weekend']].head()
```

Out[9]:

	date_issue	issue_year	issue_month	issue_day	issue_dayofweek	issue_dayname	issue_w
0	2025-01-01	2025	1	1	2	Wednesday	
1	2025-01-01	2025	1	1	2	Wednesday	
2	2025-01-01	2025	1	1	2	Wednesday	
3	2025-01-01	2025	1	1	2	Wednesday	
4	2025-01-01	2025	1	1	2	Wednesday	

1.2 Violation Analysis

In [10]:
```
# Analyze violation codes
vio_counts = citations_df['vio_code'].value_counts().reset_index()
vio_counts.columns = ['vio_code', 'count']
vio_counts['percentage'] = (vio_counts['count'] / len(citations_df)) * 100
vio_counts.head(10)
```

Out[10]:

	vio_code	count	percentage
0	86.0112(E)S DMC	17935	20.968515
1	86.0126 SDMC	16459	19.242865
2	86.0112(E)SD MC	12554	14.677376
3	86.0112(F) SDMC	7241	8.465738
4	5204(A) CVC	5746	6.717875
5	86.0105 SDMC	4010	4.688249
6	86.0119 SDMC	3238	3.785673
7	86.0111 SDMC	2749	3.213964
8	SDMC 86.2014	2333	2.727602
9	86.0121 SDMC	2116	2.473899

In [11]:

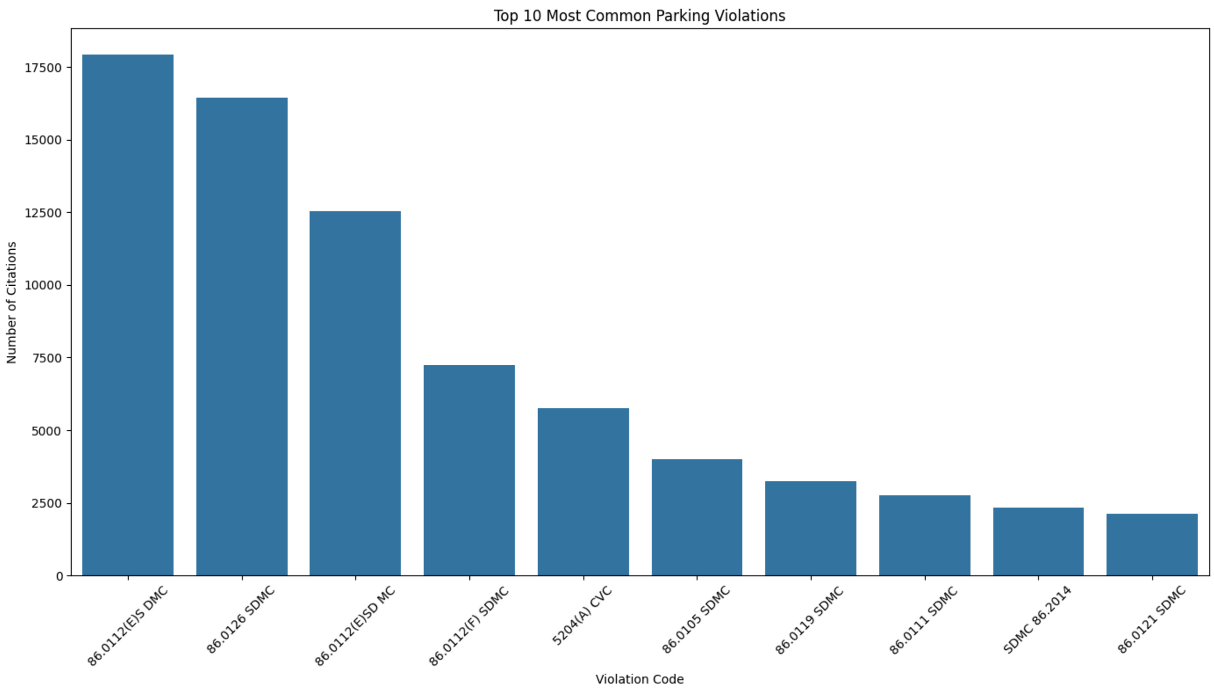
```
# Create a mapping of violation codes to descriptions
vio_mapping = citations_df[['vio_code', 'vio_desc']].drop_duplicates()
vio_mapping = dict(zip(vio_mapping['vio_code'], vio_mapping['vio_desc']))

# Display the mapping for the top 10 violation codes
{k: vio_mapping[k] for k in vio_counts.head(10)['vio_code']}
```

Out[11]:

```
{'86.0112(E)S DMC': 'VIOLATION OF SIGNS-STREET SWEEPING',
 '86.0126 SDMC': 'VIOLATION OF METERED ZONE',
 '86.0112(E)SD MC': 'VIOLATION OF SIGNS (SDMC)',
 '86.0112(F) SDMC': 'RED ZONE',
 '5204(A) CVC': 'CURRENT REGISTRATION NOT DISPLAYED',
 '86.0105 SDMC': 'PASSENGER ZONE',
 '86.0119 SDMC': 'LOADING ZONE',
 '86.0111 SDMC': 'WHEEL CRAMPING-HILL',
 'SDMC 86.2014': 'RESIDENTIAL PERMIT AREA',
 '86.0121 SDMC': 'ALLEY PARKING'}
```

In [12]:

```
# Visualize top 10 violations
plt.figure(figsize=(14, 8))
sns.barplot(x='vio_code', y='count', data=vio_counts.head(10))
plt.title('Top 10 Most Common Parking Violations')
plt.xlabel('Violation Code')
plt.ylabel('Number of Citations')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



1.3 Fine Amount Analysis

In [13]:

```
# Analyze fine amounts
print(f"Fine amount statistics:")
citations_df['vio_fine'].describe()
```

```
Fine amount statistics:
```

Out[13]:

```
count    85533.000000
mean        61.421340
std         55.831033
min          0.000000
25%         42.500000
50%         52.500000
75%         57.500000
max        826.500000
Name: vio_fine, dtype: float64
```

In [14]:

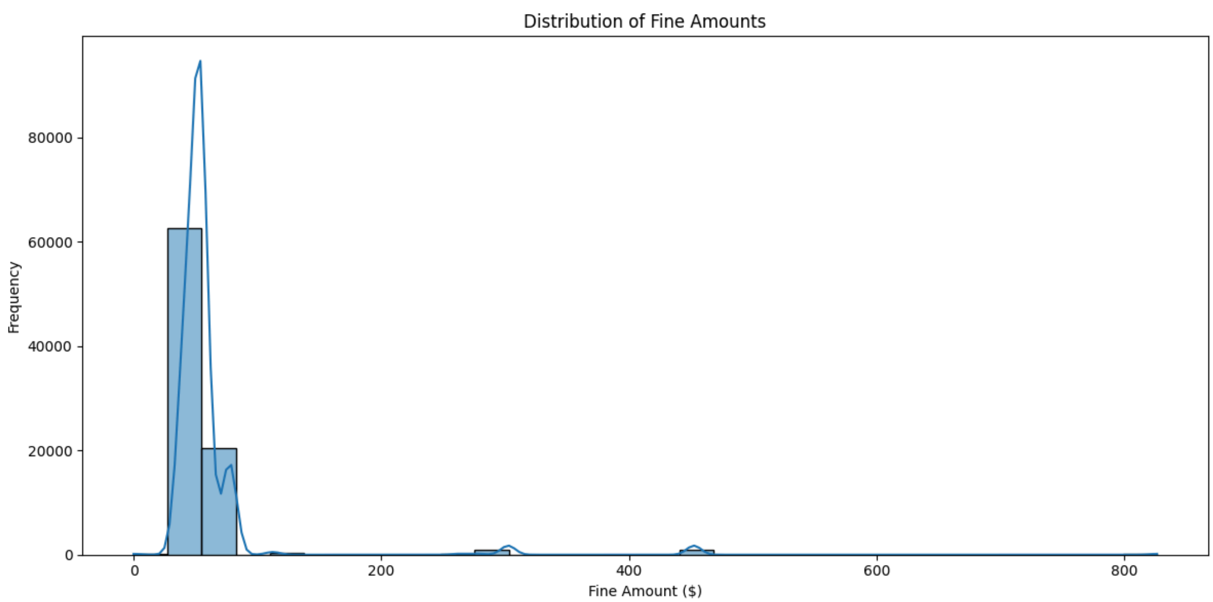
```
# Group by violation code and calculate average fine
avg_fines_by_code = citations_df.groupby('vio_code')['vio_fine'].agg(['mean', 'coun
avg_fines_by_code = avg_fines_by_code.sort_values(by='mean', ascending=False)
avg_fines_by_code.head(10)
```

Out[14]:

	vio_code	mean	count
53	86.0152(b)1 SDMC	826.500000	34
54	86.0152(b)2 SDMC	826.500000	31
55	86.0152(b)3 SDMC	826.500000	18
16	22507.8(c)CVC	452.500000	93
15	22507.8(b)CVC	452.500000	13
14	22507.8(a)CVC	418.731343	871
12	22507.8 CVC	362.000000	5
9	22500(L) CVC	302.500000	918
8	22500(I) CVC	277.500000	96
47	86.0137(I) SDMC	262.500000	92

In [15]:

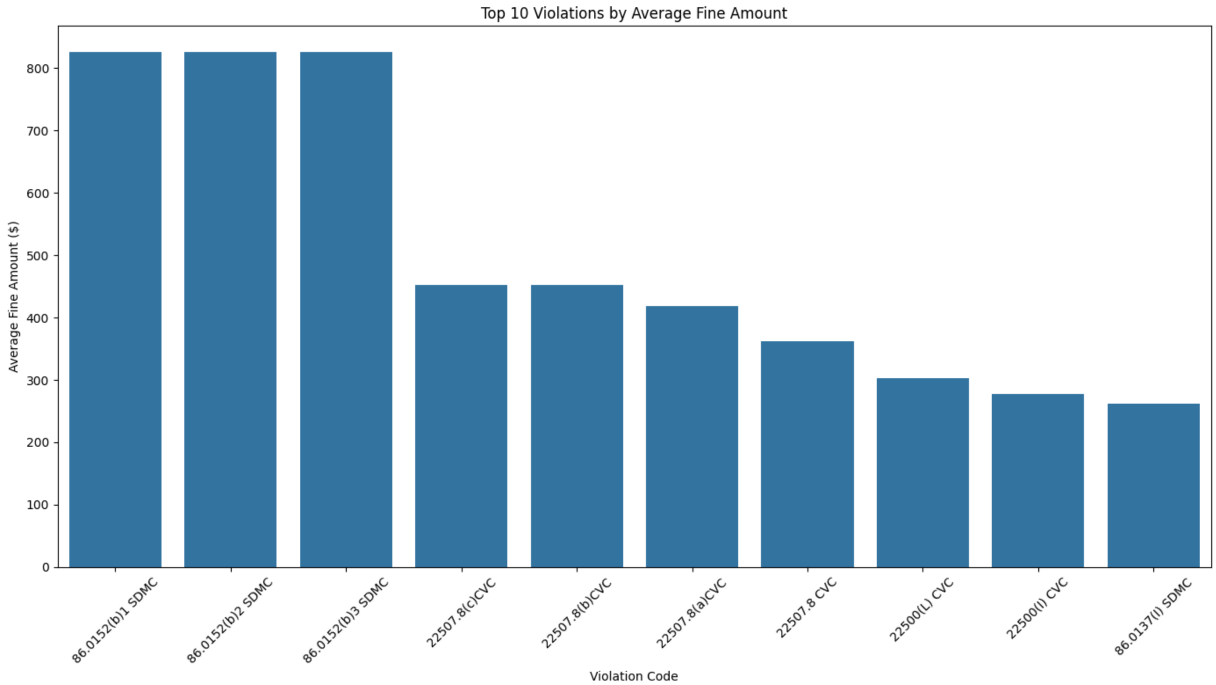
```
# Visualize fine distribution
plt.figure(figsize=(12, 6))
sns.histplot(citations_df['vio_fine'].dropna(), bins=30, kde=True)
plt.title('Distribution of Fine Amounts')
plt.xlabel('Fine Amount ($)')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



In [16]:

```
# Visualize top 10 violations by average fine
top_fines = avg_fines_by_code.head(10)
plt.figure(figsize=(14, 8))
sns.barplot(x='vio_code', y='mean', data=top_fines)
plt.title('Top 10 Violations by Average Fine Amount')
plt.xlabel('Violation Code')
plt.ylabel('Average Fine Amount ($)')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



1.4 Location Analysis

In [17]:

```
# Analyze citation locations
location_counts = citations_df['location'].value_counts().reset_index()
location_counts.columns = ['location', 'count']
location_counts['percentage'] = (location_counts['count'] / len(citations_df)) * 10
location_counts.head(10)
```

Out[17]:

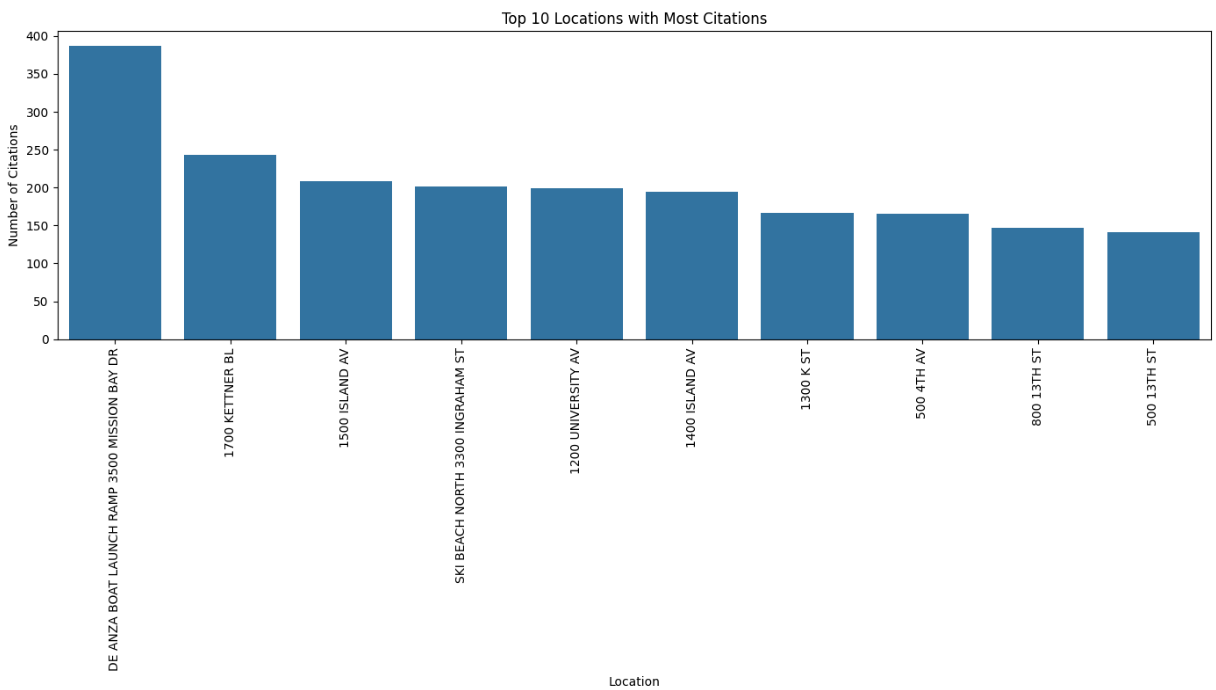
	location	count	percentage
0	DE ANZA BOAT LAUNCH RAMP 3500 MISSION BAY DR	387	0.452457
1	1700 KETTNER BL	243	0.284101
2	1500 ISLAND AV	208	0.243181
3	SKI BEACH NORTH 3300 INGRAHAM ST	202	0.236166
4	1200 UNIVERSITY AV	199	0.232659
5	1400 ISLAND AV	194	0.226813
6	1300 K ST	167	0.195246
7	500 4TH AV	166	0.194077
8	800 13TH ST	147	0.171863
9	500 13TH ST	141	0.164849

In [18]:
```
# Analyze sectors
sector_counts = citations_df['sector1'].value_counts().reset_index()
sector_counts.columns = ['sector', 'count']
sector_counts['percentage'] = (sector_counts['count'] / len(citations_df)) * 100
sector_counts
```

Out[18]:

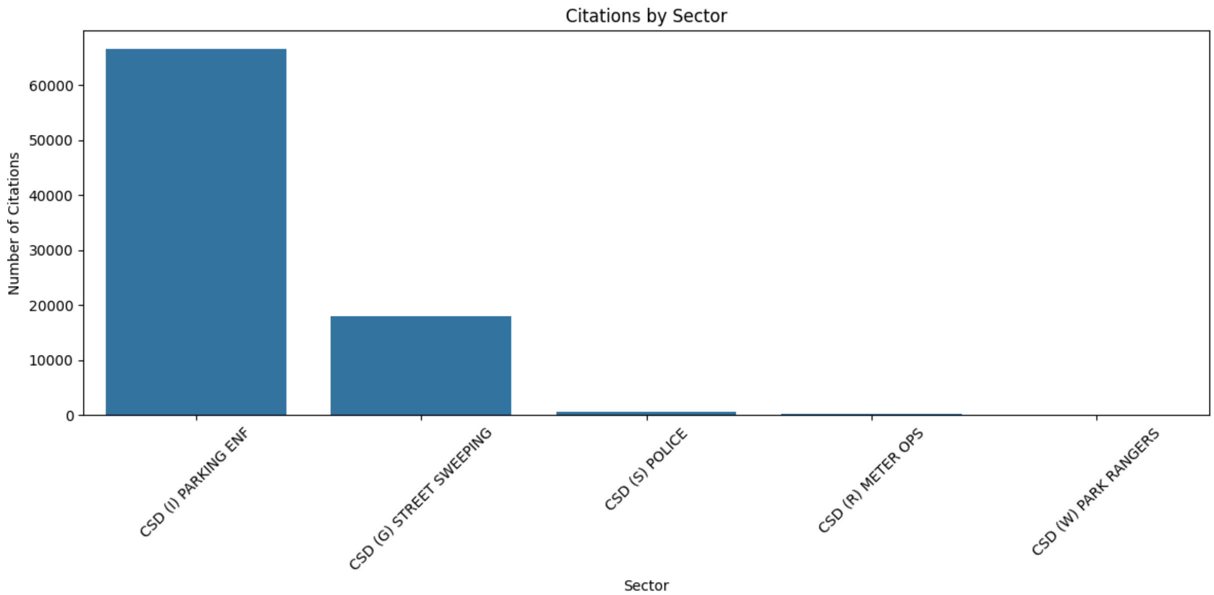
	sector	count	percentage
0	CSD (I) PARKING ENF	66588	77.850654
1	CSD (G) STREET SWEEPING	18045	21.097120
2	CSD (S) POLICE	644	0.752926
3	CSD (R) METER OPS	250	0.292285
4	CSD (W) PARK RANGERS	6	0.007015

In [19]:
```
# Visualize top 10 locations
plt.figure(figsize=(14, 8))
sns.barplot(x='location', y='count', data=location_counts.head(10))
plt.title('Top 10 Locations with Most Citations')
plt.xlabel('Location')
plt.ylabel('Number of Citations')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



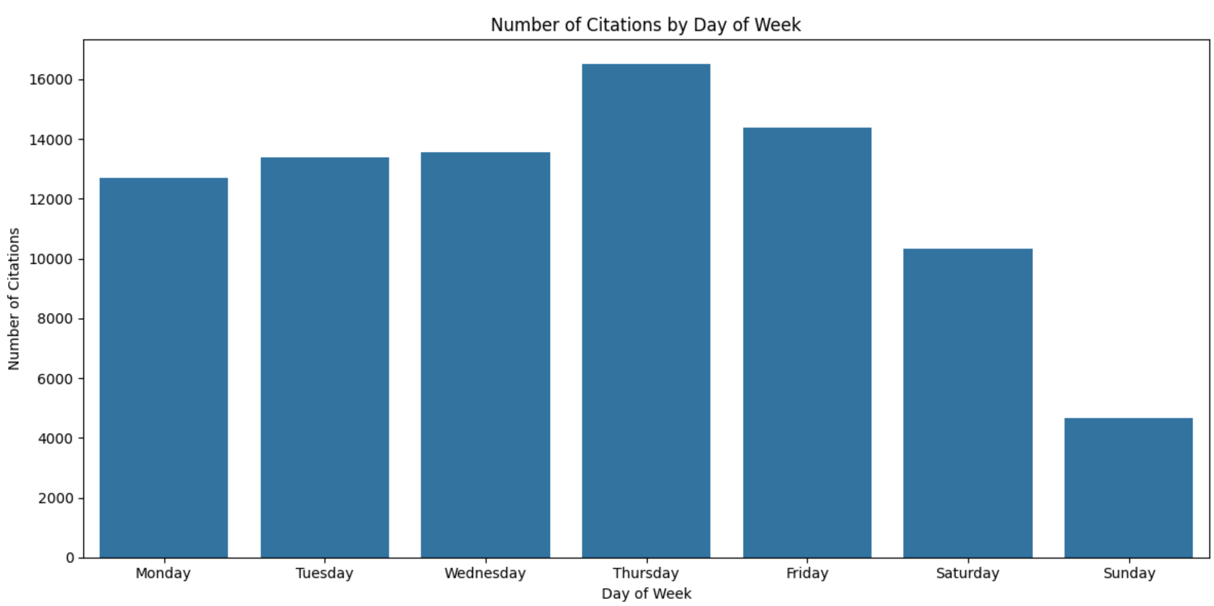
In [20]:
```
# Visualize citations by sector
plt.figure(figsize=(12, 6))
sns.barplot(x='sector', y='count', data=sector_counts)
plt.title('Citations by Sector')
plt.xlabel('Sector')
plt.ylabel('Number of Citations')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



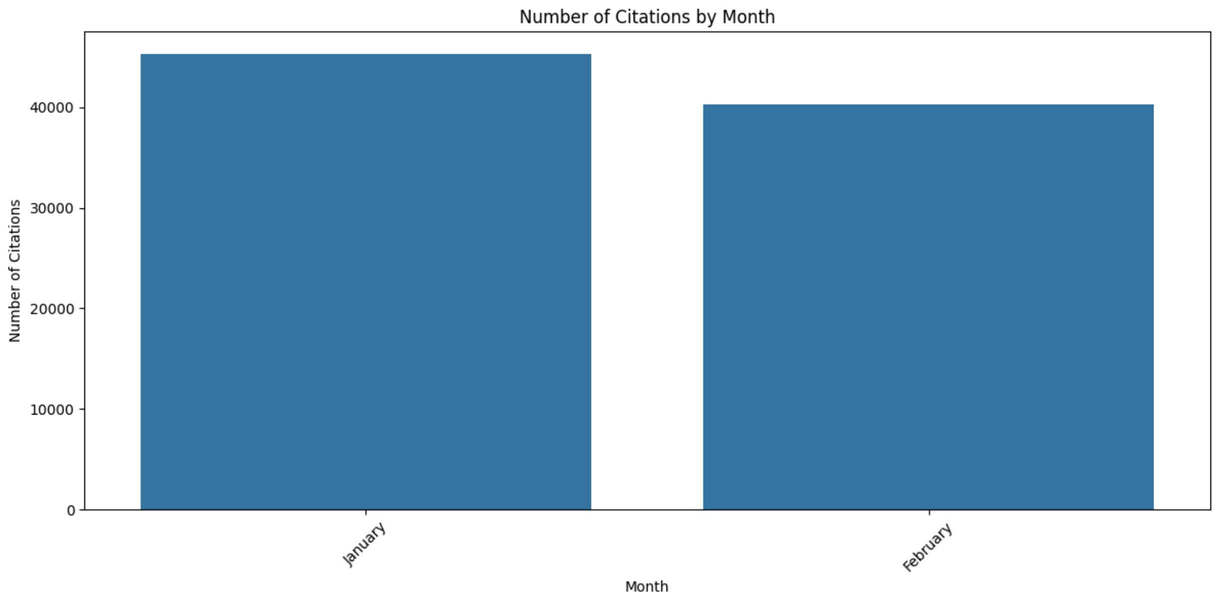
1.5 Temporal Patterns

In [21]:
```
# Analyze citations by day of week
plt.figure(figsize=(12, 6))
day_order = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "S
sns.countplot(x='issue_dayname', data=citations_df, order=day_order)
plt.title('Number of Citations by Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Number of Citations')
plt.tight_layout()
plt.show()
```



In [22]:
```
# Analyze citations by month
plt.figure(figsize=(12, 6))
```

```
month_order = [month_names[i] for i in range(1, 13) if i in citations_df['issue_mon
sns.countplot(x='issue_monthname', data=citations_df, order=month_order)
plt.title('Number of Citations by Month')
plt.xlabel('Month')
plt.ylabel('Number of Citations')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

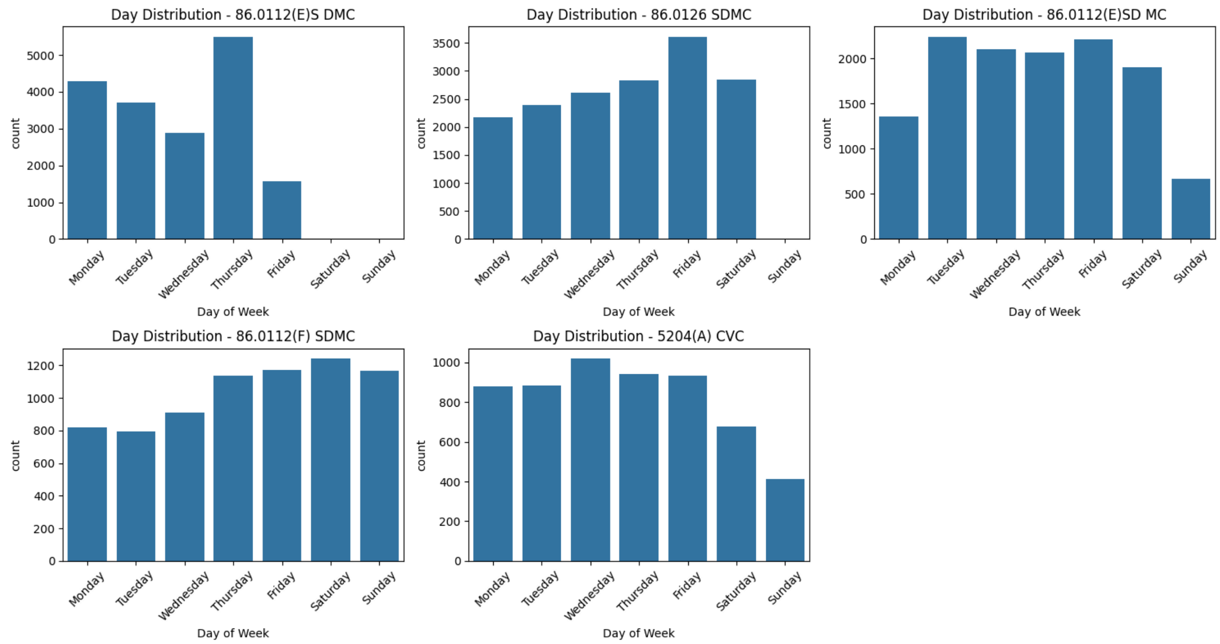


1.6 Heatmap Analysis

In [23]:
```
# Create heatmap of top violations by day of week
# Get top 10 violations for better visibility
top_10_violations = vio_counts.head(10)['vio_code'].tolist()
day_vio_counts = citations_df[citations_df['vio_code'].isin(top_10_violations)].gro
# Reorder rows to start with Monday
day_vio_counts = day_vio_counts.reindex(day_order)
plt.figure(figsize=(16, 10))
sns.heatmap(day_vio_counts, cmap="YlGnBu", annot=True, fmt=".0f", linewidths=.5)
plt.title('Heatmap of Top 10 Violations by Day of Week')
plt.xlabel('Violation Code')
plt.ylabel('Day of Week')
plt.tight_layout()
plt.show()
```

1.7 Relationship Between Variables

In [24]:
```
# Relationship between violation type and day of week
plt.figure(figsize=(15, 8))
for i, vio in enumerate(top_10_violations[:5]):  # Just show top 5 for clarity
    plt.subplot(2, 3, i+1)
    vio_data = citations_df[citations_df['vio_code'] == vio]
    sns.countplot(x='issue_dayname', data=vio_data, order=day_order)
    plt.title(f'Day Distribution - {vio}')
    plt.xlabel('Day of Week')
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



1.8 Data Quality Checks

In [25]:
```
# Check for duplicates
duplicate_count = citations_df.duplicated().sum()
print(f"Number of duplicate rows: {duplicate_count}")
```

```
Number of duplicate rows: 0
```

In [26]:
```
# Check for outliers in fine amounts
q1 = citations_df['vio_fine'].quantile(0.25)
q3 = citations_df['vio_fine'].quantile(0.75)
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

outliers = citations_df[(citations_df['vio_fine'] < lower_bound) | (citations_df['v
print(f"Number of potential fine amount outliers: {len(outliers)}")
print(f"Minimum outlier value: {outliers['vio_fine'].min()}")
print(f"Maximum outlier value: {outliers['vio_fine'].max()}")
```

```
Number of potential fine amount outliers: 2469
Minimum outlier value: 0.0
Maximum outlier value: 826.5
```

1.9 Data Preprocessing for Modeling

In [27]:
```
# Handle missing values
print("Missing values before handling:")
print(citations_df.isnull().sum())
```

```
Missing values before handling:
citation_id         0
date_issue          0
date_creation       0
location            8
sector1             0
vio_code            0
vio_desc            0
vio_fine            0
issue_year          0
issue_month         0
issue_day           0
issue_dayofweek     0
issue_dayname       0
issue_weekend       0
issue_monthname     0
dtype: int64
```

In [28]:
```
# Strategy for handling missing dates
citations_df = citations_df.dropna(subset=['date_issue']).copy()  # Remove rows wit
```

In [29]:
```
# For missing sectors or locations, fill with a placeholder
citations_df['sector1'] = citations_df['sector1'].fillna('Unknown')
citations_df['location'] = citations_df['location'].fillna('Unknown')
print("Missing values after handling:")
print(citations_df.isnull().sum())
```

```
Missing values after handling:
citation_id         0
date_issue          0
date_creation       0
location            0
sector1             0
vio_code            0
vio_desc            0
vio_fine            0
issue_year          0
issue_month         0
issue_day           0
issue_dayofweek     0
issue_dayname       0
issue_weekend       0
issue_monthname     0
dtype: int64
```

In [30]:
```
# For categorical predictors, identify columns that need encoding
categorical_cols = ['sector1', 'issue_dayname', 'issue_monthname', 'issue_weekend']
print(f"Categorical columns to encode: {categorical_cols}")
```

```
Categorical columns to encode: ['sector1', 'issue_dayname', 'issue_monthname', 'issu
e_weekend']
```

In [31]:
```
# One-hot encode top locations (for demo purposes, just encode the top 20)
top_locations = location_counts.head(20)['location'].tolist()
for loc in top_locations:
    citations_df[f'loc_{loc}'] = citations_df['location'].apply(lambda x: 1 if x ==
```

```python
print(f"Added {len(top_locations)} location dummy variables")
citations_df.head()
```

```
Added 20 location dummy variables
```

Out[31]:

	citation_id	date_issue	date_creation	location	sector1	vio_code	vio_desc
0	101636493	2025-01-01	2025-02-10	2300 PARK BLVD	CSD (I) PARKING ENF	5204(A) CVC	CURRENT REGISTRATION NOT DISPLAYED
1	101680177	2025-01-01	2025-02-10	5400 RENAISSANCE AVE	CSD (I) PARKING ENF	86.0137(G) SDMC	VEHICLE NOT MOVED 1/10 MILE IN 72 HOURS
2	101636714	2025-01-01	2025-02-10	300 S VISTA AVE	CSD (I) PARKING ENF	5204(A) CVC	CURRENT REGISTRATION NOT DISPLAYED
3	101680179	2025-01-01	2025-02-10	4200 DECORO ST	CSD (I) PARKING ENF	4000(A)1 CVC	EXPIRED REGISTRATION
4	101495542	2025-01-01	2025-02-10	14129 OLD EL CAMINO REAL	CSD (I) PARKING ENF	22500(C) CVC	SIGNS, RED ZONES

5 rows × 35 columns

1.10 Summary of Findings

In [32]:

```python
# Print summary of key findings for further modeling
print("Summary of Key Findings:")
print(f"- Dataset contains {citations_df.shape[0]} parking citations with {len(vio_
print(f"- Top 3 most common violations: {', '.join(vio_counts.head(3)['vio_code'].t
print(f"- Violations with highest average fines: {', '.join(avg_fines_by_code.head(
print(f"- Most citations occur on {citations_df['issue_dayname'].value_counts().ind
print(f"- {len(location_counts)} unique locations with citations, top location: {lo
print(f"- {citations_df['sector1'].nunique()} unique sectors with citations")
print("- Created time-based features that may help predict violation types")
```

```
Summary of Key Findings:
- Dataset contains 85533 parking citations with 60 unique violation types
- Top 3 most common violations: 86.0112(E)S DMC, 86.0126 SDMC, 86.0112(E)SD MC
- Violations with highest average fines: 86.0152(b)1 SDMC, 86.0152(b)2 SDMC, 86.0152
(b)3 SDMC
- Most citations occur on Thursdays
- 32468 unique locations with citations, top location: DE ANZA BOAT LAUNCH RAMP 3500
MISSION BAY DR
- 5 unique sectors with citations
- Created time-based features that may help predict violation types
```

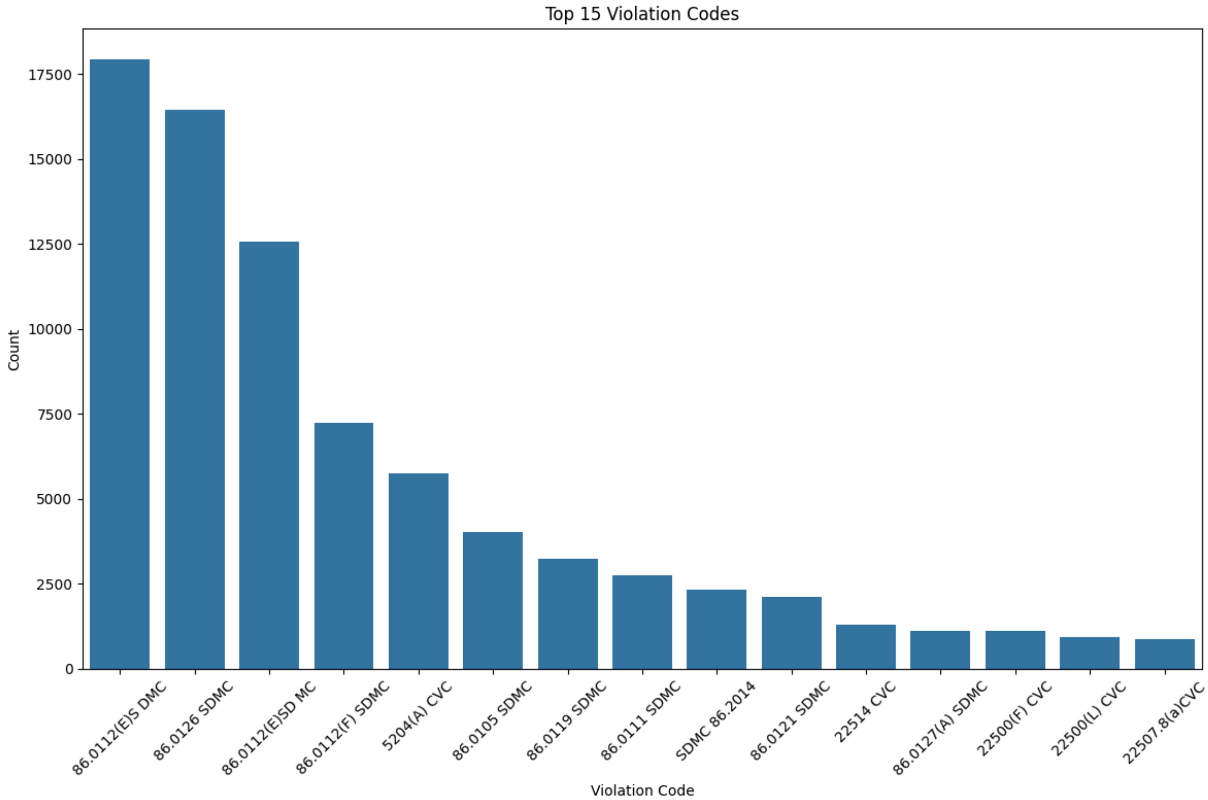
2. Feature Engineering for Parking Citations Prediction

2.1 Define Target Variable

In [33]:
```python
target_column = 'vio_code'

# Check target distribution
target_counts = citations_df[target_column].value_counts()
print(f"Number of unique violation codes: {len(target_counts)}")
print("Top 10 violation codes by frequency:")
print(target_counts.head(10))
```

```
Number of unique violation codes: 60
Top 10 violation codes by frequency:
vio_code
86.0112(E)S DMC    17935
86.0126 SDMC       16459
86.0112(E)SD MC    12554
86.0112(F) SDMC     7241
5204(A) CVC         5746
86.0105 SDMC        4010
86.0119 SDMC        3238
86.0111 SDMC        2749
SDMC 86.2014        2333
86.0121 SDMC        2116
Name: count, dtype: int64
```

In [34]:
```python
# Visualize target distribution
plt.figure(figsize=(12, 8))
top_violations = target_counts.head(15).reset_index()
top_violations.columns = ['violation', 'count']
sns.barplot(x='violation', y='count', data=top_violations)
plt.title('Top 15 Violation Codes')
plt.xlabel('Violation Code')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [35]:

```
# Check if target has too many classes - if so, we might want to focus on top N cla
if len(target_counts) > 20:
    print(f"Note: Target has {len(target_counts)} classes. Consider focusing on top

    # Get descriptions for top violations
    top_violations_list = target_counts.head(10).index.tolist()
    vio_desc_mapping = citations_df[['vio_code', 'vio_desc']].drop_duplicates().set

    print("\nTop 10 violations with descriptions:")
    for vio in top_violations_list:
        print(f"{vio}: {vio_desc_mapping.get(vio, 'No description')}")

    # For this project, we'll focus on the top 10 violation codes
    citations_filtered = citations_df[citations_df[target_column].isin(top_violatio
    print(f"\nFiltered dataset shape: {citations_filtered.shape}")
else:
    citations_filtered = citations_df.copy()
```

```
Note: Target has 60 classes. Consider focusing on top classes.

Top 10 violations with descriptions:
86.0112(E)S DMC: VIOLATION OF SIGNS-STREET SWEEPING
86.0126 SDMC: VIOLATION OF METERED ZONE
86.0112(E)SD MC: VIOLATION OF SIGNS (SDMC)
86.0112(F) SDMC: RED ZONE
5204(A) CVC: CURRENT REGISTRATION NOT DISPLAYED
86.0105 SDMC: PASSENGER ZONE
86.0119 SDMC: LOADING ZONE
86.0111 SDMC: WHEEL CRAMPING-HILL
SDMC 86.2014: RESIDENTIAL PERMIT AREA
86.0121 SDMC: ALLEY PARKING

Filtered dataset shape: (74381, 35)
```

2.2 Handle Date and Time Format

In [36]:
```python
# First, check if date_issue is already in datetime format
if not pd.api.types.is_datetime64_any_dtype(citations_filtered['date_issue']):
    # Convert to datetime format if it's not already
    citations_filtered['date_issue'] = pd.to_datetime(citations_filtered['date_issu
    print("Converted date_issue to datetime format")

print(f"Missing date values: {citations_filtered['date_issue'].isnull().sum()}")
print(f"Date range: {citations_filtered['date_issue'].min()} to {citations_filtered
```

```
Missing date values: 0
Date range: 2025-01-01 00:00:00 to 2025-02-28 00:00:00
```

In [37]:
```python
# Extract date components that may be useful
citations_filtered['issue_year'] = citations_filtered['date_issue'].dt.year
citations_filtered['issue_month'] = citations_filtered['date_issue'].dt.month
citations_filtered['issue_day'] = citations_filtered['date_issue'].dt.day
citations_filtered['issue_dayofweek'] = citations_filtered['date_issue'].dt.dayofwe
citations_filtered['issue_dayname'] = citations_filtered['date_issue'].dt.day_name(
citations_filtered['issue_quarter'] = citations_filtered['date_issue'].dt.quarter
citations_filtered['issue_weekofyear'] = citations_filtered['date_issue'].dt.isocal
```

2.3 Temporal Features

In [38]:
```python
# Weekend indicator
citations_filtered['is_weekend'] = (citations_filtered['issue_dayofweek'] >= 5).ast

# Part of week
citations_filtered['part_of_week'] = citations_filtered['issue_dayofweek'].apply(
    lambda x: 'start_week' if x < 2 else ('mid_week' if x < 5 else 'weekend')
)

# Season based on month
def get_season(month):
    if month in [12, 1, 2]:
        return 'winter'
    elif month in [3, 4, 5]:
```

```
        return 'spring'
    elif month in [6, 7, 8]:
        return 'summer'
    else:
        return 'fall'

citations_filtered['season'] = citations_filtered['issue_month'].apply(get_season)

# Part of month (beginning, middle, end)
citations_filtered['part_of_month'] = pd.cut(
    citations_filtered['issue_day'],
    bins=[0, 10, 20, 31],
    labels=['beginning', 'middle', 'end']
)

# Cyclical encoding for month and day of week (since these are cyclical variables)
citations_filtered['month_sin'] = np.sin(2 * np.pi * citations_filtered['issue_mont
citations_filtered['month_cos'] = np.cos(2 * np.pi * citations_filtered['issue_mont
citations_filtered['dayofweek_sin'] = np.sin(2 * np.pi * citations_filtered['issue_
citations_filtered['dayofweek_cos'] = np.cos(2 * np.pi * citations_filtered['issue_
```

2.4 Location-Based Features

In [39]:

```
# Count of citations per location (location popularity)
location_citation_counts = citations_filtered['location'].value_counts()
citations_filtered['location_popularity'] = citations_filtered['location'].map(loca

# Group locations by frequency (high, medium, low)
location_thresholds = [0, 50, 200, float('inf')]
location_labels = ['low_freq', 'medium_freq', 'high_freq']
citations_filtered['location_frequency_group'] = pd.cut(
    citations_filtered['location_popularity'],
    bins=location_thresholds,
    labels=location_labels
)

# Location-based violation patterns
# For each location, calculate the most common violation
location_top_violation = citations_filtered.groupby('location')[target_column].agg(
    lambda x: pd.Series.mode(x)[0] if not pd.Series.mode(x).empty else None
).to_dict()

# Add a feature indicating if this citation matches the most common violation for i
citations_filtered['matches_location_top_violation'] = (
    citations_filtered.apply(
        lambda row: row[target_column] == location_top_violation.get(row['location'
        axis=1
    )
).astype(int)

# Sector analysis
sector_citation_counts = citations_filtered['sector1'].value_counts()
citations_filtered['sector_popularity'] = citations_filtered['sector1'].map(sector_
```

2.5 Interaction Features

In [40]:
```
# Location-Day of Week interaction
citations_filtered['loc_day_interaction'] = citations_filtered['location'] + '_' +

# Location-Month interaction
citations_filtered['loc_month_interaction'] = citations_filtered['location'] + '_'

# Sector-Day of week interactions
citations_filtered['sector_day_interaction'] = citations_filtered['sector1'] + '_'

# Sector-Month interactions
citations_filtered['sector_month_interaction'] = citations_filtered['sector1'] + '_

# Season-Location interaction
citations_filtered['season_location'] = citations_filtered['season'] + '_' + citati
```

2.6 Statistical Features

In [41]:
```
# Day of week probability
day_violation_prob = {}
for day in range(7):
    day_data = citations_filtered[citations_filtered['issue_dayofweek'] == day]
    if len(day_data) > 0:
        violation_dist = day_data[target_column].value_counts(normalize=True).to_di
        day_violation_prob[day] = violation_dist

# Add day probability features for top violations
for vio in top_violations_list:
    citations_filtered[f'day_prob_{vio}'] = citations_filtered['issue_dayofweek'].a
        lambda d: day_violation_prob.get(d, {}).get(vio, 0)
    )

# Month probability
month_violation_prob = {}
for month in range(1, 13):
    month_data = citations_filtered[citations_filtered['issue_month'] == month]
    if len(month_data) > 0:
        violation_dist = month_data[target_column].value_counts(normalize=True).to_
        month_violation_prob[month] = violation_dist

# Add month probability features for top violations
for vio in top_violations_list:
    citations_filtered[f'month_prob_{vio}'] = citations_filtered['issue_month'].app
        lambda m: month_violation_prob.get(m, {}).get(vio, 0)
    )
```

2.7 Additional Features Based on Domain Knowledge

In [42]:
```
# Is holiday or special day (simplified example)
us_holidays = [
    # Format: (month, day) tuples
```

```
    (1, 1),    # New Year's Day
    (7, 4),    # Independence Day
    (12, 25),  # Christmas
    # Add more holidays as needed
]

citations_filtered['is_holiday'] = citations_filtered.apply(
    lambda row: 1 if (row['issue_month'], row['issue_day']) in us_holidays else 0,
    axis=1
)

# Days since beginning of month
citations_filtered['days_since_month_start'] = citations_filtered['issue_day'] - 1

# Days until end of month (approximate)
days_in_month = {
    1: 31, 2: 28, 3: 31, 4: 30, 5: 31, 6: 30,
    7: 31, 8: 31, 9: 30, 10: 31, 11: 30, 12: 31
}
citations_filtered['days_until_month_end'] = citations_filtered.apply(
    lambda row: days_in_month[row['issue_month']] - row['issue_day'],
    axis=1
)

# Is weekend adjacent (Friday or Monday)
citations_filtered['is_weekend_adjacent'] = citations_filtered['issue_dayofweek'].a
    lambda d: 1 if d in [0, 4] else 0  # Monday or Friday
)
```

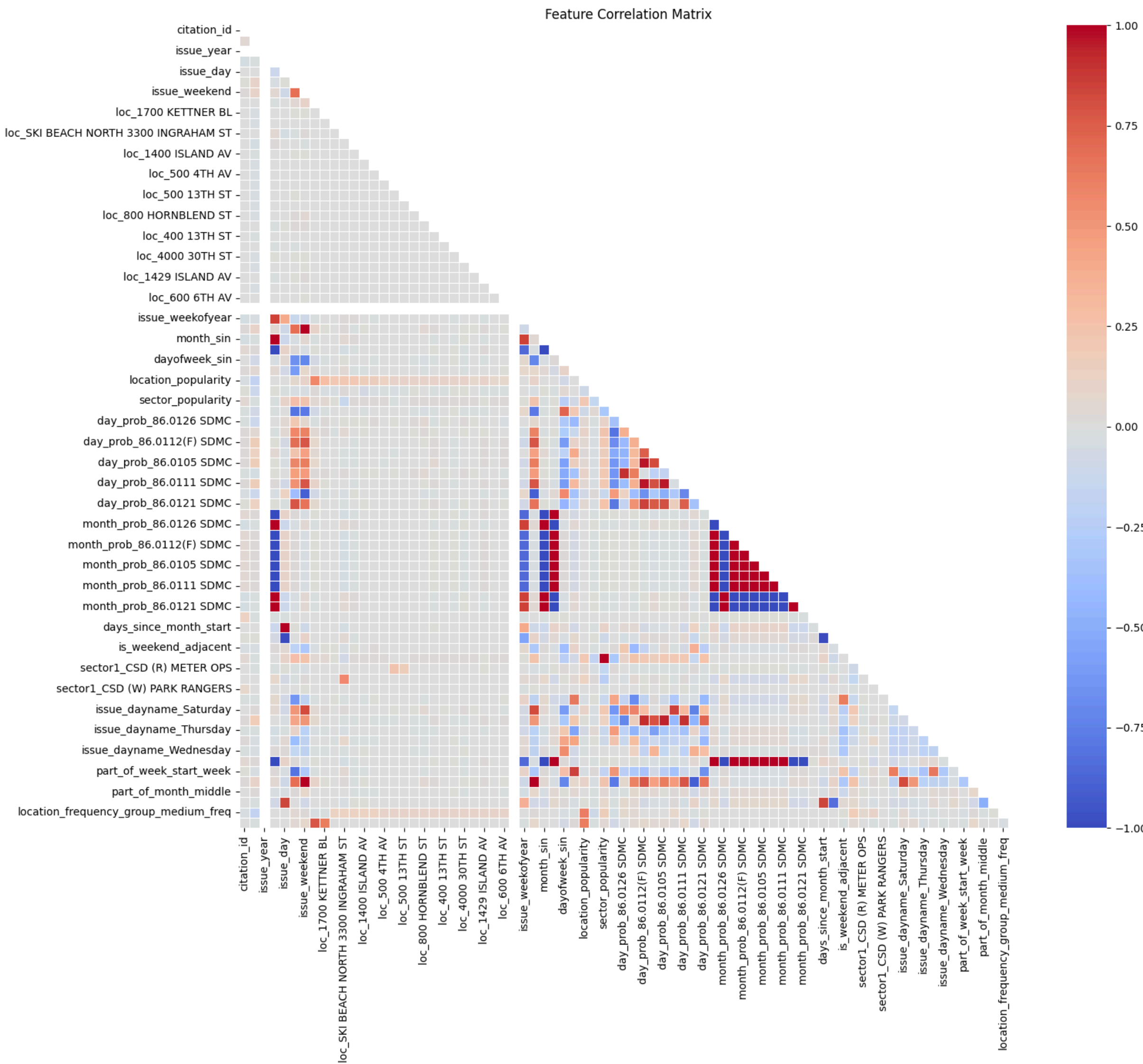
2.8 Feature Selection and Transformation

In [43]:
```
# Prepare feature set for potential dimensionality reduction

# Get list of columns excluding target and string/object columns that haven't been
non_feature_cols = [target_column, 'date_issue', 'date_creation', 'vio_desc', 'loca
                    'loc_day_interaction', 'loc_month_interaction', 'sector_day_int
                    'sector_month_interaction', 'season_location']

# Identify categorical columns that need encoding
# Identify categorical columns that need encoding
categorical_cols = [col for col in citations_filtered.columns
                    if col not in non_feature_cols
                    and (citations_filtered[col].dtype == 'object'
                         or col == 'part_of_month'
                         or col == 'location_frequency_group'
                         or pd.api.types.is_categorical_dtype(citations_filtered[co
                    and col != target_column]

print(f"Categorical columns to encode: {categorical_cols}")

# One-hot encode categorical features
citations_encoded = pd.get_dummies(
    citations_filtered,
    columns=categorical_cols,
    drop_first=True
```

```
)

print(f"After one-hot encoding categorical features, shape: {citations_encoded.shap

# Find numerical columns
numerical_cols = [col for col in citations_encoded.columns
                  if col not in non_feature_cols
                  and col != target_column
                  and pd.api.types.is_numeric_dtype(citations_encoded[col])]

print(f"Number of numerical features: {len(numerical_cols)}")

# Check correlation between numerical features
correlation_matrix = citations_encoded[numerical_cols].corr()

# Plot correlation matrix
plt.figure(figsize=(16, 14))
mask = np.triu(correlation_matrix)
sns.heatmap(correlation_matrix, mask=mask, annot=False, cmap='coolwarm',
            vmin=-1, vmax=1, linewidths=0.5)
plt.title('Feature Correlation Matrix')
plt.tight_layout()
plt.show()

# Check for highly correlated features (|r| > 0.8)
high_corr_features = set()
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > 0.8:
            feature_i = correlation_matrix.columns[i]
            feature_j = correlation_matrix.columns[j]
            high_corr_features.add(feature_i)
            print(f"High correlation between {feature_i} and {feature_j}: {correlat

print(f"Number of highly correlated features: {len(high_corr_features)}")

# Label encode the target for modeling
label_encoder = LabelEncoder()
citations_encoded['vio_code_encoded'] = label_encoder.fit_transform(citations_encod

# Identify most important features using chi-squared test (for classification)

# We'll select features for the encoded target variable

# First, let's filter only numeric columns (excluding the target and its encoded ve
X_features = citations_encoded.drop(columns=[target_column, 'vio_code_encoded'] + n
y_target = citations_encoded['vio_code_encoded']

# Apply SelectKBest with chi-squared test
k_best = min(50, X_features.shape[1])  # Select up to 50 features
selector = SelectKBest(score_func=f_classif, k=k_best)
selector.fit(X_features, y_target)

# Get feature scores
feature_scores = pd.DataFrame({
    'Feature': X_features.columns,
```

```
    'Score': selector.scores_
})

feature_scores = feature_scores.sort_values('Score', ascending=False)
print("\nTop 20 most important features:")
print(feature_scores.head(20))

# Plot top features
plt.figure(figsize=(12, 10))
top_n = 20
top_features = feature_scores.head(top_n)
sns.barplot(x='Score', y='Feature', data=top_features)
plt.title(f'Top {top_n} Most Important Features')
plt.tight_layout()
plt.show()
```

```
C:\Users\tommy\AppData\Local\Temp\ipykernel_6084\2879680381.py:15: DeprecationWarnin
g: is_categorical_dtype is deprecated and will be removed in a future version. Use i
sinstance(dtype, pd.CategoricalDtype) instead
  or pd.api.types.is_categorical_dtype(citations_filtered[col]))
Categorical columns to encode: ['sector1', 'issue_dayname', 'issue_monthname', 'part
_of_week', 'season', 'part_of_month', 'location_frequency_group']
After one-hot encoding categorical features, shape: (74381, 88)
Number of numerical features: 78
```


Feature Correlation Matrix
citation_id
issue_year
issue_day
issue_weekend
loc_1700 KETTNER BL
loc_SKI BEACH NORTH 3300 INGRAHAM ST
loc_1400 ISLAND AV
loc_500 4TH AV
loc_500 13TH ST
loc_800 HORNBLEND ST
loc_400 13TH ST
loc_4000 30TH ST
loc_1429 ISLAND AV
loc_600 6TH AV
issue_weekofyear
month_sin
dayofweek_sin
location_popularity
sector_popularity
day_prob_86.0126 SDMC
day_prob_86.0112(F) SDMC
day_prob_86.0105 SDMC
day_prob_86.0111 SDMC
day_prob_86.0121 SDMC
month_prob_86.0126 SDMC
month_prob_86.0112(F) SDMC
month_prob_86.0105 SDMC
month_prob_86.0111 SDMC
month_prob_86.0121 SDMC
days_since_month_start
is_weekend_adjacent
sector1_CSD (R) METER OPS
sector1_CSD (W) PARK RANGERS
issue_dayname_Saturday
issue_dayname_Thursday
issue_dayname_Wednesday
part_of_week_start_week
part_of_month_middle
location_frequency_group_medium_freq
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

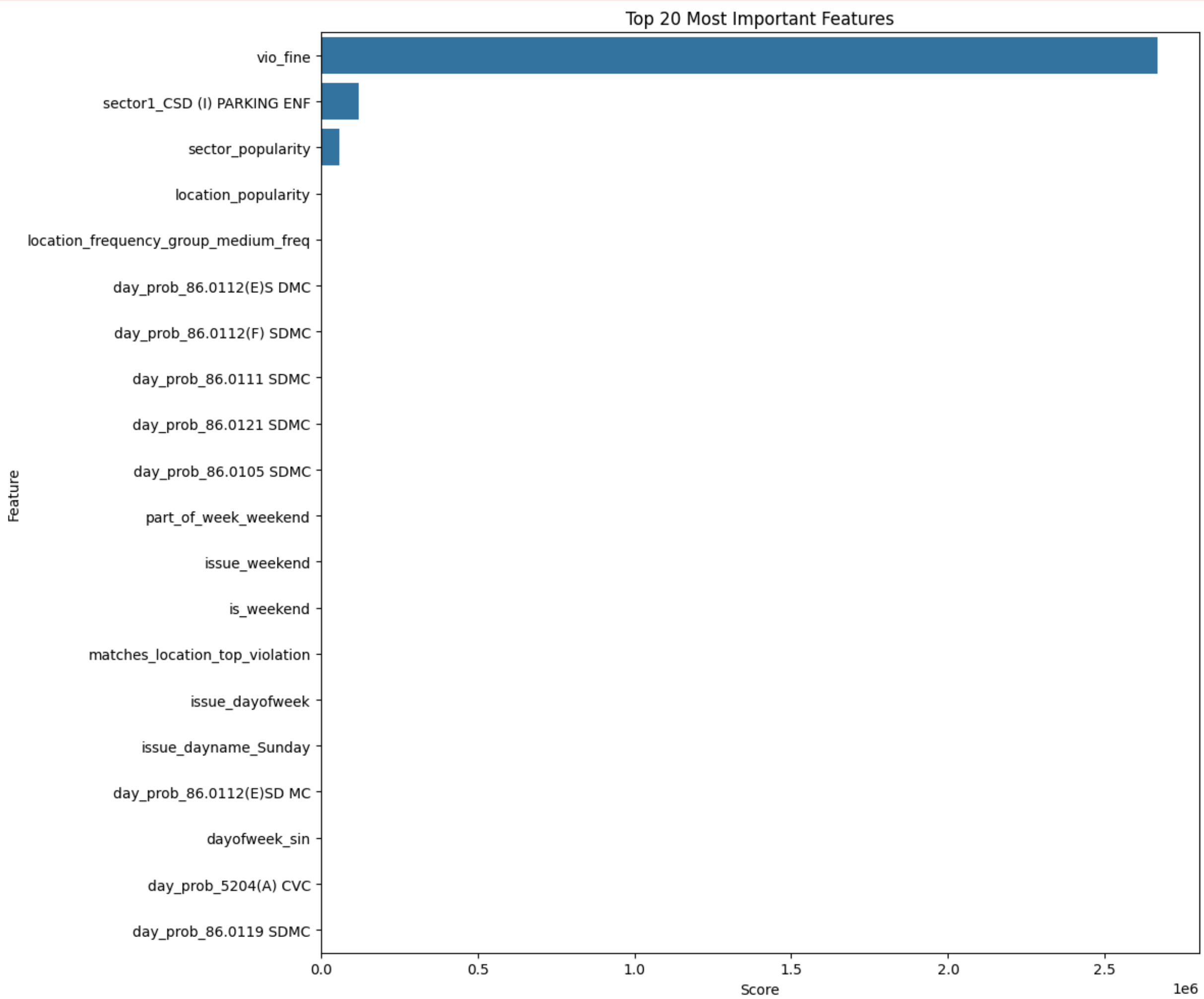
```
High correlation between issue_weekofyear and issue_month: 0.86
High correlation between is_weekend and issue_weekend: 1.00
High correlation between month_sin and issue_month: 1.00
High correlation between month_sin and issue_weekofyear: 0.86
High correlation between month_cos and issue_month: -1.00
High correlation between month_cos and issue_weekofyear: -0.86
High correlation between month_cos and month_sin: -1.00
High correlation between day_prob_86.0112(E)S DMC and issue_dayofweek: -0.81
High correlation between day_prob_86.0105 SDMC and day_prob_86.0112(F) SDMC: 0.96
High correlation between day_prob_86.0105 SDMC and day_prob_5204(A) CVC: 0.82
High correlation between day_prob_86.0119 SDMC and day_prob_86.0126 SDMC: 0.90
High correlation between day_prob_86.0111 SDMC and day_prob_86.0112(F) SDMC: 0.97
High correlation between day_prob_86.0111 SDMC and day_prob_86.0105 SDMC: 0.96
High correlation between day_prob_SDMC 86.2014 and issue_weekend: -0.91
High correlation between day_prob_SDMC 86.2014 and is_weekend: -0.91
High correlation between day_prob_86.0121 SDMC and day_prob_86.0112(F) SDMC: 0.85
High correlation between day_prob_86.0121 SDMC and day_prob_86.0105 SDMC: 0.81
High correlation between month_prob_86.0112(E)S DMC and issue_month: -1.00
High correlation between month_prob_86.0112(E)S DMC and issue_weekofyear: -0.86
High correlation between month_prob_86.0112(E)S DMC and month_sin: -1.00
High correlation between month_prob_86.0112(E)S DMC and month_cos: 1.00
High correlation between month_prob_86.0126 SDMC and issue_month: 1.00
High correlation between month_prob_86.0126 SDMC and issue_weekofyear: 0.86
High correlation between month_prob_86.0126 SDMC and month_sin: 1.00
High correlation between month_prob_86.0126 SDMC and month_cos: -1.00
High correlation between month_prob_86.0126 SDMC and month_prob_86.0112(E)S DMC: -1.
00
High correlation between month_prob_86.0112(E)SD MC and issue_month: -1.00
High correlation between month_prob_86.0112(E)SD MC and issue_weekofyear: -0.86
High correlation between month_prob_86.0112(E)SD MC and month_sin: -1.00
High correlation between month_prob_86.0112(E)SD MC and month_cos: 1.00
High correlation between month_prob_86.0112(E)SD MC and month_prob_86.0112(E)S DMC:
1.00
High correlation between month_prob_86.0112(E)SD MC and month_prob_86.0126 SDMC: -1.
00
High correlation between month_prob_86.0112(F) SDMC and issue_month: -1.00
High correlation between month_prob_86.0112(F) SDMC and issue_weekofyear: -0.86
High correlation between month_prob_86.0112(F) SDMC and month_sin: -1.00
High correlation between month_prob_86.0112(F) SDMC and month_cos: 1.00
High correlation between month_prob_86.0112(F) SDMC and month_prob_86.0112(E)S DMC:
1.00
High correlation between month_prob_86.0112(F) SDMC and month_prob_86.0126 SDMC: -1.
00
High correlation between month_prob_86.0112(F) SDMC and month_prob_86.0112(E)SD MC:
1.00
High correlation between month_prob_5204(A) CVC and issue_month: -1.00
High correlation between month_prob_5204(A) CVC and issue_weekofyear: -0.86
High correlation between month_prob_5204(A) CVC and month_sin: -1.00
High correlation between month_prob_5204(A) CVC and month_cos: 1.00
High correlation between month_prob_5204(A) CVC and month_prob_86.0112(E)S DMC: 1.00
High correlation between month_prob_5204(A) CVC and month_prob_86.0126 SDMC: -1.00
High correlation between month_prob_5204(A) CVC and month_prob_86.0112(E)SD MC: 1.00
High correlation between month_prob_5204(A) CVC and month_prob_86.0112(F) SDMC: 1.00
High correlation between month_prob_86.0105 SDMC and issue_month: -1.00
High correlation between month_prob_86.0105 SDMC and issue_weekofyear: -0.86
High correlation between month_prob_86.0105 SDMC and month_sin: -1.00
```

```
High correlation between month_prob_86.0105 SDMC and month_cos: 1.00
High correlation between month_prob_86.0105 SDMC and month_prob_86.0112(E)S DMC: 1.0
0
High correlation between month_prob_86.0105 SDMC and month_prob_86.0126 SDMC: -1.00
High correlation between month_prob_86.0105 SDMC and month_prob_86.0112(E)SD MC: 1.0
0
High correlation between month_prob_86.0105 SDMC and month_prob_86.0112(F) SDMC: 1.0
0
High correlation between month_prob_86.0105 SDMC and month_prob_5204(A) CVC: 1.00
High correlation between month_prob_86.0119 SDMC and issue_month: -1.00
High correlation between month_prob_86.0119 SDMC and issue_weekofyear: -0.86
High correlation between month_prob_86.0119 SDMC and month_sin: -1.00
High correlation between month_prob_86.0119 SDMC and month_cos: 1.00
High correlation between month_prob_86.0119 SDMC and month_prob_86.0112(E)S DMC: 1.0
0
High correlation between month_prob_86.0119 SDMC and month_prob_86.0126 SDMC: -1.00
High correlation between month_prob_86.0119 SDMC and month_prob_86.0112(E)SD MC: 1.0
0
High correlation between month_prob_86.0119 SDMC and month_prob_86.0112(F) SDMC: 1.0
0
High correlation between month_prob_86.0119 SDMC and month_prob_5204(A) CVC: 1.00
High correlation between month_prob_86.0119 SDMC and month_prob_86.0105 SDMC: 1.00
High correlation between month_prob_86.0111 SDMC and issue_month: -1.00
High correlation between month_prob_86.0111 SDMC and issue_weekofyear: -0.86
High correlation between month_prob_86.0111 SDMC and month_sin: -1.00
High correlation between month_prob_86.0111 SDMC and month_cos: 1.00
High correlation between month_prob_86.0111 SDMC and month_prob_86.0112(E)S DMC: 1.0
0
High correlation between month_prob_86.0111 SDMC and month_prob_86.0126 SDMC: -1.00
High correlation between month_prob_86.0111 SDMC and month_prob_86.0112(E)SD MC: 1.0
0
High correlation between month_prob_86.0111 SDMC and month_prob_86.0112(F) SDMC: 1.0
0
High correlation between month_prob_86.0111 SDMC and month_prob_5204(A) CVC: 1.00
High correlation between month_prob_86.0111 SDMC and month_prob_86.0105 SDMC: 1.00
High correlation between month_prob_86.0111 SDMC and month_prob_86.0119 SDMC: 1.00
High correlation between month_prob_SDMC 86.2014 and issue_month: 1.00
High correlation between month_prob_SDMC 86.2014 and issue_weekofyear: 0.86
High correlation between month_prob_SDMC 86.2014 and month_sin: 1.00
High correlation between month_prob_SDMC 86.2014 and month_cos: -1.00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0112(E)S DMC: -1.
00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0126 SDMC: 1.00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0112(E)SD MC: -1.
00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0112(F) SDMC: -1.
00
High correlation between month_prob_SDMC 86.2014 and month_prob_5204(A) CVC: -1.00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0105 SDMC: -1.00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0119 SDMC: -1.00
High correlation between month_prob_SDMC 86.2014 and month_prob_86.0111 SDMC: -1.00
High correlation between month_prob_86.0121 SDMC and issue_month: 1.00
High correlation between month_prob_86.0121 SDMC and issue_weekofyear: 0.86
High correlation between month_prob_86.0121 SDMC and month_sin: 1.00
High correlation between month_prob_86.0121 SDMC and month_cos: -1.00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0112(E)S DMC: -1.
```

```
00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0126 SDMC: 1.00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0112(E)SD MC: -1.
00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0112(F) SDMC: -1.
00
High correlation between month_prob_86.0121 SDMC and month_prob_5204(A) CVC: -1.00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0105 SDMC: -1.00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0119 SDMC: -1.00
High correlation between month_prob_86.0121 SDMC and month_prob_86.0111 SDMC: -1.00
High correlation between month_prob_86.0121 SDMC and month_prob_SDMC 86.2014: 1.00
High correlation between days_since_month_start and issue_day: 1.00
High correlation between days_until_month_end and issue_day: -0.98
High correlation between days_until_month_end and days_since_month_start: -0.98
High correlation between sector1_CSD (I) PARKING ENF and sector_popularity: 0.99
High correlation between issue_dayname_Saturday and issue_weekend: 0.82
High correlation between issue_dayname_Saturday and is_weekend: 0.82
High correlation between issue_dayname_Saturday and day_prob_86.0119 SDMC: 0.85
High correlation between issue_dayname_Sunday and day_prob_86.0112(F) SDMC: 0.92
High correlation between issue_dayname_Sunday and day_prob_86.0105 SDMC: 0.94
High correlation between issue_dayname_Sunday and day_prob_86.0111 SDMC: 0.89
High correlation between issue_monthname_January and issue_month: -1.00
High correlation between issue_monthname_January and issue_weekofyear: -0.86
High correlation between issue_monthname_January and month_sin: -1.00
High correlation between issue_monthname_January and month_cos: 1.00
High correlation between issue_monthname_January and month_prob_86.0112(E)S DMC: 1.0
0
High correlation between issue_monthname_January and month_prob_86.0126 SDMC: -1.00
High correlation between issue_monthname_January and month_prob_86.0112(E)SD MC: 1.0
0
High correlation between issue_monthname_January and month_prob_86.0112(F) SDMC: 1.0
0
High correlation between issue_monthname_January and month_prob_5204(A) CVC: 1.00
High correlation between issue_monthname_January and month_prob_86.0105 SDMC: 1.00
High correlation between issue_monthname_January and month_prob_86.0119 SDMC: 1.00
High correlation between issue_monthname_January and month_prob_86.0111 SDMC: 1.00
High correlation between issue_monthname_January and month_prob_SDMC 86.2014: -1.00
High correlation between issue_monthname_January and month_prob_86.0121 SDMC: -1.00
High correlation between part_of_week_start_week and issue_dayofweek: -0.80
High correlation between part_of_week_start_week and dayofweek_cos: 0.85
High correlation between part_of_week_weekend and issue_weekend: 1.00
High correlation between part_of_week_weekend and is_weekend: 1.00
High correlation between part_of_week_weekend and day_prob_SDMC 86.2014: -0.91
High correlation between part_of_week_weekend and issue_dayname_Saturday: 0.82
High correlation between part_of_month_end and issue_day: 0.84
High correlation between part_of_month_end and days_since_month_start: 0.84
High correlation between part_of_month_end and days_until_month_end: -0.83
Number of highly correlated features: 29

Top 20 most important features:
                                  Feature         Score
1                                vio_fine  2.667390e+06
61           sector1_CSD (I) PARKING ENF  1.213832e+05
36                      sector_popularity  5.893052e+04
34                    location_popularity  1.726473e+03
76  location_frequency_group_medium_freq  1.418400e+03
```

```
37             day_prob_86.0112(E)S DMC  1.122876e+03
40             day_prob_86.0112(F) SDMC  9.743570e+02
44                day_prob_86.0111 SDMC  9.348622e+02
46                day_prob_86.0121 SDMC  9.128669e+02
42                day_prob_86.0105 SDMC  9.104940e+02
73                 part_of_week_weekend  8.381283e+02
6                        issue_weekend  8.381283e+02
29                          is_weekend  8.381283e+02
35       matches_location_top_violation  7.630525e+02
5                      issue_dayofweek  7.630056e+02
67                 issue_dayname_Sunday  7.175014e+02
39             day_prob_86.0112(E)SD MC  6.433595e+02
32                       dayofweek_sin  6.133170e+02
41                 day_prob_5204(A) CVC  6.018460e+02
43                day_prob_86.0119 SDMC  5.258128e+02
```

```
c:\Users\tommy\miniforge3\Lib\site-packages\sklearn\feature_selection\_univariate_se
lection.py:111: UserWarning: Features [ 2 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
c:\Users\tommy\miniforge3\Lib\site-packages\sklearn\feature_selection\_univariate_se
lection.py:112: RuntimeWarning: invalid value encountered in divide
  f = msb / msw
```



2.9 Create Final Feature Set for Modeling

In [44]:
```
# Based on feature importance, keep only the most relevant features
top_features_list = feature_scores.head(50)['Feature'].tolist()  # Adjust number as

# Create final feature set
X_final = X_features[top_features_list].copy()
print(f"Final feature set shape: {X_final.shape}")

modeling_data = pd.concat([X_final, citations_encoded[['vio_code_encoded', target_c
modeling_data.head()
```

```
Final feature set shape: (74381, 50)
```

Out[44]:

	vio_fine	sector1_CSD (I) PARKING ENF	sector_popularity	location_popularity	location_frequency_group_m
0	37.5	True	55514	1	
2	37.5	True	55514	3	
5	37.5	True	55514	3	
6	37.5	True	55514	3	
7	37.5	True	55514	2	

5 rows × 52 columns

3. Model Building and Evaluation for Parking Citation Prediction

3.1 Prepare Training and Testing Data

In [45]:
```
# Define features and target
if 'vio_code' in modeling_data.columns and 'vio_code_encoded' in modeling_data.colu
    X = modeling_data.drop(['vio_code', 'vio_code_encoded'], axis=1)
    y = modeling_data['vio_code_encoded']
elif 'vio_code_encoded' in modeling_data.columns:
    X = modeling_data.drop(['vio_code_encoded'], axis=1)
    y = modeling_data['vio_code_encoded']
elif 'vio_code' in modeling_data.columns:
    from sklearn.preprocessing import LabelEncoder
    X = modeling_data.drop(['vio_code'], axis=1)
    label_encoder = LabelEncoder()
    y = label_encoder.fit_transform(modeling_data['vio_code'])
    print("Created encoded target variable 'vio_code_encoded'")
```

```python
# Verify shape
print(f"Feature set shape: {X.shape}")
print(f"Target set shape: {y.shape}")
```

```
Feature set shape: (74381, 50)
Target set shape: (74381,)
```

In [46]:
```python
# Check for NaN values in features
nan_count = X.isna().sum().sum()
nan_count
```

Out[46]: `np.int64(0)`

In [47]:
```python
# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, random_state=42, stratify=y
)

print(f"Training set size: {X_train.shape[0]} samples")
print(f"Testing set size: {X_test.shape[0]} samples")

# Feature scaling (standardization)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
Training set size: 55785 samples
Testing set size: 18596 samples
```

3.2 Implement Baseline Models

In [48]:
```python
# Check if we have too many target classes (might need to adjust models)
num_classes = len(np.unique(y))
print(f"Number of target classes: {num_classes}")

# Define baseline models with adjusted parameters if needed
baseline_models = {
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42,
                                             multi_class='multinomial',
                                             solver='lbfgs'),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42,
                                           n_jobs=-1),
    'KNN': KNeighborsClassifier(n_neighbors=5),
}

# If the number of classes is manageable, include more models
if num_classes < 100:  # For very large numbers of classes, some models might be to
    baseline_models['Gradient Boosting'] = GradientBoostingClassifier(
        n_estimators=100, random_state=42)
    baseline_models['SVM'] = SVC(probability=True, random_state=42,
                                decision_function_shape='ovr')
```

```
Number of target classes: 10
```

In [49]:
```
# Function to evaluate model performance
def evaluate_model(name, model, X_train, X_test, y_train, y_test):
    print(f"\nEvaluating {name}...")

    # Train the model and measure training time
    start_time = time.time()
    model.fit(X_train, y_train)
    train_time = time.time() - start_time

    # Make predictions
    start_time = time.time()
    y_pred = model.predict(X_test)
    inference_time = time.time() - start_time

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision, recall, f1, _ = precision_recall_fscore_support(y_test, y_pred, aver

    print(f"Training time: {train_time:.2f} seconds")
    print(f"Inference time: {inference_time:.2f} seconds")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision (weighted): {precision:.4f}")
    print(f"Recall (weighted): {recall:.4f}")
    print(f"F1 score (weighted): {f1:.4f}")

    # Generate classification report (abbreviated for large number of classes)
    if num_classes > 20:
        # Get most common classes in test set for focused reporting
        top_classes = np.unique(y_test, return_counts=True)
        top_class_indices = np.argsort(top_classes[1])[-10:]  # Top 10 most frequen
        top_class_values = top_classes[0][top_class_indices]

        # Create a mask for the top classes
        mask = np.isin(y_test, top_class_values)
        test_subset = y_test[mask]
        pred_subset = y_pred[mask]

        print("\nClassification Report (Top 10 most frequent classes):")
        print(classification_report(test_subset, pred_subset))
    else:
        print("\nClassification Report:")
        print(classification_report(y_test, y_pred))

    return {
        'name': name,
        'model': model,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'train_time': train_time,
        'inference_time': inference_time
    }
```

In [50]:
```
# Evaluate each baseline model
baseline_results = []
for name, model in baseline_models.items():
    try:
        result = evaluate_model(name, model, X_train_scaled, X_test_scaled, y_train
        baseline_results.append(result)
    except Exception as e:
        print(f"Error evaluating {name}: {str(e)}")

# Compare baseline models
if baseline_results:
    baseline_df = pd.DataFrame(baseline_results)
    print("\nBaseline Model Comparison:")
    print(baseline_df[['name', 'accuracy', 'precision', 'recall', 'f1', 'train_time

    # Plot model performance comparison
    plt.figure(figsize=(12, 8))
    performance_metrics = baseline_df[['name', 'accuracy', 'precision', 'recall', '
    performance_metrics = performance_metrics.melt(
        id_vars='name',
        var_name='metric',
        value_name='value'
    )
    sns.barplot(x='name', y='value', hue='metric', data=performance_metrics)
    plt.title('Baseline Model Performance Comparison')
    plt.xlabel('Model')
    plt.ylabel('Score')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.savefig('baseline_model_comparison.png')
    plt.show()
```

```
Evaluating Logistic Regression...
```

```
c:\Users\tommy\miniforge3\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(
c:\Users\tommy\miniforge3\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))
c:\Users\tommy\miniforge3\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))
c:\Users\tommy\miniforge3\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))
c:\Users\tommy\miniforge3\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))
```

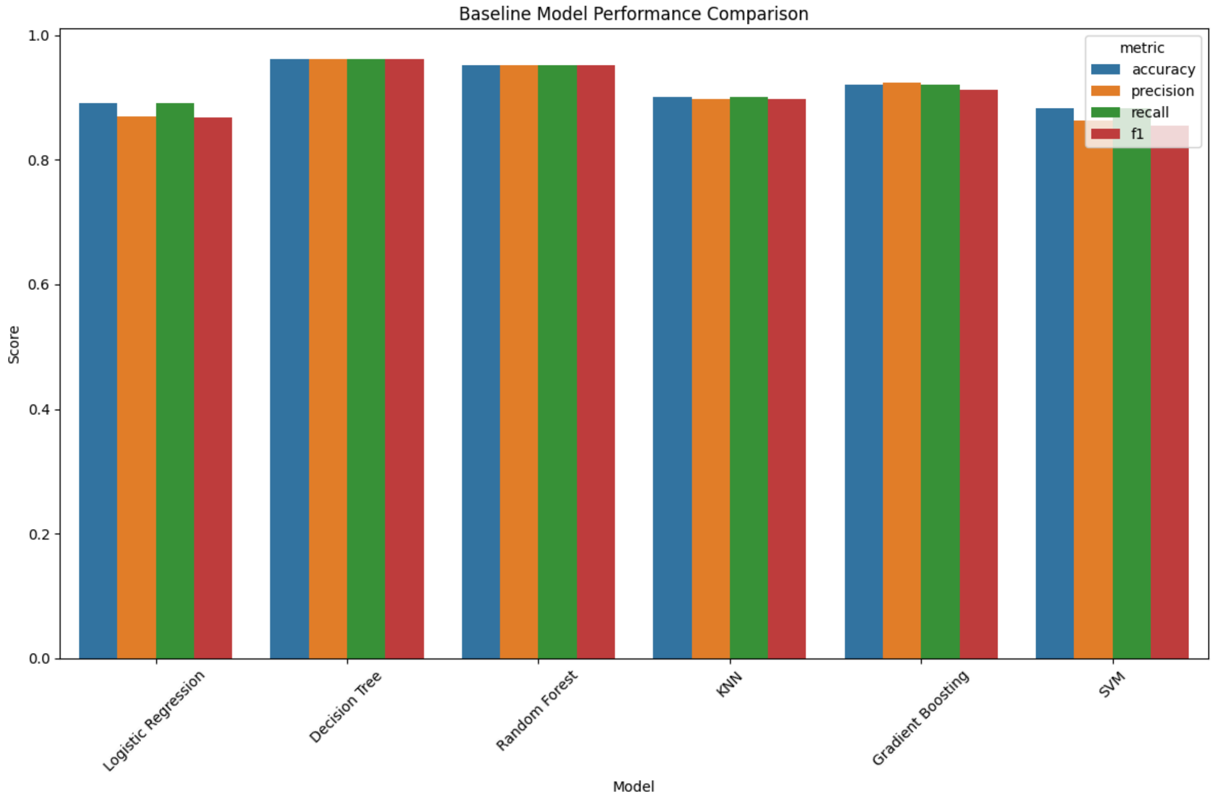
```
Training time: 3.47 seconds
Inference time: 0.00 seconds
Accuracy: 0.8918
Precision (weighted): 0.8703
Recall (weighted): 0.8918
F1 score (weighted): 0.8688

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.68      0.18      0.28      1003
           2       0.65      0.61      0.63       687
           3       1.00      1.00      1.00      4484
           4       0.68      0.97      0.80      3139
           5       1.00      1.00      1.00      1810
           6       1.00      1.00      1.00       809
           7       0.53      0.57      0.55       529
           8       1.00      1.00      1.00      4115
           9       0.00      0.00      0.00       583

    accuracy                           0.89     18596
   macro avg       0.75      0.73      0.73     18596
weighted avg       0.87      0.89      0.87     18596


Evaluating Decision Tree...
Training time: 0.14 seconds
Inference time: 0.00 seconds
Accuracy: 0.9624
Precision (weighted): 0.9621
Recall (weighted): 0.9624
F1 score (weighted): 0.9622

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.76      0.73      0.75      1003
           2       0.91      0.92      0.91       687
           3       1.00      1.00      1.00      4484
           4       0.91      0.92      0.92      3139
           5       1.00      1.00      1.00      1810
           6       1.00      1.00      1.00       809
           7       0.89      0.88      0.88       529
           8       1.00      1.00      1.00      4115
           9       0.88      0.92      0.90       583

    accuracy                           0.96     18596
   macro avg       0.94      0.94      0.94     18596
weighted avg       0.96      0.96      0.96     18596


Evaluating Random Forest...
Training time: 0.28 seconds
Inference time: 0.05 seconds
```

```
Accuracy: 0.9527
Precision (weighted): 0.9517
Recall (weighted): 0.9527
F1 score (weighted): 0.9519

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.75      0.65      0.70      1003
           2       0.88      0.89      0.88       687
           3       1.00      1.00      1.00      4484
           4       0.88      0.92      0.90      3139
           5       1.00      1.00      1.00      1810
           6       0.98      0.99      0.98       809
           7       0.87      0.84      0.86       529
           8       1.00      1.00      1.00      4115
           9       0.82      0.83      0.82       583

    accuracy                           0.95     18596
   macro avg       0.92      0.91      0.91     18596
weighted avg       0.95      0.95      0.95     18596


Evaluating KNN...
Training time: 0.01 seconds
Inference time: 0.65 seconds
Accuracy: 0.9004
Precision (weighted): 0.8973
Recall (weighted): 0.9004
F1 score (weighted): 0.8977

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1437
           1       0.54      0.44      0.49      1003
           2       0.71      0.74      0.72       687
           3       0.99      1.00      1.00      4484
           4       0.77      0.86      0.81      3139
           5       1.00      0.99      0.99      1810
           6       0.92      0.89      0.90       809
           7       0.74      0.65      0.69       529
           8       0.99      0.99      0.99      4115
           9       0.62      0.47      0.54       583

    accuracy                           0.90     18596
   macro avg       0.83      0.80      0.81     18596
weighted avg       0.90      0.90      0.90     18596


Evaluating Gradient Boosting...
Training time: 54.21 seconds
Inference time: 0.17 seconds
Accuracy: 0.9207
Precision (weighted): 0.9239
```

```
Recall (weighted): 0.9207
F1 score (weighted): 0.9116

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.79      0.31      0.44      1003
           2       0.73      0.83      0.78       687
           3       1.00      1.00      1.00      4484
           4       0.75      0.96      0.84      3139
           5       1.00      1.00      1.00      1810
           6       1.00      1.00      1.00       809
           7       0.73      0.61      0.67       529
           8       1.00      1.00      1.00      4115
           9       0.87      0.43      0.57       583

    accuracy                           0.92     18596
   macro avg       0.89      0.81      0.83     18596
weighted avg       0.92      0.92      0.91     18596


Evaluating SVM...
```

```
c:\Users\tommy\miniforge3\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))
c:\Users\tommy\miniforge3\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))
c:\Users\tommy\miniforge3\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))
c:\Users\tommy\miniforge3\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))
```

```
Training time: 71.78 seconds
Inference time: 14.97 seconds
Accuracy: 0.8826
Precision (weighted): 0.8638
Recall (weighted): 0.8826
F1 score (weighted): 0.8554

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.77      0.13      0.22      1003
           2       0.60      0.64      0.62       687
           3       0.99      1.00      1.00      4484
           4       0.68      0.98      0.80      3139
           5       1.00      1.00      1.00      1810
           6       0.78      0.90      0.84       809
           7       0.56      0.38      0.46       529
           8       1.00      1.00      1.00      4115
           9       0.00      0.00      0.00       583

    accuracy                           0.88     18596
   macro avg       0.74      0.70      0.69     18596
weighted avg       0.86      0.88      0.86     18596


Baseline Model Comparison:
                  name  accuracy  precision    recall        f1  train_time  \
0  Logistic Regression  0.891751   0.870263  0.891751  0.868784    3.466088
1        Decision Tree  0.962411   0.962126  0.962411  0.962237    0.141453
2        Random Forest  0.952678   0.951675  0.952678  0.951863    0.284862
3                  KNN  0.900409   0.897259  0.900409  0.897708    0.007035
4    Gradient Boosting  0.920682   0.923889  0.920682  0.911602   54.206543
5                  SVM  0.882609   0.863849  0.882609  0.855420   71.775686

   inference_time
0        0.002000
1        0.004609
2        0.048787
3        0.646066
4        0.173364
5       14.971078
```



3.3 Implement Advanced Models

In [51]:
```
# Try XGBoost model with adjusted parameters
try:
    xgb_model = xgb.XGBClassifier(
        objective='multi:softprob',
        num_class=num_classes,
        n_estimators=100,
        learning_rate=0.1,
        max_depth=6,
        random_state=42,
        n_jobs=-1
    )

    # Evaluate XGBoost
    xgb_result = evaluate_model('XGBoost', xgb_model, X_train_scaled, X_test_scaled
    baseline_results.append(xgb_result)
except Exception as e:
    print(f"Error with XGBoost model: {str(e)}")
```

```
Evaluating XGBoost...
Training time: 0.67 seconds
Inference time: 0.01 seconds
Accuracy: 0.9268
Precision (weighted): 0.9301
Recall (weighted): 0.9268
F1 score (weighted): 0.9179

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.81      0.34      0.48      1003
           2       0.84      0.88      0.86       687
           3       1.00      1.00      1.00      4484
           4       0.75      0.96      0.84      3139
           5       1.00      1.00      1.00      1810
           6       1.00      1.00      1.00       809
           7       0.83      0.78      0.81       529
           8       1.00      1.00      1.00      4115
           9       0.82      0.34      0.48       583

    accuracy                           0.93     18596
   macro avg       0.91      0.83      0.85     18596
weighted avg       0.93      0.93      0.92     18596
```

In [52]:

```
# Try LightGBM model with adjusted parameters
print("\nTraining LightGBM model...")
try:
    lgb_model = lgb.LGBMClassifier(
        objective='multiclass',
        num_class=num_classes,
        n_estimators=100,
        learning_rate=0.1,
        max_depth=6,
        random_state=42,
        n_jobs=-1
    )

    # Evaluate LightGBM
    lgb_result = evaluate_model('LightGBM', lgb_model, X_train_scaled, X_test_scale
    baseline_results.append(lgb_result)
except Exception as e:
    print(f"Error with LightGBM model: {str(e)}")
```

```
Training LightGBM model...

Evaluating LightGBM...
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing wa
s 0.001676 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 668
[LightGBM] [Info] Number of data points in the train set: 55785, number of used feat
ures: 50
[LightGBM] [Info] Start training from score -2.560799
[LightGBM] [Info] Start training from score -2.920562
[LightGBM] [Info] Start training from score -3.297829
[LightGBM] [Info] Start training from score -1.422452
[LightGBM] [Info] Start training from score -1.779201
[LightGBM] [Info] Start training from score -2.329382
[LightGBM] [Info] Start training from score -3.134025
[LightGBM] [Info] Start training from score -3.559660
[LightGBM] [Info] Start training from score -1.508335
[LightGBM] [Info] Start training from score -3.461889
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
Training time: 0.96 seconds
Inference time: 0.04 seconds
Accuracy: 0.9432
Precision (weighted): 0.9437
Recall (weighted): 0.9432
F1 score (weighted): 0.9392

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.84      0.44      0.58      1003
           2       0.87      0.90      0.88       687
           3       1.00      1.00      1.00      4484
           4       0.81      0.95      0.87      3139
```

```
           5       1.00      1.00      1.00      1810
           6       1.00      1.00      1.00       809
           7       0.87      0.82      0.84       529
           8       1.00      1.00      1.00      4115
           9       0.79      0.70      0.75       583

    accuracy                           0.94     18596
   macro avg       0.92      0.88      0.89     18596
weighted avg       0.94      0.94      0.94     18596
```

```
c:\Users\tommy\miniforge3\Lib\site-packages\sklearn\utils\validation.py:2739: UserWa
rning: X does not have valid feature names, but LGBMClassifier was fitted with featu
re names
  warnings.warn(
```

In [53]:

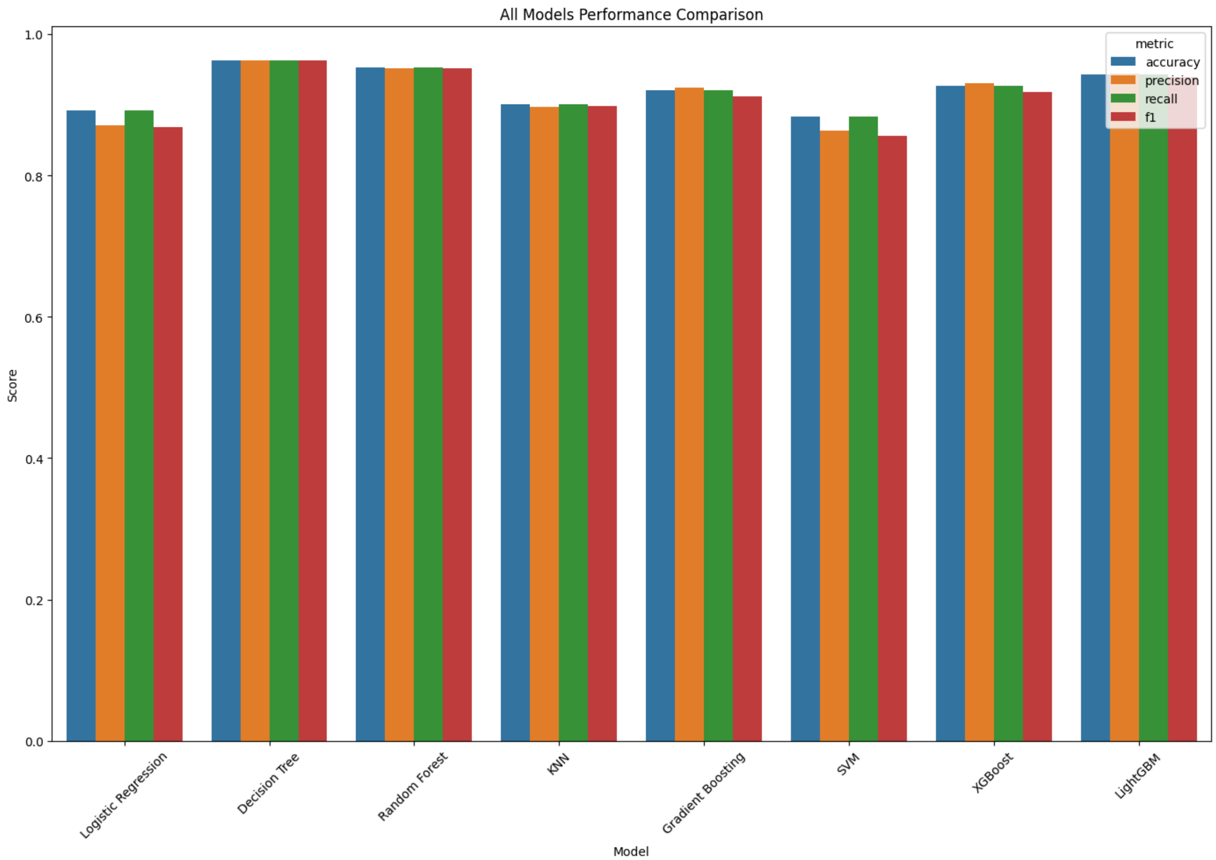
```python
# Update results with advanced models
all_results = baseline_results
all_models_df = pd.DataFrame(all_results)

# Compare all models
print("\nAll Models Comparison:")
print(all_models_df[['name', 'accuracy', 'precision', 'recall', 'f1', 'train_time',
```

```
All Models Comparison:
                  name  accuracy  precision    recall        f1  train_time  \
0  Logistic Regression  0.891751   0.870263  0.891751  0.868784    3.466088
1        Decision Tree  0.962411   0.962126  0.962411  0.962237    0.141453
2        Random Forest  0.952678   0.951675  0.952678  0.951863    0.284862
3                  KNN  0.900409   0.897259  0.900409  0.897708    0.007035
4    Gradient Boosting  0.920682   0.923889  0.920682  0.911602   54.206543
5                  SVM  0.882609   0.863849  0.882609  0.855420   71.775686
6              XGBoost  0.926812   0.930129  0.926812  0.917875    0.671095
7             LightGBM  0.943160   0.943708  0.943160  0.939196    0.958045

   inference_time
0        0.002000
1        0.004609
2        0.048787
3        0.646066
4        0.173364
5       14.971078
6        0.007002
7        0.042040
```

In [54]:

```python
# Plot performance comparison for all models
plt.figure(figsize=(14, 10))
performance_metrics = all_models_df[['name', 'accuracy', 'precision', 'recall', 'f1
performance_metrics = performance_metrics.melt(
    id_vars='name',
    var_name='metric',
    value_name='value'
)
sns.barplot(x='name', y='value', hue='metric', data=performance_metrics)
plt.title('All Models Performance Comparison')
plt.xlabel('Model')
plt.ylabel('Score')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('all_models_comparison.png')
plt.show()
```



3.4 Identify and Optimize Best Model

In [55]:

```
# Find the best model based on F1 score
best_model_idx = all_models_df['f1'].idxmax()
best_model_result = all_models_df.loc[best_model_idx]
best_model_name = best_model_result['name']
print(f"Best performing model based on F1 score: {best_model_name} with F1 score of

# Define parameter grids for hyperparameter tuning
param_grids = {
    'Logistic Regression': {
        'C': [0.1, 1, 10],
        'solver': ['newton-cg', 'lbfgs', 'sag'],
        'max_iter': [1000, 2000]
    },
    'Decision Tree': {
        'max_depth': [None, 10, 20, 30],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4]
    },
    'Random Forest': {
        'n_estimators': [100, 200],
        'max_depth': [None, 10, 20],
        'min_samples_split': [2, 5],
```

```
        'min_samples_leaf': [1, 2]
    },
    'Gradient Boosting': {
        'n_estimators': [100, 200],
        'learning_rate': [0.01, 0.1],
        'max_depth': [3, 5],
        'min_samples_split': [2, 5]
    },
    'KNN': {
        'n_neighbors': [3, 5, 7],
        'weights': ['uniform', 'distance'],
        'p': [1, 2]
    },
    'SVM': {
        'C': [0.1, 1, 10],
        'kernel': ['linear', 'rbf'],
        'gamma': ['scale', 'auto']
    },
    'XGBoost': {
        'n_estimators': [100, 200],
        'learning_rate': [0.01, 0.1],
        'max_depth': [3, 5, 7],
        'subsample': [0.8, 1.0],
        'colsample_bytree': [0.8, 1.0]
    },
    'LightGBM': {
        'n_estimators': [100, 200],
        'learning_rate': [0.01, 0.1],
        'max_depth': [3, 5, 7],
        'num_leaves': [31, 63, 127]
    }
}

# Perform hyperparameter tuning
print(f"Performing hyperparameter tuning for {best_model_name}...")

# Get model class and parameter grid
best_model = all_results[best_model_idx]['model']
param_grid = param_grids[best_model_name]

# Setup grid search with cross-validation
grid_search = GridSearchCV(
    estimator=best_model,
    param_grid=param_grid,
    scoring='f1_weighted',
    cv=3,  # Using 3-fold CV for speed, increase for better estimates
    n_jobs=-1,
    verbose=1
)

# Fit grid search to the data
grid_search.fit(X_train_scaled, y_train)

print(f"Best parameters: {grid_search.best_params_}")
print(f"Best cross-validation score: {grid_search.best_score_:.4f}")
```

```python
# Evaluate the tuned model
best_tuned_model = grid_search.best_estimator_
tuned_result = evaluate_model(f"{best_model_name} (Tuned)",
                              best_tuned_model,
                              X_train_scaled, X_test_scaled,
                              y_train, y_test)

# Compare with the baseline model
print("\nComparison of Baseline vs. Tuned Model:")
baseline_f1 = best_model_result['f1']
tuned_f1 = tuned_result['f1']
improvement = (tuned_f1 - baseline_f1) / baseline_f1 * 100
print(f"F1 Score: {baseline_f1:.4f} -> {tuned_f1:.4f}")
print(f"Improvement: {improvement:.2f}%")

# Update the best model for further analysis
best_model_object = best_tuned_model
```

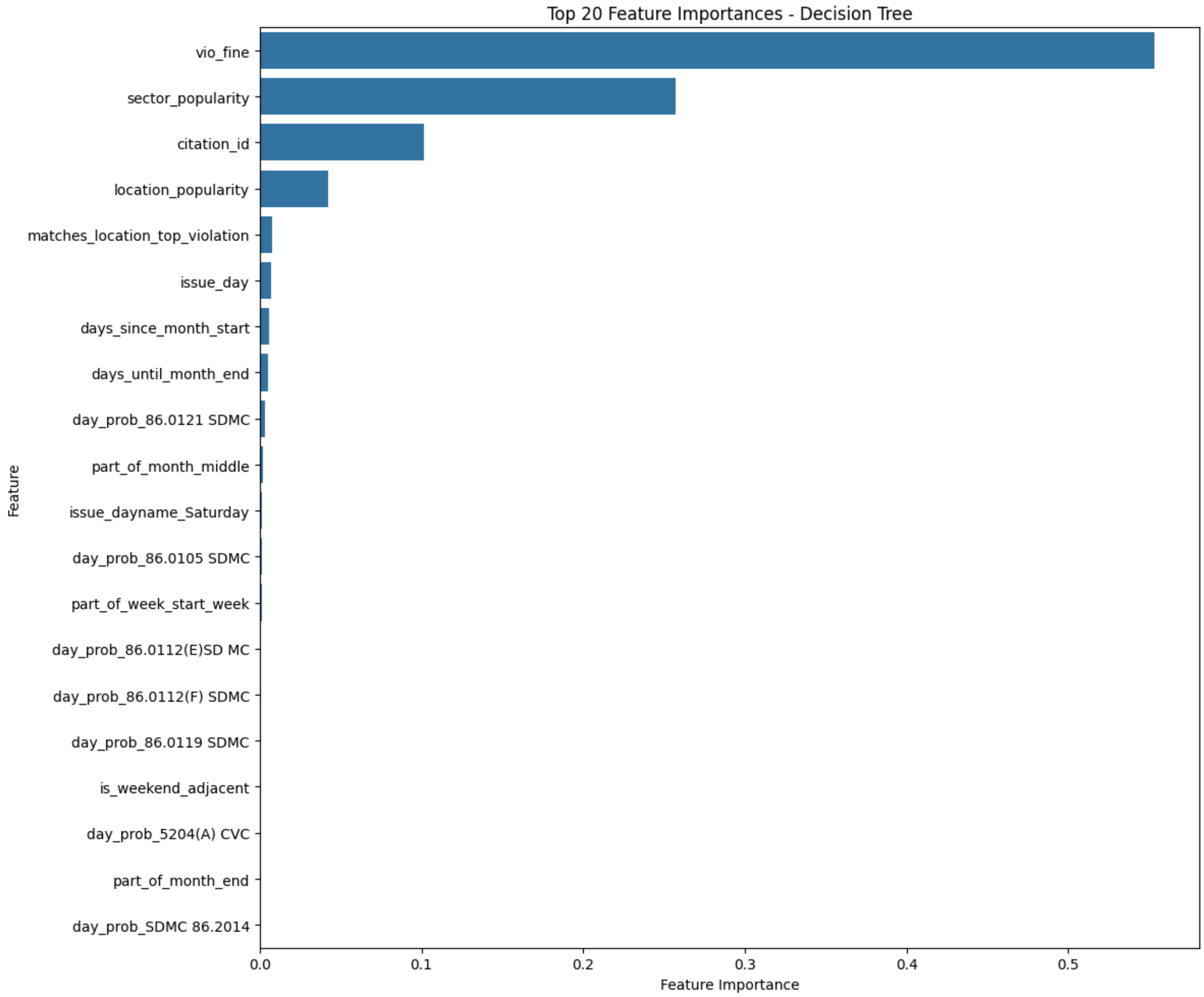
```
Best performing model based on F1 score: Decision Tree with F1 score of 0.9622
Performing hyperparameter tuning for Decision Tree...
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Best parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best cross-validation score: 0.9513

Evaluating Decision Tree (Tuned)...
Training time: 0.15 seconds
Inference time: 0.00 seconds
Accuracy: 0.9624
Precision (weighted): 0.9621
Recall (weighted): 0.9624
F1 score (weighted): 0.9622

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1437
           1       0.76      0.73      0.75      1003
           2       0.91      0.92      0.91       687
           3       1.00      1.00      1.00      4484
           4       0.91      0.92      0.92      3139
           5       1.00      1.00      1.00      1810
           6       1.00      1.00      1.00       809
           7       0.89      0.88      0.88       529
           8       1.00      1.00      1.00      4115
           9       0.88      0.92      0.90       583

    accuracy                           0.96     18596
   macro avg       0.94      0.94      0.94     18596
weighted avg       0.96      0.96      0.96     18596


Comparison of Baseline vs. Tuned Model:
F1 Score: 0.9622 -> 0.9622
Improvement: 0.00%
```

3.5 Feature Importance Analysis

In [56]:
```
# # Try to extract feature importance from the best model
# if hasattr(best_model_object, 'feature_importances_'):
# Get feature importances
feature_importances = best_model_object.feature_importances_

# Create a dataframe for easier manipulation
importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importances
})

# Sort by importance
importance_df = importance_df.sort_values('Importance', ascending=False)

# Display top 20 important features
print("\nTop 20 Most Important Features:")
print(importance_df.head(20))

# Plot feature importances
plt.figure(figsize=(12, 10))
sns.barplot(x='Importance', y='Feature', data=importance_df.head(20))
plt.title(f'Top 20 Feature Importances - {best_model_name}')
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.tight_layout()
plt.savefig('feature_importance.png')
plt.show()

# elif hasattr(best_model_object, 'coef_'):
#     # For linear models like Logistic Regression
#     # Get feature coefficients
#     if len(best_model_object.coef_.shape) == 2:
#         # For multi-class models
#         # Take the mean absolute coefficient across all classes
#         coefficients = np.mean(np.abs(best_model_object.coef_), axis=0)
#     else:
#         # For binary classification
#         coefficients = np.abs(best_model_object.coef_)

#     # Create a dataframe for easier manipulation
#     importance_df = pd.DataFrame({
#         'Feature': X.columns,
#         'Coefficient': coefficients
#     })

#     # Sort by absolute coefficient value
#     importance_df = importance_df.sort_values('Coefficient', ascending=False)

#     # Display top 20 features by coefficient magnitude
#     print("\nTop 20 Features by Coefficient Magnitude:")
#     print(importance_df.head(20))

#     # Plot feature coefficients
#     plt.figure(figsize=(12, 10))
#     sns.barplot(x='Coefficient', y='Feature', data=importance_df.head(20))
```

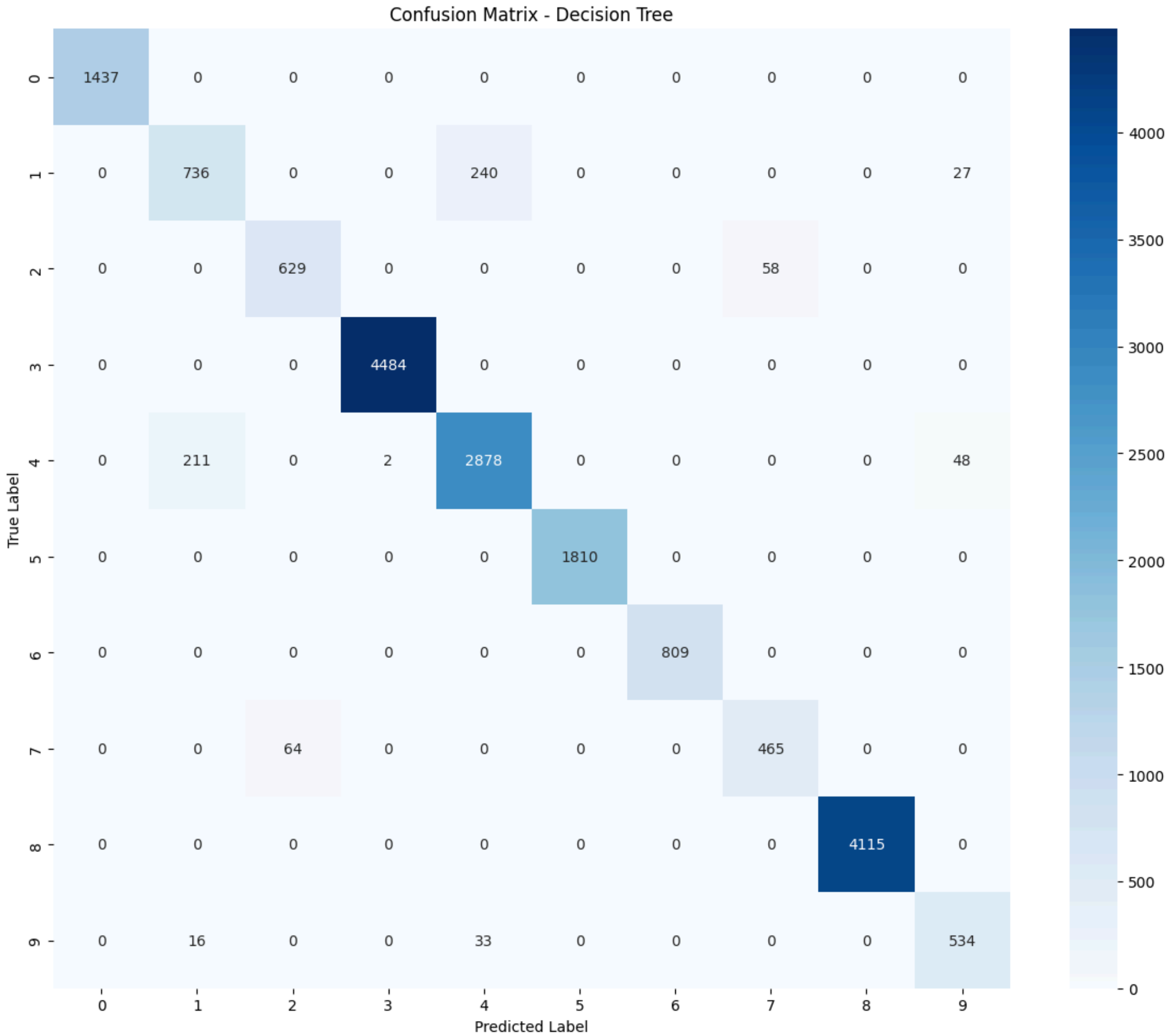
```
#     plt.title(f'Top 20 Feature Coefficients - {best_model_name}')
#     plt.xlabel('Absolute Coefficient Value')
#     plt.ylabel('Feature')
#     plt.tight_layout()
#     plt.savefig('feature_coefficients.png')
#     plt.show()

# else:
#     print("Feature importance not available for this model type.")
```

```
Top 20 Most Important Features:
                          Feature  Importance
0                        vio_fine    0.553309
2               sector_popularity    0.257170
38                    citation_id    0.101817
3             location_popularity    0.042387
13  matches_location_top_violation    0.007885
36                      issue_day    0.006997
37          days_since_month_start    0.005950
34            days_until_month_end    0.005117
8             day_prob_86.0121 SDMC    0.003113
48            part_of_month_middle    0.002044
20          issue_dayname_Saturday    0.001542
9             day_prob_86.0105 SDMC    0.001235
23         part_of_week_start_week    0.001188
16       day_prob_86.0112(E)SD MC    0.001080
6        day_prob_86.0112(F) SDMC    0.001016
19            day_prob_86.0119 SDMC    0.000976
47             is_weekend_adjacent    0.000933
18            day_prob_5204(A) CVC    0.000836
43               part_of_month_end    0.000658
22            day_prob_SDMC 86.2014    0.000654
```



3.6 Confusion Matrix Analysis

In [57]:
```
# Generate predictions with the best model
y_pred = best_model_object.predict(X_test_scaled)

# Create standard confusion matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(12, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title(f'Confusion Matrix - {best_model_name}')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.savefig('confusion_matrix.png')
plt.show()

# Calculate per-class metrics
print("\nPer-class Performance Metrics:")
class_report = classification_report(y_test, y_pred, output_dict=True)
class_df = pd.DataFrame(class_report).T
print(class_df)
```



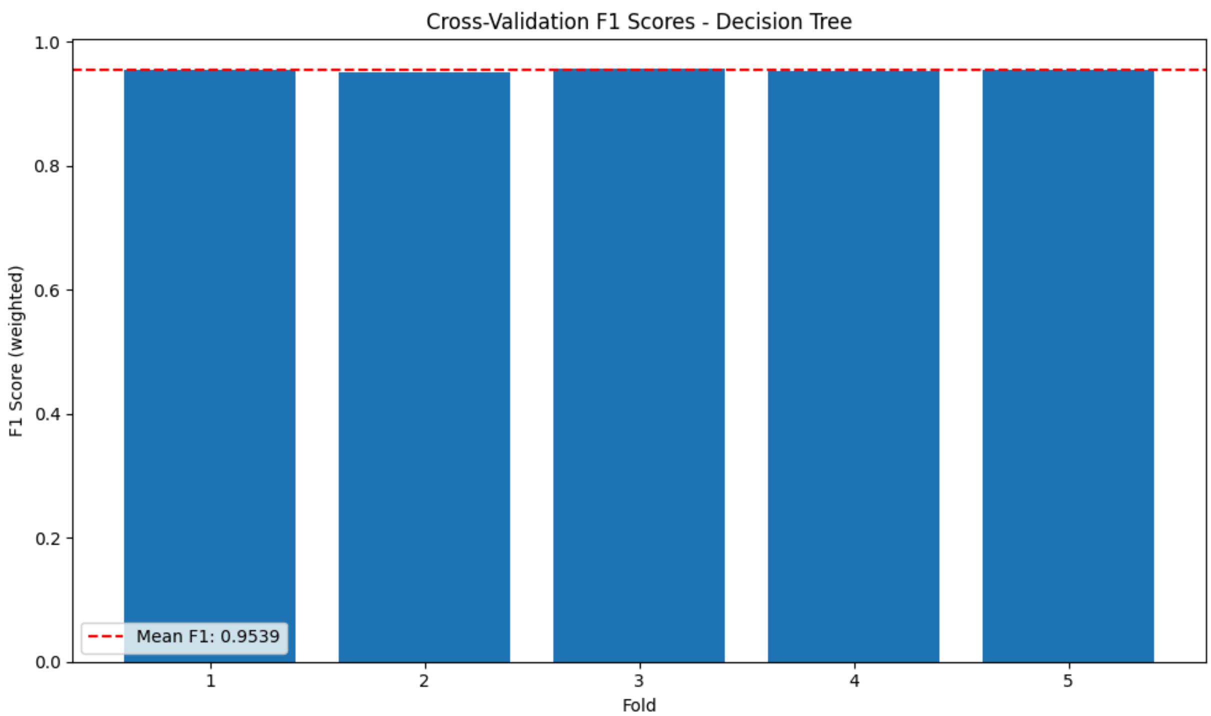

```
Per-class Performance Metrics:
              precision    recall  f1-score       support
0              1.000000  1.000000  1.000000   1437.000000
1              0.764278  0.733799  0.748728   1003.000000
2              0.907648  0.915575  0.911594    687.000000
3              0.999554  1.000000  0.999777   4484.000000
4              0.913361  0.916853  0.915103   3139.000000
5              1.000000  1.000000  1.000000   1810.000000
6              1.000000  1.000000  1.000000    809.000000
7              0.889101  0.879017  0.884030    529.000000
8              1.000000  1.000000  1.000000   4115.000000
9              0.876847  0.915952  0.895973    583.000000
accuracy       0.962411  0.962411  0.962411      0.962411
macro avg      0.935079  0.936120  0.935521  18596.000000
weighted avg   0.962126  0.962411  0.962237  18596.000000
```

3.7 Cross-Validation Analysis

In [ ]:
```
# Perform cross-validation with the best model
cv_scores = cross_val_score(
    best_model_object,
    X_train_scaled,
    y_train,
```

```
    cv=5,
    scoring='f1_weighted',
    n_jobs=-1
)

print(f"Cross-validation F1 scores: {cv_scores}")
print(f"Mean F1 score: {cv_scores.mean():.4f}")
print(f"Standard deviation: {cv_scores.std():.4f}")

# Plot cross-validation scores
plt.figure(figsize=(10, 6))
plt.bar(range(1, len(cv_scores) + 1), cv_scores)
plt.axhline(y=cv_scores.mean(), color='r', linestyle='--',
            label=f'Mean F1: {cv_scores.mean():.4f}')
plt.xlabel('Fold')
plt.ylabel('F1 Score (weighted)')
plt.title(f'Cross-Validation F1 Scores - {best_model_name}')
plt.legend()
plt.tight_layout()
plt.savefig('cross_validation_scores.png')
plt.show()
```

```
Cross-validation F1 scores: [0.95450965 0.95118905 0.95588837 0.95357989 0.95414508]
Mean F1 score: 0.9539
Standard deviation: 0.0015
```




```
--- Model Building and Evaluation Complete ---
Next steps: Complete your analysis for the final report
```