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Machine Learning Approaches for Predicting Peak-Hour Urban Traffic Accidents

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Abstract: Traffic accidents during rush hours are a big problem for urban transportation. They kill people and cost a lot of money, so we need accurate predicting tools to help us make smart decisions before they happen. Real-life accident data often has nonlinear temporal dependencies and complex spatial variations that are hard for traditional statistical methods to explain. To solve these problems, a system for time-series forecasting is created to predict traffic accidents during rush hour using the Accident Prediction dataset from Kaggle, which is free for everyone to use. The data go through preprocessing steps like cleaning, normalization, exploratory analysis, categorical encoding, and feature engineering based on location and peak-hour characteristics. There are several prediction models used, such as a Negative Binomial generalized linear model, SARIMAX with external variables, a multilayer perceptron with lagged inputs, and a long short-term memory network for capturing trends over long periods of time. Mean error, mean absolute error, root mean square error, mean absolute percentage error, and mean absolute scaled error are all ways to measure how well a model works. The results show that the LSTM model does a better job of predicting the future, with an MAE of about 1.35 and an RMSE of about 1.85. LIME and SHAP are used to add explainability, and a Flask-based interface lets users make predictions, which improves the accuracy of predictions and makes them more useful for improving road safety in cities.

*“**Index Terms:** Multi-Layer Perceptron (MLP), Negative Binomial (NB), Pearson Correlation Analysis, Prediction Model, Seasonal Auto Regressive Integrated Moving Average (SARIMA-X), Traffic Accident Rate.”*

1. INTRODUCTION

Traffic accidents are a big public health and socioeconomic problem on a global scale. They cause a lot of deaths, injuries, and damage to infrastructure around the world. Rapid development, more people driving cars, and more complicated traffic patterns have all made accidents more likely, especially during rush hours when there are a lot of people traveling [1]. International health and transportation groups have long said that road safety is an important part of sustainable development and that we need data-driven plans to lower the number and severity of accidents [2]. As a result, many countries have made long-term plans and laws about road safety that aim to lower the harm caused by traffic by using systematic research and early action [3].

Even with all of these efforts, it is still hard to correctly predict traffic accidents because crashes are random and the way that traffic flow, human behavior, and road characteristics change over time. Previous research has looked at predicting accidents using a variety of modeling approaches, mainly focused on certain spatial units or time scales that are added together [4, 5]. But there isn't a lot of agreement on how the different modeling points of view read accident patterns over time, especially at fine-grained time resolutions that are important during rush hours [6]. Furthermore, there is still a lack of comparative research into how different model classes represent time-dependent accident variability. This means that there is a methodological gap in understanding their relative strengths and weaknesses for traffic safety analysis [7].

The main goal of this study is to create a complete analytical framework for predicting traffic accidents during rush hour by using past accident data that has been enhanced with relevant traffic and roadway attributes. The study looks at accident events as time-series processes to compare and contrast how different modeling paradigms' representative methods predict what will happen next. This study tries to give a complete picture of temporal accident prediction by looking at model outputs in the same way every time. This gives us a better idea of how changes in time and other things in the environment affect how well accident predictions work [8].

This study is important because it could help with planning for road safety based on facts and managing traffic in a responsible way. Accurate predictions of accidents that will happen during rush hours can help transportation agencies find high-risk times, make the best use of their resources, and plan specific safety measures. The comparison approach used in this study also helps to improve methods by teaching researchers and practitioners about the best modeling approaches for time-series accident analysis. In the end, the results are meant to help lawmakers reach long-term goals for road safety and lower the cost of accidents to society [9, 10].

2. LITERATURE REVIEW

Early studies on traffic accident modeling mostly used statistical methods to look at how often accidents happen and figure out what causes them. Quddus [11] looked into time-series count data models for traffic accidents and showed that these models can be used to show how crash data changes over time. The study was useful for longitudinal analysis, but it also showed problems with overdispersion and not being able to show complicated traffic dynamics in a flexible way. Roland et al. [12] did more recent work that expanded the temporal modeling perspective by predicting car accidents on an urban scale. This showed that data-driven approaches can improve prediction accuracy, but the study was still very specific to the context and didn't offer many opportunities to compare different modeling paradigms.

Time-series forecasting has also been looked at as a way to figure out how outside problems affect road safety. Sekadakis et al. [13] looked at impact trends during the COVID-19 pandemic. This shows that time-series models can pick up on sudden changes in the structure of accident patterns. Even though the study had some good points, it mostly looked at national averages, which might not show differences in specific areas or during peak hours that are important for planning practical safety. Wang et al. [14] compared safety models at different levels of traffic aggregation, pointing out that time resolution has a big impact on how well models work. In spite of this, their study didn't directly look at how different model classes behave in consistent time-series settings.

In addition to the usual studies on road safety, research into risk analysis has added to our understanding of how to model accidents. Shikder et al. [15] looked at risk incidents in the transportation of dangerous materials. They showed how important operational and contextual factors are for predicting safety results. Even though these kinds of studies are useful, they often put risk assessment ahead of predicting when a lot of traffic crashes will happen. Xu and Huang [16] looked at spatial heterogeneity in crash modeling and showed that taking into account differences that are unique to a place makes the models more accurate. But methods that focus on space might miss temporal relationships that are important for predicting accidents that happen during rush hour.

The significance of localized data in safety models has been emphasized even more by jurisdiction-specific analyses. Young and Park [17] showed that safety performance functions that are specific to a town work better than generalized models. This shows how important it is to have context-aware prediction frameworks. Joshua and Garber's [18] earlier foundational studies used regression-based methods to predict accident rates. These methods were easy to use, but they weren't very good at dealing with patterns that weren't linear or that changed over time. In the same way, Jovanis and Chang [19] modeled accident relationships with exposure measures like miles driven. This gave them useful information about normalizing risk while using mostly fixed assumptions.

Lastly, studies that compare different count regression methods have shown that there are trade-offs between the methods. Miaou [20] showed that more complex count-based formulas can better deal with accident data that is too spread out than simpler models. Even though these studies improve traffic safety models as a whole, they mostly look at single methods or aggregate time or space scales. It is still not possible to compare different modeling views in a systematic way for fine-grained, peak-hour time-series accident forecasting. This study fills in that gap by providing a unified framework for comparing predictive behaviors across various model paradigms using consistent temporal data. This helps us learn more about how to predict traffic accidents that happen at certain times.

3. MATERIALS AND METHODS

The suggested method is meant to predict traffic accidents during rush hours by using spatial and temporal features from a dataset that anyone can

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access. The framework uses a unified modeling pipeline to turn accident records into structured time-series models that show behavior that changes over time and depends on where it happens. Intersection-aware data partitioning keeps the consistency of space, and lag-based and categorical peak-hour models improve the dynamics of time. Several complementary predictive paradigms are used to deal with different types of data, such as accident numbers that are spread out too much, seasonal changes, and relationships that don't follow a straight line. A recurring forecasting component is added to improve long-range temporal learning even more. This makes it easier to model how accidents change over time that are very complicated. Artificial intelligence methods that can be explained help make models more clear by measuring how features affect predictions and making predictions easier to understand. In addition, a lightweight deployment layer makes real-time inference possible and makes it easy to reach. The overall goal of the system is to provide reliable, understandable, and usable peak-hour accident predictions to help with data-driven traffic safety management in cities.

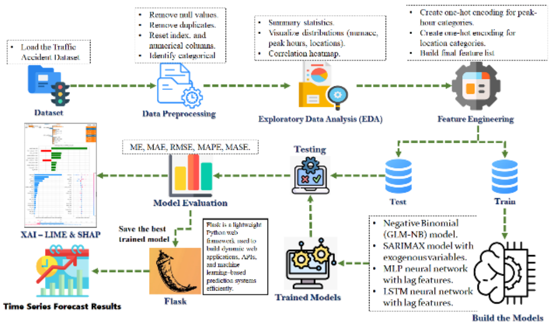

Fig.1 Proposed Architecture

The suggested system architecture starts with collecting datasets and encoding labels. Next, the PPS method is used to choose features. It is possible to see the processing data and divide it into training and testing sets. A lot of machine learning models are created and taught, and then their accuracy, precision, recall, F1-score, and cross-validation accuracy are used to rate them. Flask is used to save and launch the best-performing trained model. XAI methods like LIME and SHAP are used to better explain model predictions and make things clearer.

a) Dataset Collection:

The study uses a Traffic Peak-Hour Accident dataset that can be found in an open Kaggle source and is free for anyone to use. The dataset has 924 records, and each one shows an observation of a traffic crash at an urban intersection. There are both numerical and categorical attributes in it, like intersection identifiers, peak-hour categories, location types, geometric features, traffic volume indicators, and a goal variable that shows the number of accidents. The dataset is complete, well-structured, and can be used to model spatial and temporal accident trends. This means it can be used for studies that try to predict traffic accidents during rush hours.

	intsec	peakhour	location	noleg	sighead	wdADTmaj	wdADTmin	numacc
0	1	mp1	South	6	2	750	305	3
1	1	mp2	South	6	2	1136	422	2
2	1	ap1	South	6	2	1722	500	12
3	1	ap2	South	6	2	1097	282	5
4	1	ep1	South	6	2	939	533	4

Fig. 2 Traffic Accident Dataset

b) Pre-Processing:

This part talks about the important steps that are taken before the data is processed to make sure that it is of good quality, that features are represented correctly, and that reliable spatial–temporal modeling can be used to accurately predict traffic accidents during rush hours.

Data Inspection and Exploratory Analysis: A first look at the data and some exploratory analysis were done to figure out the dataset's structure, quality, and statistical features. In this step, we looked at different types of data, how features were distributed, what the main trends were, and how variable accident-related characteristics were. Visual exploration was used to look at trends of accident frequency across busy times, locations, and intersections. This step is necessary to find things about the data like skewness, variability, and possible modeling problems. This helps make the right choices about cleaning and modeling.

Data Cleaning and Quality Assurance: The information was cleaned to make sure it was reliable and consistent before it was used for modeling. The information was checked for duplicate records and missing values, which can both change the results of statistical analyses and make forecasts less accurate. The dataset stayed full and accurate because no null or duplicate entries were found. To keep the data structure organized, index resetting was used. This step is very important for keeping the data accurate, stopping data leaks that weren't meant to happen, and making sure that the model works consistently and reliably.

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Categorical Feature Encoding: Using encoding methods, categorical variables that showed peak-hour groups and spatial location zones were turned into numerical ones. This conversion makes it possible for statistical and machine learning models that need numerical inputs to work well with categorical traits. By storing information about peak hours and locations, the system can see how accident trends change over time and in different places. This step makes the model more expressive and makes sure that qualitative traffic traits make a real difference in how well the forecast works.

Correlation and Dependency Analysis: To look at the linear relationships between traffic volumes, geometric characteristics, temporal indicators, and accident frequency, a correlation analysis was done. This step helps find important factors and possible multicollinearity among features by finding pairwise correlations. When you look at dependency structures visually, you can see how traffic and space factors affect the likelihood of an accident. Knowing these connections helps you choose the right features, makes models easier to understand, and makes future predictive modeling more reliable.

c) Training and Testing:

The dataset was split into training and testing subsets using unique intersection identifiers to keep the data segments from being dependent on each other in terms of space. This plan keeps information from getting lost between places and makes sure that the review of the model takes into account how it applies to intersections that haven't been seen yet. Setting aside a certain number of intersections for tests makes the method more like how things will be in new urban areas. This step is necessary for a fair evaluation of spatial–temporal predicting capability and a strong evaluation of performance.

d) Algorithms:

Negative Binomial Model: The Negative Binomial model is used to look at crash frequency data that is too spread out. By allowing variances that are greater than the mean, it makes count-based predictions that are strong and easy to understand. This provides a solid starting point for modeling different types of traffic accidents.

SARIMAX Model: The SARIMAX model takes into account how accident time series change over time and with the seasons, as well as outside factors that can affect them. Its organized way of showing autoregressive and moving-average parts makes short-term forecasts more stable when traffic and peak-hour conditions change.

Multilayer Perceptron (MLP): Layered nonlinear transformations are used by the multilayer perceptron to describe the nonlinear relationships between past inputs and future accident counts. This feature lets you learn patterns in a variety of ways and make them more useful in situations where accident dynamics don't follow a straight line.

Long Short-Term Memory (LSTM): By keeping important past data for longer periods of time, the long short-term memory network models accident patterns that happen one after the other. Its gated memory structure makes it more reliable and accurate at predicting changing accident trends that are affected by long-term relationships.

4. EXPERIMENTAL RESULTS

MAE: Absolute Error is the amount of mistake in your measures. It's the difference between what was recorded and what was "true." To give you an example, if the scale says you weigh 90 pounds but you know you really weigh 89 pounds, the scale is off by 1 pound.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

RMSE: Root mean square error (RMSE) is a way to find the average difference between what a statistical model said would happen and what actually happened. It is the standard deviation of the residuals in math terms. The residuals show how far away the regression line is from the data points.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left||y(i) - \hat{y}(i)|\right|^2}{N}} \quad (2)$$

Table.1 Performance Evaluation Table

Model	ME	MAE	RMSE	MAPE	MASE
NB	**0.050722**	**1.540643**	**2.243663**	**0.460515**	**0.595413**
SARIMA-X	0.085867	1.389943	1.947731	0.473590	0.537172
MLP	0.140733	1.357603	1.849476	0.441441	0.524674
LSTM	0.057551	1.354583	1.848039	0.434560	0.523507

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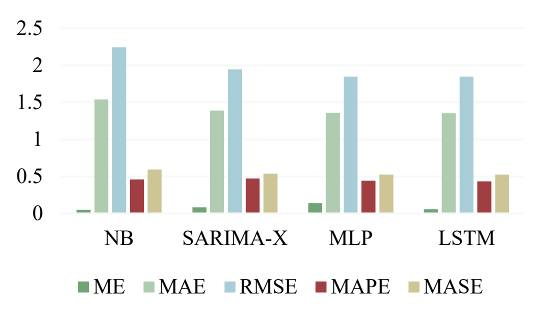
In the table, standard error metrics are used to compare the forecasting performance of different models. The LSTM model has the lowest total prediction errors, which means it is more accurate and reliable for predicting accidents during peak hours.

Graph.1 Comparison Graph



The bar chart shows how error rates change across forecasting models. It shows that performance always gets better from statistical to deep learning approaches, with the LSTM model having the lowest total error rates.

Fig.3 Enter the input data

The input result shows that the user's credentials were entered correctly and were confirmed by the system. This means that the submission was successful and the user is now ready to move on to peak hour traffic accident forecasting analysis with safe authentication and access.

Fig. 4 Predicted Result

The predicted output shows a peak-hour traffic accident risk analysis based on the parameters that were entered. It shows predicted results using multiple machine learning models to help make accurate, data-driven decisions about traffic safety.

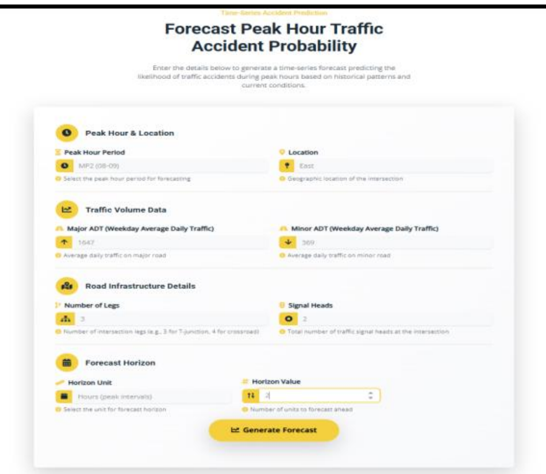


Fig. 5 Enter the input data

FIG. 5 displays a web-based dashboard for predicting the likelihood of a traffic accident during rush hour. The dashboard takes into account factors like peak hour, location, traffic volume, road infrastructure, and future horizon parameters for analysis.

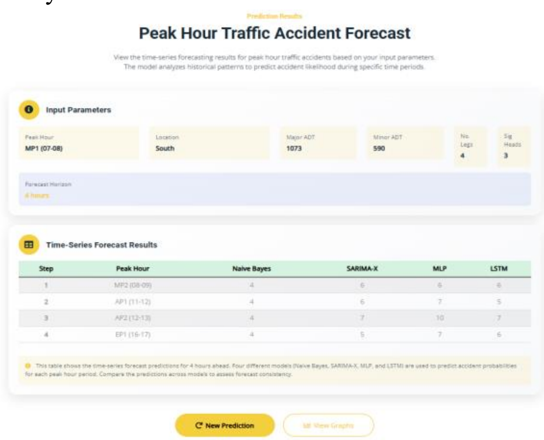


Fig. 6 Predicted Result

Figure 6 shows the PEAK HOUR output MP1 (07–08), which shows time-series traffic accident predictions made by Naive Bayes, SARIMAX, MLP, and LSTM models over a set of hourly prediction intervals.

5. CONCLUSION

This method is meant to meet the very important need for accurate peak-hour traffic accident forecasting in cities, where timely forecasting can help with safety-focused planning and decision-making. A complete time-series forecasting pipeline is set up to model spatial and temporal accident patterns using a Kaggle dataset called Accident Prediction that is open to the public. Cleaning, normalizing, exploratory data analysis, categorical encoding, and feature engineering based on peak-

hour and location characteristics are all part of the method. Several modeling approaches are used to look at how well forecasting works. These include a Negative Binomial generalized linear model for count data that is too spread out, a SARIMAX model with exogenous variables to capture seasonal and temporal trends, and a multilayer perceptron neural network using lagged inputs to model relationships that don't follow a straight line. Standard error-based measures, like mean error, mean absolute error, root mean square error, mean absolute percentage error, and mean absolute scaled error, are used to judge performance. A long short-term memory network is added to improve temporal modeling even more. This makes it possible to learn about long-range temporal relationships more effectively. This improvement shows better ability to predict, with a mean absolute error of about 1.35. This proves that deep temporal modeling works for predicting accidents. When LIME and SHAP are combined, they make things easier to understand by showing how different features affect each other. Using a Flask-based interface for release lets users make their own predictions. Overall, the system provides a solid, easy-to-understand, and useful answer that improves automated decision support for managing traffic accidents during rush hours.
In the future, improvements might focus on making forecasts more accurate by adding more contextual factors like weather, traffic volume, road geometry, and event-based delays that better reflect how things change in the real world. Adding real-time data streams from traffic monitors and smart transportation systems could help predict accidents in a more dynamic and adaptable way. To use the best parts of both statistical and deep learning models, advanced hybrid and ensemble learning methods could be looked into. Adding support for spatio-temporal visual analytics to explainability methods can also help stakeholders understand better. Cloud-based deployment can improve scalability, making it easier to watch traffic safety on a large scale and help people make smart decisions.

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