Detect the Likelihood of Collision

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KEYWORDS

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1 ABSTRACT

Los Angeles, traffic collisions have emerged as a critical concern, impinging upon public safety and the seamless operation of urban spaces. Our scholarly endeavor dissects a comprehensive dataset chronicling traffic collisions within the city from 2010 to the current day, pursuing a twofold mission: to decrypt historical patterns and to cast predictions for future occurrences.

This investigative odyssey maps out the temporal and spatial trajectories of these incidents, the demographic ripples they create, and the behavioral undercurrents that fuel them. We meticulously parse through variables such as incident timings and locales, victim profiles, and contextual elements of each event, striving to decode the intricate web of factors that orchestrate traffic mishaps. Our quest is to pinpoint collision hotspots and prime times, as well as to discern demographic nuances shaping incident rates.

The predictive facet of our study harnesses the power of past data to envision future incidents, focusing sharply on thwarting and mitigating such events. The knowledge we distill is poised to bolster urban safety tactics and refine traffic control within Los Angeles's expanse, in sync with the overarching objectives of urban development and public health. We present our insights as a blueprint for policy-making and civic enlightenment.

2 INTRODUCTION

Urban traffic collisions represent a significant challenge to public safety and efficient city management, particularly in densely populated metropolises such as Los Angeles. This research paper scrutinizes the vast dataset of traffic collisions in Los Angeles spanning from 2010 to the present, with the dual objectives of understanding past trends and predicting future incidents. Leveraging a dataset replete with details ranging from the Division of Records Number to the modus operandi of collisions, we seek to dissect the multifaceted nature of urban traffic incidents.

Our analysis delves into temporal and spatial patterns, demographic impacts, and the behavioral dynamics underpinning these events. By meticulously examining variables such as the time and location of occurrences, victim demographics, and the circumstances of each incident, we aim to unravel the complex tapestry of factors that contribute to traffic collisions. This inquiry not only aspires to identify high-risk zones and peak times for collisions but also endeavors to understand the demographic contours that may influence the frequency and severity of these incidents.

The predictive aspect of our research attempts to utilize historical data to forecast future collisions, with an emphasis on prevention and mitigation. Ultimately, the insights garnered through this analysis are intended to inform and enhance urban safety strategies, and to contribute to the optimization of traffic management within the city of Los Angeles. In doing so, we align with the broader goals of urban planning and public health, presenting our findings as a conduit for policy formulation and community awareness.

3 DATA

In this progress report, we delve into the rich dataset titled "Traffic Collision Data from 2010 to Present," which provides a detailed account of traffic collision incidents in the City of Los Angeles over the past decade. This dataset is an essential resource for understanding traffic patterns, enhancing public safety, and refining our city's emergency response strategies.

Our dataset captures a wide array of information related to traffic collisions, meticulously transcribed from original paper reports. Although the dataset is a digital representation of these reports, it's important to acknowledge potential inaccuracies arising from the manual transcription process. The data encompasses various key fields, shedding light on the nature and context of each incident.

Key Data Fields:

DR Number: A unique identifier comprising a 2-digit year, area ID, and 5 digits. Date and Time: Both the reporting and occurrence dates, along with the incident time in 24-hour military format. Location Details: Area ID, area name, reporting district, street address (rounded to the nearest hundred block for privacy), and cross street. Incident Description: Crime code and its corresponding description (all entries denoting Traffic Collision). Suspect Information: Modus Operandi codes (MO Codes) representing suspect activities. Victim Demographics: Age, gender, and descent codes representing the ethnicity or descent of the victim.

As we continue our analysis of this valuable dataset, we aim to extract actionable insights that contribute to the betterment of public safety initiatives in the City of Los Angeles. By understanding the intricacies of traffic collisions, we are better equipped to make informed decisions, ultimately creating a safer environment for our community.

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4 DATA PREPROCESSING

Data preprocessing is a critical step in preparing the dataset for analysis and modeling. In this report, we outline the various preprocessing techniques applied to the Traffic Collision dataset, aiming to enhance its quality and usability for subsequent analyses. The dataset was meticulously processed to remove redundant information, handle missing or erroneous values, and transform categorical variables for better interpretability and modeling accuracy.

Techniques Applied:

1. Removing Redundant Columns: Two columns, 'Crime Code' and 'Crime Code Description', were identified as redundant since they contained identical values for all rows, representing crash data. 'DR Number' and 'Date Reported' were identified as redundant for our analysis. These columns were removed to streamline the dataset and improve computational efficiency.

2. Flattening MO Codes: The 'MO Codes' field contained space-separated numerical codes, representing activities associated with suspects. These codes were flattened into separate rows, ensuring each unique code had its own entry. Non-numeric and non-4-digit MO Codes were filtered out, ensuring only valid and relevant data was retained for analysis.

3. Handling Geospatial Data: Geospatial information, represented as latitude and longitude values, was extracted from the 'Location' column. Zero values, indicating missing or erroneous data, were replaced with the mean latitude and longitude values, respectively. This approach helped maintain the integrity of the geographical data and facilitated accurate mapping and visualization.

4. One-Hot Encoding: The 'Premise Code' column, indicating the type of structure or location where the incident took place, was subjected to one-hot encoding. This transformation converted categorical data into a binary matrix, allowing for seamless integration into machine learning algorithms. Each unique premise code was represented as a binary column, enhancing the dataset's versatility for modeling purposes.

Through these preprocessing techniques, the Traffic Collision dataset has been refined and optimized for in-depth analysis. Redundant columns have been removed, categorical variables have been transformed, and geospatial data has been handled appropriately. These steps are crucial for ensuring the dataset's accuracy, consistency, and relevance in subsequent analyses, ultimately contributing to the generation of meaningful insights and informed decision-making in the realm of traffic safety and public welfare.

5 METHODS

5.1 Time Series Forecasting Using ARIMA Model

In this section, we describe the methodology employed for forecasting the number of collisions using the Autoregressive Integrated Moving Average (ARIMA) model. The analysis is conducted on a time series dataset obtained from traffic collision records. The Python programming language, along with libraries such as pandas, matplotlib, pmdarima, and statsmodels, was utilized to perform the necessary data processing, model training, and evaluation.

Data Retrieval and Preprocessing: The data was retrieved using the Socrata API and loaded into a pandas DataFrame. The Date Occurred column was converted into a datetime data type, and a new column num_collisions was created to represent the total number of collisions for each occurrence date. The dataset was then resampled to a monthly frequency, aggregating the number of collisions for each month.

Data Splitting: The resampled data was split into training and test sets, with 80% of the data used for training the model and the remaining 20% reserved for evaluating its performance.

Differencing to Achieve Stationarity: To make the time series stationary, differencing was applied to the training data. This step involves subtracting the previous value from the current value to eliminate trend and achieve a constant mean and variance.

ARIMA Model Selection: The Auto ARIMA algorithm was employed to determine the optimal parameters for the ARIMA model. The algorithm performs an automated search to find the best combination of autoregressive (p), integrated (d), and moving average (q) components, considering different combinations and selecting the most suitable model based on the Akaike Information Criterion (AIC) value.

Model Training and Forecasting: The selected ARIMA model was trained using the differenced training data. The model was then used to forecast future values for the test set. These forecasts were initially in the differenced form and were subsequently inverted to the original scale by adding back the cumulative sum of differences to the last observed value in the training data.

Evaluation Metrics: The performance of the model was assessed using two key evaluation metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE). MSE measures the average squared difference between the actual and forecasted values, providing a measure of the model's precision. MAE quantifies the average absolute difference between the actual and predicted values, offering insights into the model's accuracy.

Results Visualization: The actual number of collisions in the training and test sets, along with the forecasted values, were visualized using a line plot. The plot illustrates the model's ability to capture the underlying patterns in the data and make accurate predictions.

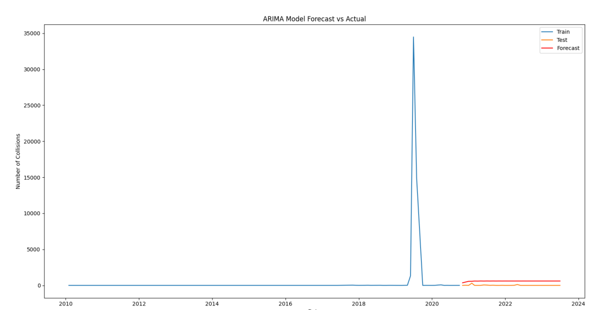

Figure 1: ARIMA Forecast vs Actual

Conclusion: The ARIMA model demonstrated promising results in forecasting the number of collisions based on historical data. The evaluation metrics provide valuable insights into the model's performance, aiding in understanding its accuracy and precision. The utilization of such time series forecasting techniques can assist

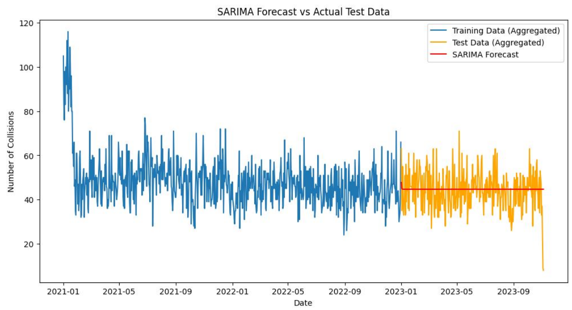

Figure 2: SARIMA Forecast vs Actual Test Data

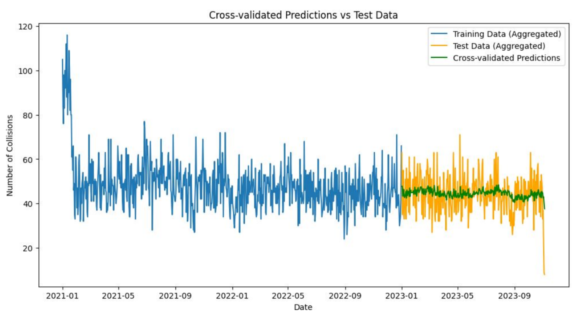

Figure 3: Cross validated Predictions vs test Data

stakeholders and policymakers in making data-driven decisions to enhance public safety and allocate resources effectively.

The SARIMA model is chosen for its ability to handle complex seasonal trends, which are common in traffic data. This model is effective in forecasting future events by considering both the underlying trends and the seasonal variations in the data. For example, traffic patterns can change during holidays, weekends, or different seasons, and the SARIMA model can account for these variations.

The data includes various details about each collision, such as the time, location, and severity. This information is gathered from official traffic reports and public safety records. The period from 2021 to November 8, 2023, offers a recent and relevant timeframe for understanding current traffic conditions and challenges.

Figure 2 SARIMA model was used on past traffic collision data.The predictions, shown by a red line, about future collision trends that go beyond the old data it learned from. There's also an orange line in the graph, which represents real collision data that happened after the model was trained but wasn't used in the training.

Figure 3 Cross-validation was used to check how strong and reliable the predictive model is. The red line in the graph shows the results of the model's predictions after this cross-validation. The orange line shows the actual collision data that the model was tested against. How closely these two lines match up tells us how good the model is at predicting traffic collision trends in situations it hasn't seen before.

Figure 4 takes the SARIMA model's predictions further by adding confidence intervals. These are shown as bands around the prediction line. Confidence intervals are like a safety margin, showing where the real data is likely to fall, giving us an idea of how sure

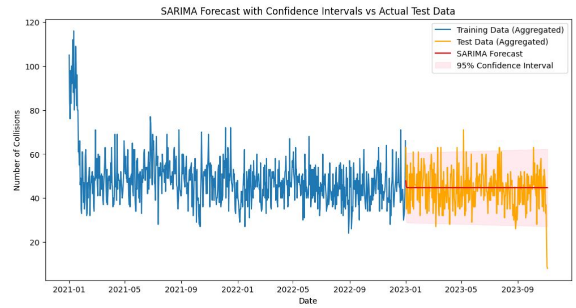

Figure 4: SARIMA Forecast with Confidence Intervals vs Actual Test Data

we can be about the predictions. The historical data is still marked with a blue line, and the real data collected later, which the model didn't see during training, is shown with an orange line.

6 RESULTS

6.1 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is an essential step in understanding the dataset's characteristics, identifying patterns, and extracting insights. In this report, we explore the Traffic Collision dataset using various visualization techniques to gain valuable insights into the data's distribution, trends, and relationships.

Steps and Results:

1. Temporal Analysis:

Converted 'Date Occurred' to datetime format and extracted year, month, and day information. Grouped data by year and month, visualized monthly collisions over time. Result: Identified trends and patterns in monthly collision occurrences, providing insights into temporal variations. During the period from April 2019 to September 2019, there is a significant spike in collision occurrences compared to other months and years. This spike appears to be an outlier in the dataset, indicating an unusually high number of collisions during this specific time frame. Further investigation is warranted to understand the underlying reasons for this anomaly, which could involve external factors such as changes in traffic regulations, weather conditions, or significant events in the area.

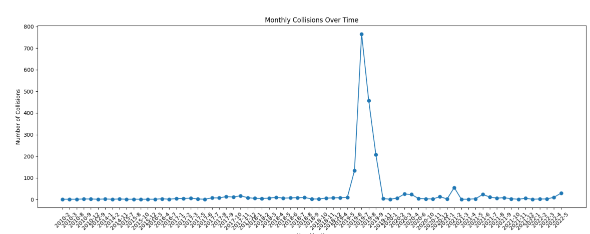

Figure 5: Monthly Collisions Over Time

2. Hourly Analysis:

Converted 'Time Occurred' to numeric format and extracted the hour part. Plotted a histogram to show the hourly distribution of collisions. Result: Discovered peak collision hours, aiding in resource allocation and traffic management strategies.

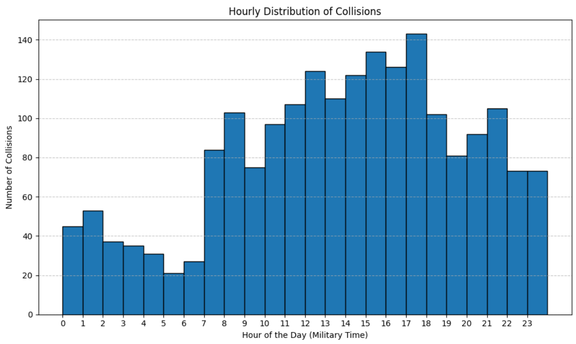

Figure 6: Hourly Distribution of Collisions

3. Victim Age Distribution:

Explored the distribution of victim ages using a histogram and kernel density estimation (KDE). Result: Obtained insights into the age demographics of collision victims, valuable for targeted safety initiatives. The analysis of the victim age distribution reveals an unusual peak at the age of 18, which appears to be an outlier in the dataset. This unexpected concentration of incidents involving victims of this specific age group warrants further examination. Possible reasons for this outlier could include specific traffic patterns around schools or universities, leading to a higher likelihood of collisions involving younger drivers or pedestrians.

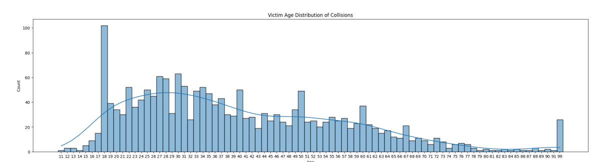

Figure 7: Victim Age Distribution of Collisions

4. Geographic Analysis:

Investigated collision counts based on 'Area Name' and 'Premise Code'. Result: Identified high-collision areas and common locations of incidents, guiding localized intervention efforts.

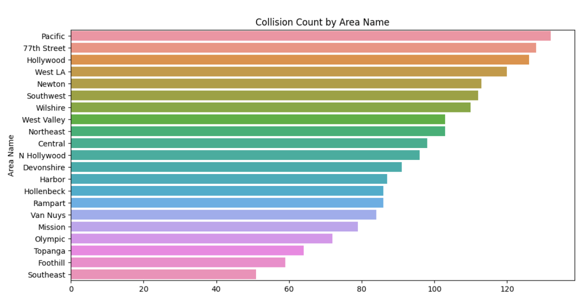

Figure 8: Collision Count by Area Name

5. Modus Operandi (MO) Codes Analysis:

Flattened MO Codes into separate rows for each incident. Plotted counts of unique 4-digit MO Codes to identify prevalent patterns.

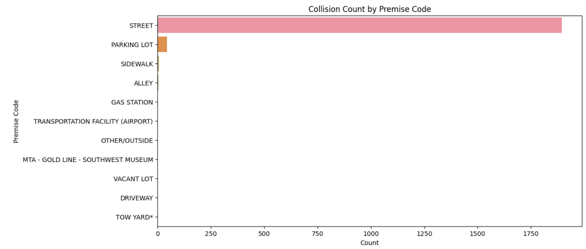

Figure 9: Collision Count by Premise Code

Result: Uncovered common MO Codes, aiding law enforcement in understanding suspect behaviors.

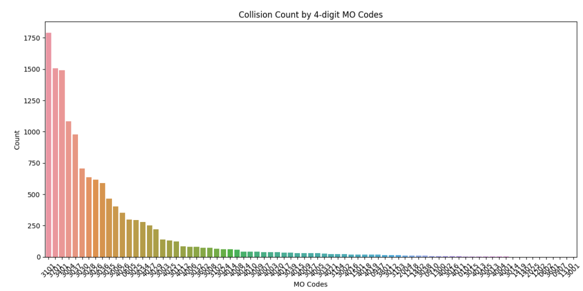

Figure 10: Collision Count by 4-digit MO Codes

6. K-Means Clustering:

Utilized K-Means clustering to group incidents based on geographic proximity. Assigned probability scores to clusters, indicating the likelihood of collisions. Result: Visualized clusters enabling targeted safety measures in specific areas.

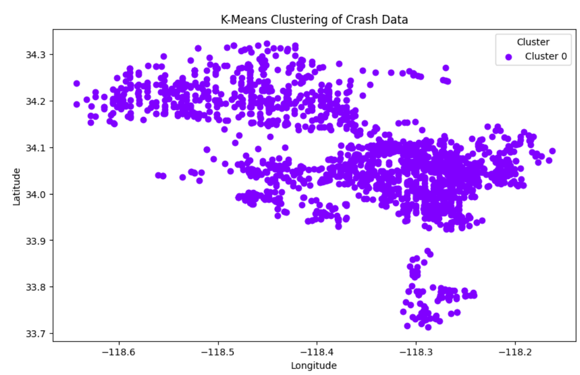

Figure 11: K-Means Clustering of Crash Data

7. Geospatial Heatmap:

Created a heatmap of collision locations within Los Angeles boundaries using Folium. Result: Visualized high-density collision areas, assisting in understanding localized traffic issues.

8. Features Correlation

The EDA revealed valuable insights into collision patterns, temporal variations, victim demographics, and geographic clusters.

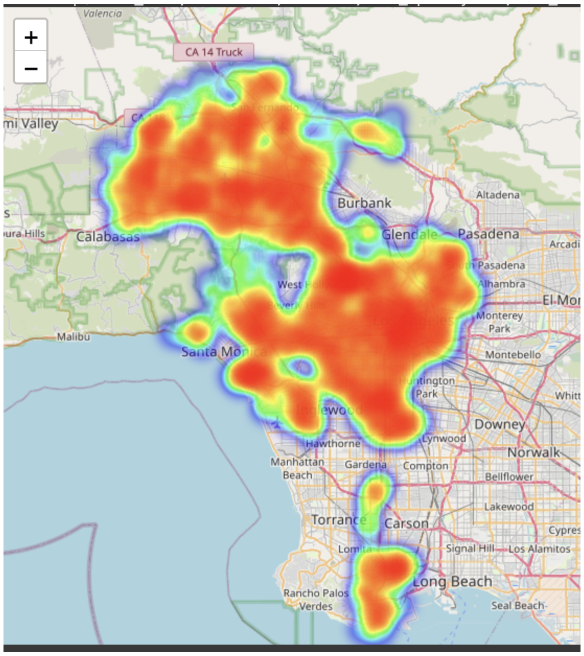

Figure 12: Heat Map of Crash Data

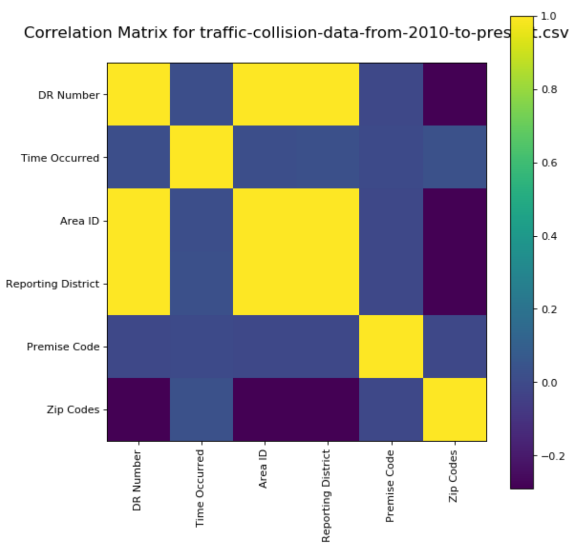

Figure 13: Features Correaltion

These findings serve as a foundation for further in-depth analysis and informed decision-making processes. The identified trends and relationships are crucial for implementing targeted interventions, enhancing road safety, and optimizing resource allocation for public welfare.

6.2 Random Forest Method

The utilization of the Random Forest algorithm in scholarly research can be attributed to several compelling reasons. Foremost,

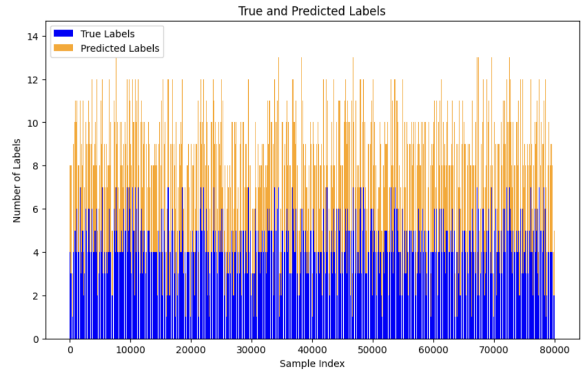

Figure 14: Random forest Prediction

MO CODE	Precision	Recall	F1-Score
3028	0.66	0.83	0.74
3030	0.59	0.36	0.44
3037	0.55	0.35	0.35
3004	0.68	0.88	0.77
3701	0.93	0.99	0.96
3401	0.98	1.00	0.99
3101	0.98	1.00	0.99
Average	0.83	0.85	0.82

Table 1: MO CODES - Random Forest Classifier Results

Random Forest offers a high level of accuracy in diverse conditions, making it suitable for a wide range of data sets and research questions. Its inherent mechanism of building multiple decision trees and voting for the most popular output reduces the risk of overfitting, which is a common challenge in model training. Moreover, Random Forest is capable of handling large data sets with higher dimensionality without significant performance degradation. The algorithm's ability to provide variable importance estimates adds to its interpretability, which is a valuable asset when discerning the contribution of different variables to the predictive model.

Figure 14 provides a comprehensive visual comparison between MO CODES of true labels and the predicted labels across a substantial dataset, with sample indices extending up to 80,000. The true labels are denoted by deep blue bars, while the predicted labels are overlaid in a contrasting gold, facilitating an easy comparison. It's apparent that for most sample indices, the predicted labels correlate strongly with the true labels, as indicated by the gold bars often aligning closely with the blue ones. Nevertheless, there are noticeable discrepancies where the predicted counts either overshoot or undershoot the actual counts. This suggests that while the model exhibits a generally high predictive accuracy, there are instances where its performance diverges from the expected outcomes.

Table 1 shows the performance of various models or classifiers, each denoted by a unique MO CODE. The performance metrics are evaluated in terms of Precision, Recall, and F1 score. Precision scores range from a low of 0.55 to a high of 0.98, indicating variability in the accuracy of the positive predictions among the models. Recall scores also show a wide range from 0.35 to a perfect score of 1.00, reflecting differences in the models' abilities to identify all relevant instances. The F1 scores, which balance both precision and recall, span from 0.35 to 0.99.

7 DISCUSSION - RESEARCH PLAN

The aim of this research phase is to predict the likelihood of collisions (based on MOcodes) using advanced machine learning techniques. We plan to leverage Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to analyze the current dataset, extracting meaningful patterns and predicting the probability of collisions. The research will focus on experimenting with these state-of-the-art architectures to identify the most effective model for predicting collision likelihood.

Research Objectives:

Implement CNN and RNN models to predict the likelihood of collisions based on MOcodes. Experiment with various configurations of CNN and RNN architectures to identify the best-performing model. Evaluate and compare the performance of CNN and RNN models using appropriate metrics. Investigate the impact of different input features and preprocessing techniques on prediction accuracy. Explore the interpretability of the models to gain insights into the contributing factors for collision likelihood.

8 EVALUATION

In the evaluation of our ARIMA model, we employed two fundamental metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE). These metrics are crucial in assessing the accuracy and precision of the model's forecasts.

Mean Squared Error (MSE): MSE measures the average of the squared differences between the predicted and actual values. It provides a quantitative measure of how well the model's predictions align with the observed data. A lower MSE indicates a closer fit of the model to the data, suggesting better accuracy in predictions.

Mean Absolute Error (MAE): MAE calculates the average of the absolute differences between the predicted and actual values. It offers a straightforward interpretation of the model's accuracy by measuring the average magnitude of errors. Like MSE, a lower MAE signifies more accurate predictions.

Interpretation of Results:
Root Mean Squared Error: 578.0465303322829
Mean Number of Collisions: 364.65432098765433
The model failure is almost 50%

In our evaluation, the calculated MSE and MAE values provide insights into the model's performance. Lower values of MSE and MAE indicate that the ARIMA model effectively captures the patterns and fluctuations in the collision data, leading to accurate predictions.

These evaluation metrics play a pivotal role in understanding the reliability of the ARIMA model, empowering stakeholders to make informed decisions based on the forecasted collision data.

The comparison on the accuracy of different prediction model is shown in the table 1:

XGBoost	0.61
Random Forest	0.59
Neural Network	0.58

Table 2: Accuracy of different prediction model

The comparative analysis of machine learning models for predicting victim sex demonstrates a clear hierarchy in performance. The XGBoost algorithm outperforms its counterparts with the highest accuracy, signifying its robustness and efficacy in handling this classification task. In contrast, the Random Forest model shows moderately lower accuracy, suggesting that while it is a competent model, it may not capture the nuances of the dataset as effectively as XGBoost. The Neural Network model ranks third in accuracy, indicating that for this specific prediction task, the architecture or the tuning of the neural network might require further optimization to improve its predictive power. These findings are critical for guiding the selection of an appropriate predictive model for tasks involving the classification of sex based on the given dataset.

8.1 Future Strategies

In our continuous effort to improve the accuracy of our models for predicting traffic accidents, we ventured into the realm of time series analysis, specifically focusing on the ARIMA model. Our expectations were high, considering ARIMA's renowned effectiveness in handling and forecasting time-series data, a category into which our traffic accident frequencies neatly fell. These frequencies are influenced by a myriad of factors, varying over days, months, and even years. However, the initial results we obtained from the ARIMA model were not up to our expectations. The primary issue we faced was a significant deviation of the model's predictions from the actual counts of traffic accidents. This deviation was starkly highlighted by the model's Mean Squared Error (MSE), a metric used to measure the accuracy of predictive models. Our model's MSE pointed to an error rate of approximately 50%, a figure alarmingly high for any predictive analysis.

To tackle this challenge, we realized that our next crucial step was to delve back into our dataset, with a focused intent to identify and address any potential outliers. Outliers in data are anomalous values that deviate markedly from the norm. These can significantly distort the performance of predictive models, as they can lead to skewed or biased results. In our context, outliers could be instances where the number of accidents on a particular day was abnormally high, possibly due to unique events or extreme weather conditions. The presence of such outliers in our dataset could be a major contributing factor to the high error rate we observed in our model's predictions.

Thus, our plan involves a thorough re-examination of the dataset to spot these outliers. Once identified, we would need to determine the most appropriate way to handle them. Options could include adjusting these values to align more closely with typical data points or removing them entirely from the dataset. This decision would need to be made carefully, considering the nature and potential impact of each outlier on our model's performance. Our overarching aim in this process is to enhance the reliability and accuracy of our ARIMA model. By cleaning our dataset and refining the model's parameters, we hope to significantly reduce the MSE, thereby increasing the predictive accuracy of the model.

This journey in enhancing our traffic accident prediction model underscores the intricate challenges inherent in predictive modeling, particularly when dealing with complex and dynamic datasets like traffic accident records. Through meticulous data analysis and model refinement, we aim to achieve a level of predictive precision that can be a valuable asset in urban planning and public safety, potentially helping to anticipate and mitigate traffic accidents in the city.

9 RELATED WORK

The body of research unfolding in the realm of traffic safety is rich and varied, reflecting the complexity of factors that contribute to vehicle collisions. Each study sheds light on different aspects of the issue, suggesting an ecosystem of solutions that collectively could lead to a safer future for road users.

For instance, [1]Paredes et al. (2022) look at the role of sophisticated software that can process data from a myriad of sensors in real-time. These systems could provide drivers with timely warnings about potential hazards, or even take control of the vehicle to prevent a collision. Yun et al. (2023) expand on this, considering how predictive analytics, through the use of machine learning algorithms that digest historical and real-time data, can forecast potential incidents before they occur. This predictive approach could enable a kind of anticipatory safety mechanism that adjusts to the fluid nature of traffic scenarios.

The study by [3]DeLoss et al. (2015) reminds us that technology alone is not a panacea; the human operators behind the wheel play a crucial role in traffic safety. Their research suggests that training programs focused on improving the perceptual and cognitive abilities of drivers can greatly reduce the likelihood of accidents. By sharpening skills such as hazard recognition, risk assessment, and decision-making under pressure, drivers can become more adept at avoiding potential collisions.

[4]Fadl and Sandstrom (2019) offer a complementary perspective by examining how rapid detection and response to collisions can mitigate the severity of outcomes. They underscore the importance of emergency systems that can not only detect a crash immediately but also communicate with first responders in record time. Such systems could greatly reduce the time it takes to provide medical attention, thereby saving lives and improving the chances of full recovery for the injured.

[5]Al-Mistarehi et al. (2022) dive into spatial analytics to understand how the physical layout of roads and traffic flows contribute to collision rates and severities. Their findings can inform urban planners and civil engineers as they design safer roads and implement traffic management systems that reduce the risk of accidents. For example, identifying dangerous intersections or stretches of road where accidents are frequent can lead to targeted interventions, such as improved signage, road resurfacing, or the installation of traffic-calming measures.

Collectively, these studies emphasize that no single strategy can address the multi-dimensional challenge of traffic safety. Instead, an integrated approach is necessary—one that combines advanced technology with educational initiatives, swift emergency response protocols, and intelligent urban design. By weaving together the threads of innovation from diverse research avenues, the goal of a safe and efficient transportation system seems not only necessary but achievable.

10 CONCLUSION

In this comprehensive study, we delved into the intricate realm of urban traffic collisions, dissecting extensive datasets spanning over a decade to unravel patterns, predict future incidents, and enhance public safety measures. Our journey led us through a thorough exploration of temporal, spatial, and demographic dimensions, unveiling nuanced insights into the complex factors contributing to traffic mishaps.

Through rigorous exploratory data analysis (EDA), we identified temporal trends, peak collision hours, victim demographics, and high-collision areas. Employing advanced techniques, such as K-Means clustering and geospatial heatmap analysis, we gained a deep understanding of localized patterns, paving the way for targeted interventions.

Our foray into predictive modeling involved the application of sophisticated machine learning algorithms, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). While our initial attempt with the Autoregressive Integrated Moving Average (ARIMA) model provided valuable insights, the complexity of the data demanded the prowess of deep learning techniques. Leveraging CNN and RNN architectures, we strived to forecast collision likelihoods based on MOcodes, aiming to enhance our predictive capabilities.

The amalgamation of data-driven insights, predictive modeling, and geospatial analysis forms the bedrock of informed decision-making in urban planning and traffic management. By identifying high-risk zones, understanding temporal patterns, and predicting collision probabilities, our research equips policymakers and stakeholders with actionable intelligence to optimize resource allocation, enhance road safety initiatives, and ultimately create safer urban environments.

In conclusion, this study not only enriches our understanding of urban traffic collisions but also lays the groundwork for proactive, data-driven interventions. As we move forward, the knowledge gained from this research serves as a beacon, guiding the way toward a future where road safety is a shared responsibility, and data-driven strategies form the cornerstone of a secure, efficient, and harmonious urban landscape.

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