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Hybrid machine-learning algorithms for predicting the number of road accident patients in Golestan Province using time-series data

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Abstract

Background: This study employs hybrid machine learning algorithms to analyze the number of patients resulting from road accidents in hospitals in Golestan Province over a five-year period from March 2020 to March 2025. It also aims to predict the number of traffic accident patients from March 2025 to March 2027.

Methods: In this retrospective study, a five-year dataset covering March 2020 to March 2025 was used. Hybrid machine-learning algorithms, including SARIMA-LSTM and CNN-LSTM, were applied for analysis and prediction in comparison with the traditional Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The performance of these algorithms was evaluated using root mean square error (RMSE), mean absolute error (MAE), and root mean square logarithmic error (RMSLE).

Results: The observed number of patients referred following road accidents in Golestan Province increased from 13,679 in 2020 to 20,323 in 2025. A statistically significant difference was observed in patient numbers between men and women (P-Value < 0.001), with five-year increases of 45% for men and 60% for women. For predictions covering March 2025-March 2027, the CNN-LSTM model achieved the lowest error metrics (MAE (%) = 4.5, RMSE = 6.50, RMSLE = 0.21), followed by SARIMA-LSTM (MAE (%) = 8.60, RMSE = 12.45, RMSLE 0.65= 0.15), whereas the conventional SARIMA model exhibited the highest errors (MAE (%) = 12.69, RMSE = 15.37, RMSLE = 0.78).

Conclusion: These findings may assist policymakers and health managers in improving health services through optimal resource allocation and enhanced planning. Furthermore, the use of machine-learning models in hospitals is recommended to support the management and prediction of traffic-accident-related patient volumes.

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Highlights

What is current knowledge?

Various methods have been employed to predict traffic accidents, including classical time series models (e.g., SARIMA) and machine learning approaches (e.g., LSTM, CNN). Although seasonal fluctuations in traffic accidents are widely recognized, region-specific analyses, particularly those focusing on patient volumes and hospital demand, remain limited. Furthermore, limited attention has been given to directly comparing the predictive performance of different machine learning methods for patient volumes in provincial settings over multi-year periods.

What is new here?

This study presents the first application of hybrid machine learning models for predicting road accident patient volumes in a provincial setting, with the CNN-LSTM model identified as the most accurate approach, outperforming both SARIMA and SARIMA-LSTM in forecasting patient volumes. Ultimately, the integration of machine learning into hospital management has the potential to transform reactive healthcare responses into proactive, data-driven, and anticipatory strategies.

Introduction

Road traffic accidents represent a major global challenge, carrying significant human costs as well as substantial economic and social consequences. In this regard, the provision of timely and efficient emergency medical services plays a key role in mitigating the consequences of these accidents. Therefore, accurately predicting the number of accidents and estimating the demand for medical services is an important consideration, as such predictions form the basis for optimal planning in the allocation of medical resources (1). However, the continuous fluctuations in the number of accidents and the level of demand for medical services particularly in recent years, have underscored the need for effective and intelligent resource allocation at the tactical, operational, and strategic levels. Analysis of historical data in this study reveals distinct seasonal trends and patterns in accident occurrence; notably, the demand for pre-hospital emergency services increases significantly during certain months, such as summer. Predicting these fluctuations can facilitate improved awareness and optimal management, thereby enabling appropriate planning for periods of heightened demand to minimize service delays. Previous studies have employed various methods to predict accident rates (2). In this context, methodologies range from classical statistical analyses such as time-series models and spatiotemporal data mining to advanced approaches including machine learning and neural networks (3,4). Each of these methods possesses its own strengths and limitations (3). For instance, Wang et al. emphasized a broad range of machine learning models and neural networks (4). Similarly, Masini reviewed recent advances in supervised learning models, encompassing penalized linear models, feedforward and recurrent neural networks, and random tree-based tools (5). In addition, a new regression prediction strategy was presented in a study by Zha et al., which demonstrated that the Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) algorithm outperformed other conventional methods, achieving a mean absolute percentage error (MAPE) of 7.7% (6). Angadi et al. demonstrated that

LSTM networks provide the most accurate ten-year forecasts of road accident data for city planning (7). Their results indicated that combining classical and modern models can yield more accurate and efficient outcomes. For example, a study comparing SARIMA, LSTM, and SARIMA-LSTM models found that the hybrid model performed better than the individual models. Some studies also reported that the combined model was able to reduce error metrics such as RMSE, MAE, and MAPE by up to 50% compared with the SARIMA model. These findings suggest that integrating classical time-series methods with machine learning models can effectively address data complexity and enhance prediction accuracy (8). They conducted a study comparing the effectiveness of SARIMA and LSTM models for predicting Leishmaniasis. Using three evaluation criteria, mean average precision (MAP), root mean square (RMS), and mean absolute error (MA) the results showed that the LSTM model outperformed the SARIMA model in predicting monthly incidence (8). Zhao et al. (9), in their paper on water consumption forecasting, proposed an improved mechanism (e.g., an attention-based fusion) and demonstrated that their proposed ANN-LSTM-A model achieved better performance in predicting domestic hot water consumption than the standard ANN, LSTM, and ANN-LSTM models. This work provides an effective reference for the rational selection of water supply plans and energy consumption optimization (9). A study conducted in the United States on COVID-19 data showed that the hybrid SARIMA-LSTM method outperformed both the SARIMA and LSTM models individually, yielding lower RMSE and MAE values (10). Similarly, a study conducted in Latin America on inflation data from five emerging economies reported that the proposed SARIMA-LSTM hybrid model achieved higher accuracy in predicting inflation compared with SARIMA and LSTM models used separately (11). In a study in which Behboudi et al. (12) reviewed 191 articles on traffic accident prediction published over the past five years, they found that the existing studies focused on predicting accident risk, frequency, severity, duration, as well as conducting general statistical analyses of accident data (12). These studies demonstrated that the effectiveness of treatment resources, improvement in prediction accuracy, and management of traffic data complexity can be evaluated using advanced machine learning algorithms (13,14).

Despite the growing body of research on traffic accident prediction using various classical and machine-learning models, most existing studies have focused on general accident risk, frequency, or severity, often without considering region-specific seasonal fluctuations or the resulting demand for hospital services (12). Furthermore, limited attention has been given to direct comparisons of the predictive performance of different machine-learning methods specifically for patient volumes resulting from road accidents in provincial settings over multi-year periods. To address this gap, the present study aims to analyze the five-year trend (March 2020-March 2025) in road accident patients admitted to hospitals in Golestan Province, Iran. Using two machine-learning methods, the study then forecasts the number of such patients for the two-year period from March 2025 to March 2027. The objective is to identify the method that provides more accurate predictions based on error metrics, including root mean square error, mean absolute error, and root mean square logarithmic error, thereby enabling evidence-based and temporally responsive planning of emergency medical resources in a region with pronounced seasonal fluctuations in demand.

Methods

This study is a retrospective cohort study conducted on all patients with road traffic accidents who were referred to hospitals affiliated with Golestan University of Medical Sciences during a five-year period (March 2020 to March 2025). The required data were extracted from the electronic hospital information system (HIS). The primary variable for time-series forecasting was the monthly count of road accident patients. Additional variables, including gender, age, type of service provision (Inpatient or Outpatient), and discharge status (Recovery, Death, or Transfer) were used only in the initial descriptive and comparative analyses to characterize the study population, and were not incorporated as exogenous inputs into the time-series models themselves.

Data preprocessing

The monthly time-series of patient counts was preprocessed as follows. Missing values were absent in the aggregated monthly counts. The Augmented Dickey-Fuller (ADF) test was applied, and seasonal differencing was performed where necessary to achieve stationarity. No normalization was applied to the target variable. The data spanned 60 months and exhibited clear seasonality with an annual period (12 months), as evidenced by recurring peaks during mid-year months across all years.

Time-series modeling framework

A chronological train-test split was used (First 48 months for training and the last 12 months for testing). Rolling-window (Walk-Forward) validation was applied with one-step-ahead forecasting, using a fixed input window of 12 past months to predict the next month. Rolling-origin time-series cross-validation (3 folds) guided hyperparameter tuning. SARIMA parameters were selected via grid search (AIC). LSTM and CNN hyperparameters (Units, Dropout, Batch size, Epochs) were tuned based on validation loss.

Train-test split and validation strategy

Given the temporal nature of the data, a chronological train-test split was used: the first 48 months (March 2020-March 2024) served as the training set, and the remaining 12 months (March 2024-March 2025) were used as the test set. This 48/12 split (80%/20%) preserved the temporal order. Rolling-window (Walk-Forward) validation was applied with a fixed training window of 48 months. At each step, each model was retrained using the most recent 48 months of data. For each one-step-ahead forecast, an input (Look-Back) window of the past 12 months was used to predict the next month. Both the training window and the look-back window were rolled forward simultaneously after each prediction.

Justification of sample size

With 60 monthly observations, this study is best viewed as a preliminary or proof-of-concept investigation. Hybrid models, such as SARIMA-LSTM and CNN-LSTM, typically benefit from 100-150 or more observations. However, 60 monthly points (i.e., five years) represent the full available historical data from the hospital information system for this region. Thus, the limited sample size is acknowledged as a key limitation; the present results are intended to demonstrate feasibility and comparative model performance rather than to provide definitive operational forecasts. Future work with longer data accumulation will be needed for robust hybrid model deployment.

Predictive models

Three predictive models were implemented and compared for time-series forecasting of monthly road accident patient referrals.

1. SARIMA model

The SARIMA model was used to model linear, trend, and seasonal components in time-series data. This time-series forecasting model combines autoregressive (AR) and moving average (MA) components, making it suitable for fitting data that exhibit trends and seasonal fluctuations. The AR component captures past dependencies in the SARIMA model, while the MA component reflects the effect of past error values on current forecasts. The parameters of this model include: p, the order of autoregression; d, the degree of differencing required to achieve stationarity; and q, the order of the moving average.

2. SARIMA-LSTM hybrid model

The SARIMA-LSTM hybrid model is designed to combine the strengths of SARIMA in modeling linear and seasonal patterns with the ability of LSTM (Long Short-Term Memory) neural networks to identify nonlinear relationships and long-term dependencies in data. LSTM is a type of recurrent neural network (RNN) designed to learn and retain long-term information in sequential data. LSTM utilizes gates such as the forget gate, input gate, and output gate to control the flow of information. This architecture enables LSTM to understand long-term dependencies in data, making it suitable for time-series forecasting, natural language processing, and tasks requiring long-term memory. SARIMA-LSTM is a powerful combination of two time-series forecasting models: SARIMA and LSTM. This hybrid approach is designed to address forecasting challenges in complex and variable sequence data.

In SARIMA-LSTM, the output of the LSTM is used as input to the SARIMA model. This combination allows the model to leverage both long-term dependencies and short-term fluctuations in a nested manner. In this architecture, LSTM functions as a higher layer, and its output captures both the long-term memory and short-term fluctuations in the data.

- **LSTM stage:** In this stage, the LSTM processes the sequential data and produces a long-term memory representation. The LSTM gates enable the network to retain important information and understand long-term dependencies.
- **SARIMA stage:** The output of the LSTM stage is then used as input for the SARIMA model. SARIMA utilizes past dependencies and trends in the data to perform time-series forecasts.

The main advantage of SARIMA-LSTM lies in its ability to learn both long-term dependencies and short-term fluctuations in the data. This model can provide more accurate forecasts, particularly for complex time-series that exhibit trends and seasonal fluctuations. Overall, SARIMA-LSTM is an advanced and powerful approach to time-series forecasting that leverages the strengths of both SARIMA and LSTM models.

3. CNN-LSTM hybrid model

The CNN-LSTM hybrid model combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) to leverage the strengths of both architectures. The CNN extracts spatial features and local patterns from input data, and LSTM captures temporal dependencies and sequential patterns over time. This combination is particularly powerful for spatio-temporal data in which both spatial structure and temporal dynamics are relevant. The CNN-LSTM hybrid model aims to automatically extract complex features and identify spatiotemporal patterns (Such as high-occurrence points) through convolutional layers (CNN) and subsequently model temporal dependencies using LSTM layers. By combining CNN and LSTM, the output of the CNN is used as the input to the LSTM. This integration allows the model to extract local features via the CNN and capture temporal dependencies via the LSTM. Moreover, to ensure full reproducibility, we have explicitly reported the hyperparameter search ranges and final selected values for all models. For the SARIMA model, a grid search was performed over the following ranges: $p \in \{0,1,2,3\}$, $d \in \{0,1,2\}$, $q \in \{0,1,2,3\}$, $P \in \{0,1,2\}$, $D \in \{0,1\}$, $Q \in \{0,1,2\}$, with a fixed seasonal period of 12 months; the final selected parameters were p=2, d=1, q=1, P=1, D=1, Q=1. For the LSTM and CNN-LSTM hybrid models, hyperparameters were tuned using rolling-origin time-series cross-validation (3 folds) over the following search spaces: LSTM units $\in \{32, 64, 128, 256\}$, dropout rate $\in \{0.1, 0.2, 0.3, 0.5\}$, batch size $\in \{16, 32, 64\}$, and epochs $\in \{50, 100, 200\}$; for the CNN component, filters $\in \{32, 64, 128\}$ and kernel size $\in \{2, 3, 5\}$. The final selected values were LSTM units = 128, dropout = 0.2, batch size = 32, epochs = 100, CNN filters = 64, and kernel size = 3. All deep learning models were implemented in TensorFlow/Keras with fixed random seeds for reproducibility.

Due to the stochastic nature of neural network training, each deep learning model (LSTM and CNN-LSTM) was trained and evaluated five times using different random seeds (42, 123, 456, 789, 101112). All reported results are presented as mean ± standard deviation across the five runs.

Model performance evaluation

The predictive accuracy and performance of the above models were evaluated and compared using the following three common metrics (14).

a. Mean Absolute Error (MAE) measures the average absolute value of the errors:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_{t}\right|$$

b. Root Mean Square Error (RMSE) is more sensitive to large errors and is of great importance in resource planning.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}$$

c. Root Mean Square Logarithmic Error (RMSLE) assesses the relative accuracy of the model, especially when the data distribution is not normal.

$$RMSLE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\log(1+Y_t) - \log(1+\hat{Y}_t)\right)^2}$$

All statistical analyses were performed using Python 3.10 (pandas, numpy, scikit-learn, statsmodels, TensorFlow/Keras) and R 4.5.2 (tidyverse, forecast, keras).

Results

This study was based on road-traffic-accident data recorded in hospitals affiliated with the University of Medical Sciences in the geographical region of Golestan Province. The data spanned five consecutive years. During the five-year period from March 2020 to March 2025, a total of 89,856 individuals were treated following road accidents in Golestan Province. Of these, 1,535 (1.7%) died from injuries sustained, while the remaining 88,321 (98.3%) were treated and discharged after partial recovery. The findings indicate that 74.9% of the victims were male and 25.1% were female. The mean age of the victims was 30.12 years (Standard deviation = 16.95).

An independent-samples t-test revealed a statistically significant difference in mean age between men and women ($t = 5.23$, $df = 89{,}854$, P-Value < 0.001), with male victims having a slightly lower mean age (29.5 years) than female victims (31.8 years). Significant differences were observed between male and female patients with respect to their type of care (Inpatient or Outpatient) and treatment outcomes (Discharge after recovery or Death) (Chi-square test, P-Value < 0.05 for both comparisons). The data also show statistically significant associations: a chi-square test indicated a significant relationship between age group (Categorized as ≤ 30 years, 31-60 years, > 60 years) and type of care received ($\chi^2 = 45.2$, $df = 2$, P-Value < 0.001), and between age group and treatment outcome ($\chi^2 = 38.7$, $df = 2$, P-Value < 0.001). Additionally, a point-biserial correlation between age (Continuous) and outcome (Recovered vs. Deceased) was significant ($r = 0.12$, P-Value < 0.001).

On average, 63.4% of patients were treated as outpatients, while 36.6% required hospitalization. The five-year trend shows a gradual increase in the percentage of outpatient cases. The average age of deceased patients (39.1 years) was higher than that of recovered patients (30.0 years). Men accounted for 83.8% of all recoveries and 83.3% of all deaths, and the death-to-recovery ratio was 1.9% in men and 1.1% in women. Table 1 presents the annual frequency and percentage distribution of all patients involved in traffic accidents in Golestan Province from 2020 to 2024, categorized by type of admission (Outpatient vs. Hospitalization) and type of discharge (Recovered vs. Death), categorized by sex, type of admission (Outpatient vs. Hospitalization), and type of discharge (Recovered vs. Death), with total sum across years and p-values for sex comparisons. The total number of patients increased from 13,679 in 2020 to 20,484 in 2022, followed by a decrease in 2023 (19,386) before rising again to 20,323 in 2024. This represents an overall increase of approximately 48.6% over the five-year period. Note that the data follows the Iranian calendar year (e.g., 2024 extends from March 20, 2024, to March 20, 2025).

The proportion of outpatient cases increased from 61.8% in 2020 to 65.25% in 2024. Conversely, the proportion of hospitalized patients decreased from 38.2% in 2020 to 34.75% in 2024. The absolute number of hospitalized patients fluctuated, peaking at 7,665 in 2022 before declining in subsequent years. The majority of patients (Approximately 98%) were recovered upon discharge across all years, with percentages ranging from 98.15% to 98.41%. The death rate fluctuated between 1.59% and 1.85% annually. The highest number of deaths was recorded in 2023 (356 deaths).

Figure 1 shows the seasonal patterns and monthly trends of traffic accident patients from March 2020 to March 2025. Across all years, the number of patients increased from the beginning of the year, reached a peak during the middle months, and declined toward the end of the year. The lowest patient volumes occurred in the early months (January-March), while the highest volumes were observed in the mid-year months (June-September). In 2020, monthly patient counts ranged from approximately 1,500 to 2,200. By 2022, monthly counts ranged from approximately 1,900 to 2,600. The peak months for traffic accident patients occurred between June and September across all years. The difference between peak and trough months was approximately 600-700 patients in 2020 and approximately 700-800 patients by 2022.

Figure 2 presents the trends in traffic accident patients from March 2020 to March 2025. The historical data show an upward trajectory in the number of traffic accident patients over the five-year period, with total annual patients increasing from 13,679 in 2020 to 20,323 in 2024. The historical data also display seasonal fluctuations, with peaks occurring during mid-year months (June-September) and troughs during early and late months. The CNN-LSTM model predicts a continued increase in the number of traffic accident patients from March 2025 to March 2027, with seasonal peaks continuing to occur during mid-year months.

Figure 3 shows trends in traffic accident patients from March 2020 to March 2025 and predictions from March 2025 to March 2027 using the SARIMA-LSTM hybrid machine learning model. The historical data show an increase from 13,679 patients in 2020 to 20,323 patients in 2024, with seasonal fluctuations showing recurring peaks during mid-year months and troughs during early and late months. The SARIMA-LSTM hybrid model predicts a continued upward trend in accident patient volumes from March 2025 to March 2027, preserving the seasonal pattern observed in the historical data. The traditional SARIMA model also predicts a general upward trend; however, its forecast shows a smoother trajectory with less sensitivity to seasonal fluctuations.

Table 2 presents a comparison of the predictive performance of three forecasting models-CNN-LSTM, SARIMA-LSTM, and SARIMA-using three evaluation metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Root Mean Square Logarithmic Error (RMSLE). The CNN-LSTM hybrid model achieved the lowest MAE (4.50%), RMSE (6.50), and RMSLE (0.21). The SARIMA-LSTM hybrid model achieved an MAE of 8.60%, RMSE of 12.45, and RMSLE of 0.65. The SARIMA model achieved the highest error values: MAE of 12.69%, RMSE of 15.37, and RMSLE of 0.78.

The predicted monthly patient counts for the forecast period (March 2025- March 2027) are presented in Table 3. The CNN-LSTM model predicted a mean of 1,537.3 patients per month (SD = 167.9; Median = 1,500), while the SARIMA-LSTM model predicted a mean of 1,609.4 patients per month (SD = 207.7; Median = 1,628).

Table 1. Frequency and annual percentage distribution of traffic accident patients in Golestan Province from March 2020 to March 2024, categorized by sex, type of admission (Outpatient vs. Hospitalization), and type of discharge (Recovered vs. Death).

Time Period	Sex	Number of patients (n)	Percentage (%)	Type of admission (n, %)	Treatment outcome (n, %)	Recovered	Death
				Outpatient	Hospitalization		
March 2020	Male	10,245	74.9	6,334 (61.8)	3,911 (38.2)	10,078 (98.4)	167 (1.6)
	Female	3,434	25.1	2,123 (61.8)	1,311 (38.2)	3,374 (98.3)	60 (1.7)
March 2021	Male	11,972	74.9	7,256 (60.6)	4,716 (39.4)	11,750 (98.2)	222 (1.8)
	Female	4,012	25.1	2,436 (60.7)	1,576 (39.3)	3,938 (98.1)	74 (1.9)
March 2022	Male	15,342	74.9	9,598 (62.6)	5,744 (37.4)	15,100 (98.4)	242 (1.6)
	Female	5,142	25.1	3,221 (62.6)	1,921 (37.4)	5,058 (98.4)	84 (1.6)
March 2023	Male	14,518	74.9	9,462 (65.2)	5,056 (34.8)	14,250 (98.2)	268 (1.8)
	Female	4,868	25.1	3,176 (65.2)	1,692 (34.8)	4,780 (98.2)	88 (1.8)
March 2024	Male	15,222	74.9	9,930 (65.2)	5,292 (34.8)	14,970 (98.4)	252 (1.6)
	Female	5,101	25.1	3,330 (65.3)	1,771 (34.7)	5,023 (98.5)	78 (1.5)
Total	Male	67,299	74.9	42,580 (63.3)	24,719 (36.7)	66,148 (98.3)	1,151 (1.7)
	Female	22,557	25.1	14,286 (63.3)	8,271 (36.7)	22,173 (98.3)	384 (1.7)

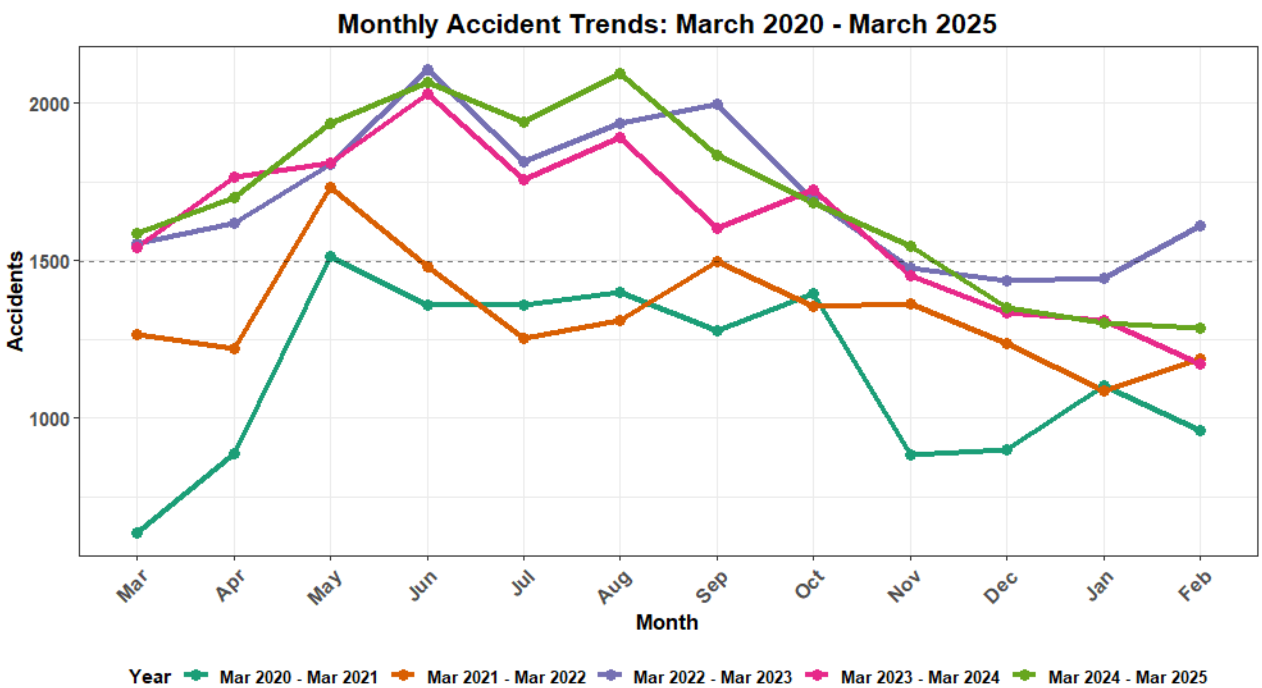

Figure 1. Seasonal patterns and monthly trends of traffic accident patients by year (March 2020-March 2025)

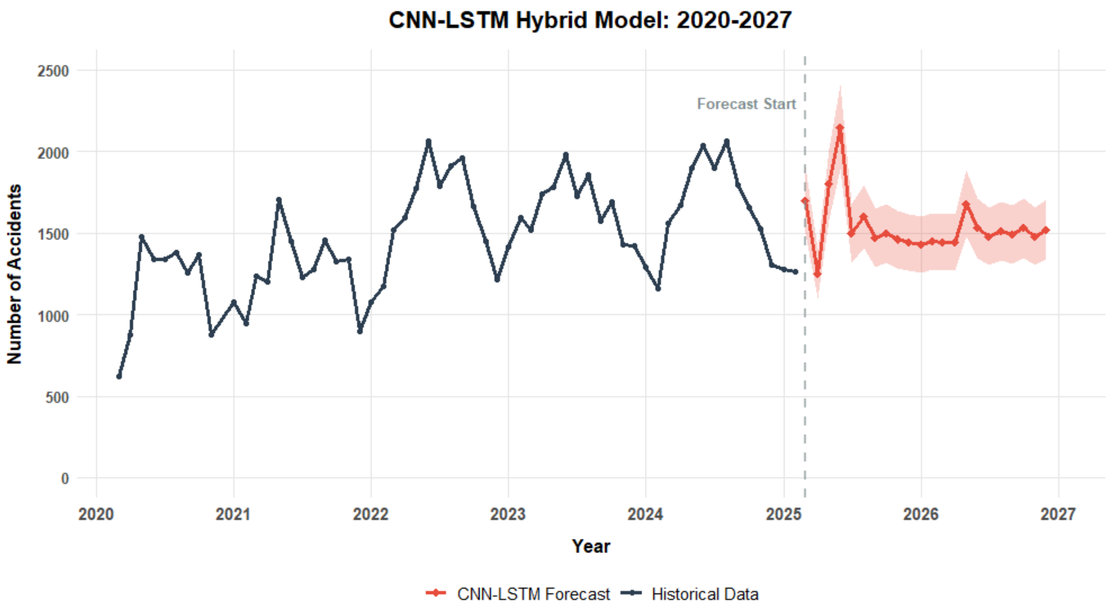

Figure 2. Trends in traffic accident patients from March 2020 to March 2025 and predictions from March 2025 to March 2027 using the CNN-LSTM hybrid machine learning model

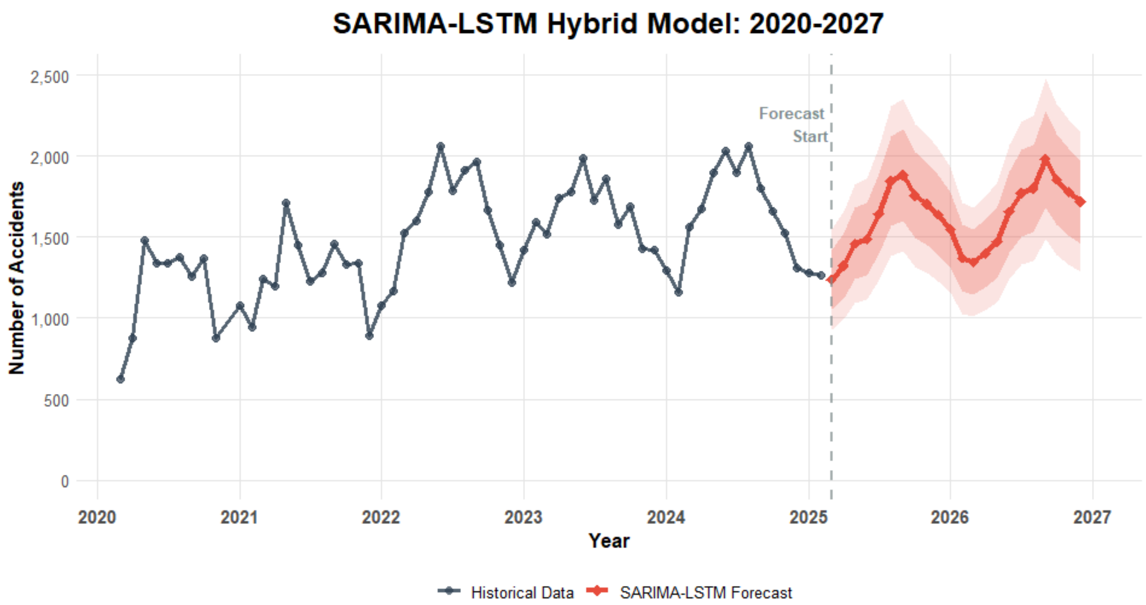

Figure 3. Trends in traffic accident patients from March 2020 to March 2025 and predictions from March 2025 to March 2027 using the SARIMA-LSTM hybrid machine learning model

Table 2. Comparison of predictions generated by hybrid machine learning algorithms, evaluated using mean absolute error, root mean square error, and root mean square logarithmic error

Algorithms	MAE (%)	RMSE	RMSLE
CNN-LSTM	4.50	6.50	0.21
SARIMA-LSTM	8.60	12.45	0.65
SARIMA	12.69	15.37	0.78

Table 3. Summary of predicted monthly patient counts from March 2025 to March 2027

Model	Mean	SD	Median
SARIMA-LSTM	1,609.4	207.7	1,628
CNN-LSTM	1,537.3	167.9	1,500

Discussion

The results of this study, based on five years of road-traffic-accident patient data from Golestan Province (March 2020-March 2025), demonstrate a growing burden of road traffic accidents. As shown in Table 1, total patients increased from 13,679 in 2020 to 20,323 in 2024 (48.6% increase), and deaths rose from 227 to 330 (45.4% increase). These trends impose considerable strain on the healthcare system and underscore the need for preventive and preparedness strategies.

The observed seasonal pattern in this study suggests a seasonal influence on traffic accident frequency, potentially attributable to factors such as increased travel during summer vacations, favorable weather conditions leading to higher road usage, or cultural and holiday-related travel patterns. This seasonal pattern reflects the recurring influence of travel behavior, weather conditions, and holiday periods on traffic accident frequency. Furthermore, the widening range between peak and trough months (From approximately 600-700 patients in 2020 to 700-800 patients in 2022) suggests that seasonal surges in accidents have become more pronounced in recent years, placing greater strain on emergency and healthcare resources during peak periods.

The increasing trend in traffic accident patients observed in Golestan Province is consistent with findings from other regions. For instance, studies from other provinces in Iran have reported annual increases in road traffic injuries ranging from 30-50% over similar time periods (2). Internationally, a systematic review by Behboudi et al. (12), which examined 191 articles on traffic accident prediction, noted that many low- and middle-income countries face rising trends in accident-related morbidity due to rapid motorization without corresponding safety infrastructure improvements. The present study's finding that males comprise approximately 75% of victims aligns with global literature, which consistently reports male predominance (typically 70-80%) in road traffic injuries, attributed to higher exposure, risk-taking behaviors, and occupational driving patterns.

Advantages and necessity of the hybrid models used

The present study advances beyond conventional modeling by implementing and comparing two hybrid frameworks: SARIMA-LSTM and CNN-LSTM. The need for hybrid approaches arises from the inherent complexity of health-related time-series data, which contain both linear/seasonal components (Capturable by SARIMA) and nonlinear/long-term dependencies requiring neural network architectures. As shown in Table 2, both hybrid models outperformed the traditional SARIMA model across all evaluation metrics, confirming the value of hybridization for medical time-series forecasting. The CNN-LSTM model achieved the highest accuracy (MAE 4.50%, RMSE 6.50, RMSLE 0.21), followed by SARIMA-LSTM (MAE 8.60%, RMSE 12.45, RMSLE 0.65), with SARIMA demonstrating the poorest performance (MAE 12.69%, RMSE 15.37, RMSLE 0.78). This difference highlights the advantage of the hybrid approach, which integrates LSTM's capacity to capture nonlinear relationships and long-term dependencies with SARIMA's strength in modeling linear and seasonal components. These results are comparable to findings in related domains. For instance, Zha et al. (6) reported a mean absolute percentage error (MAPE) of 7.7% for CNN-LSTM in a forecasting context. Zhao et al. (9) demonstrated that combining classical and modern models yields more accurate outcomes. Additionally, studies on COVID-19 forecasting and water consumption prediction have similarly shown that hybrid SARIMA-LSTM models outperform individual models, with error reductions of up to 50% compared with SARIMA alone.

The superior performance of CNN-LSTM over SARIMA-LSTM in the present study may be attributable to the dataset's characteristics, including strong local temporal patterns and nonlinear fluctuations that convolutional layers are well-suited to extract. CNN layers can automatically identify relevant features (e.g., peak shapes, rising/falling edges) without manual specification, providing an advantage over the residual-based SARIMA-LSTM approach.

The forecast outputs suggest that seasonal peaks will persist and may increase proportionally with the rising baseline. The magnitude of seasonal peaks may increase in proportion to the rising baseline, potentially exacerbating resource demands during high-incidence periods. The forecasting outputs can serve as quantitative early warning systems for hospital administrators in Golestan Province. For example, anticipating hospitalization increases prior to summer travel periods enable optimization of bed allocation, blood product inventories, medication supplies, and staff scheduling. At a strategic level, these forecasts can inform investment priorities for medical center expansion and pre-hospital emergency services.

Ultimately, this study demonstrates that integrating machine learning into health management, specifically through CNN-LSTM and SARIMA-LSTM hybrid models, provides a strategic tool for transforming reactive healthcare systems into proactive, data-informed, and potentially life-saving systems. The CNN-LSTM model, in particular, offers superior accuracy in forecasting road traffic accident patient volumes in settings characterized by pronounced seasonality and increasing trends.

Several limitations should be acknowledged. First, with only 60 monthly observations, the study is best viewed as a preliminary or proof-of-concept investigation; hybrid models typically benefit from 100-150 observations. Second, external influencing variables (e.g., traffic volume, weather conditions, road infrastructure changes) were not incorporated as exogenous inputs. Third, the study is limited to a single province, which may limit generalizability to other regions with different demographic or geographic characteristics. Additionally, although we have now performed multiple runs to account for stochastic variability in neural network training, the original analysis was based on single-run results, and the overall sample size of 60 months remains a constraint.

Conclusion

The findings of this study show that hybrid machine learning models, particularly CNN-LSTM, significantly outperform traditional time series approaches in predicting road accident patient volumes in provincial settings with pronounced seasonal patterns. The findings reveal a growing burden of road traffic accidents in Golestan Province, with a 48.6% increase over five years and a higher rising trend among female patients (60%) compared to males (45%). By providing accurate short-term forecasts, these models can serve as early warning systems to guide proactive resource allocation, bed management, and emergency preparedness during seasonal demand surges. The integration of machine learning into hospital management systems is recommended to transform reactive healthcare responses into data-driven, anticipatory strategies, ultimately improving patient outcomes and reducing healthcare system strain.

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Ethical Statement

Ethical approval was granted by the Research Ethics Committee of Golestan University of Medical Sciences with the following specifications: IR.GOUMS.REC.1404.148.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Author Contributions

M.B, as the corresponding author, contributed to the study process, including conceptualization, processing, bioinformatics and machine-learning workflow methodology, interpretation, and manuscript revision. H.K., as the first author, contributed to conceptualization, data collection, study design, and manuscript drafting. M.M. contributed primarily to the clinical aspects of this study.

Data Availability Statement

The datasets utilized and/or analyzed in this study can be obtained from the corresponding author upon reasonable request.

Use of Artificial Intelligence

The authors used AI tools solely for language refinement and grammatical correction.

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