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Preliminary communication

A Hybrid CNN-LSTM Model for Traffic Accident Frequency Forecasting During the Tourist Season

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Abstract: Population density in major tourist centers of the world increases significantly during the tourist season. Estimating the frequency of traffic accidents during the upcoming tourist season is of particular interest to many stakeholders, such as local governments. The objective of this study is to propose a hybrid deep learning model, based on convolutional neural network (CNN) and long short term memory (LSTM) models to predict the frequency of traffic accidents during the tourism season. The dataset used in the study includes daily frequencies of traffic accidents with fatalities and injuries that occurred in Antalya between January 2012 and December 2017. In the next phase of the study, seasonal autoregressive integrated moving average (SARIMA), Facebook prophet and deep learning methods including LSTM and the proposed Hybrid CNN-LSTM were tested to predict traffic accident frequencies in Antalya. The experimental results show that the root mean square error (*RMSE*) of the proposed model is less than 2480, 13266 and 186 compared to SARIMA, prophet and LSTM models, respectively. Also, the *R*-squared value of the proposed model is greater than 0.016, 0.103 and 0.001 compared to SARIMA, prophet and LSTM models, respectively. It is clear that the proposed hybrid CNN-LSTM model was more successful in predicting traffic accidents when compared to the other models.

Keywords: convolutional neural network; SARIMA model; time series analysis; tourism; traffic accident forecasting

1 INTRODUCTION

One of the most important problems of today's countries is traffic accidents. While 1.35 million people die in these accidents every year, almost 50 million people are injured. While traffic accidents are the first cause of death for young people between 5 and 29 years old, it is the eighth cause of death for people of all ages [1]. All financial losses caused by traffic accidents are equivalent to 2.2 - 2.7% of countries' gross domestic product [2]. Traffic accidents cause not only financial losses, but also moral losses, which cannot be measured with any cost. Therefore, it is clear that the actual damage cannot fully reflect the reality.

The number of traffic accidents in Turkey is higher than the world average. In the accidents that occurred in Turkey in 2015 - 2020, 287531 people were injured, while the average annual loss of life was 6545 [3].

As a result of traffic accidents in Turkey, direct and indirect costs amounted to 2.2% of GNP [4]. However, according to the report published by the World Bank in 2017, a 50% reduction in deaths would result in an increase in GNP per capita of between 7% and 22% [5]. Thanks to the accident prediction models (APMs) proposed by researchers in recent years, significant contributions have been made to local authorities in road safety research. It can be seen that the researches mostly focuses on accident frequency (number of accidents per year) and accident severity (level of injuries caused by accidents) [6].

In this study, accident frequency was estimated using current APMs. Antalya, one of the most important centres of summer tourism in the world, was selected for the study. Antalya, with a population of 2.6 million in 2021, hosted 9 million tourists by air and sea in the same year [7]. Especially between May and October, tourism in Antalya is at its peak. In this study, SARIMA, traditional time series method, Facebook prophet and deep learning methods including LSTM and CNN were tested for predicting traffic accident frequency in Antalya.

There are many APMs that have been developed in recent years, such as the time series approach or the artificial intelligence-based approach. The model proposed in this study is based on CNN, which takes a completely different approach from other models.

The aim of this study is to propose a hybrid deep learning model based on CNN and LSTM models to predict the frequency of traffic accidents during the tourism season. In this way, the change in the number of traffic accidents caused by the increase in population due to tourism is revealed.

The rest of this document is outlined as follows. In the next section, a brief summary of studies applying traditional methods and advanced machine learning techniques to traffic accident prediction is given. Section 3 explains the APMs used for accident frequency estimation. Section 4 presents the results of the proposed models. In the next section, the results are interpreted. In the last section, some ideas for future research are presented by interpreting the research results.

2 RELATED WORKS

The various APMs were developed for studies on the frequency of traffic accident. In these studies, it is clear that APMs based on classical time series and artificial intelligence have been proposed for solving problems. In this section, some related studies are discussed.

Ihuezeet al. [8] and Twenefouret al. [9] used auto regressive integrated moving average with exogeneous (ARIMAX) and autoregressive moving average (ARMA) models, respectively, which are classical time-series techniques. Nanga et al. [10] and Yousefzadeh-Chabok et al. [11] preferred the SARIMA model. It can be said that it is an important factor if it is related to the population of the regions where traffic accident prediction studies are conducted. In the literature, some classical time series studies have been carried out with the data obtained in Nigeria [8], Iran [11] and Ghana [9, 10]. Ihueze et al. [8] and Twenefour et al. [9] predicted crash frequency, while Yousefzadeh-Chabok et al. [11] estimated fatalities. In classical time-series studies, the size of the dataset obtained is also important. Accordingly, the longest-term data set [9] is 30 years, while the shortest-term data set [11] is 6 years. Ihueze et al. [8] and Twenefour et al. [9] used 1 year of the dataset for testing. On the other hand, Nanga et al. [10] and Yousefzadeh-Chabok et al. [11] created a test dataset of 7 and 4 years, respectively. The researchers used metrics such as mean absolute percentage error (*MAPE*), *RMSE*, and *R*-squared for model performance. Twenefour et al. [9] used the Akaike information criterion (*AIC*) and Bayesian information criterion (*BIC*) in addition to these metrics.

It can be said that in addition to statistical techniques such as ARIMA and SARIMA, studies based on neural networks are also used to estimate traffic accident frequencies. In the study of Çodur and Tortum [12], a prediction model for traffic accidents in Erzurum, one of the cities in Turkey, between the years 2005 - 2019 was developed using artificial neural networks. The *R*-squared value, which reflects the performance of the model, was found to be 0.90.

Some researchers have also developed a predictive model based on Facebook Prophet. Feng et al. [13] created a trend estimation for traffic accidents using traffic accident data that occurred in the UK between 2005 and 2016. The year 2017 was used as the test set in the study. The experiments were conducted using Facebook Prophet and LSTM models. The Facebook Prophet model was found to be more successful with a lower *RMSE*.

It can be said that deep learning architectures have achieved significant success in estimating time series problems in recent years. Recurrent neural networks (RNN) and CNNs are important deep learning architectures. The datasets from the USA [14-16] and China [17] were used to predict traffic accidents with CNN and LSTM, a type of RNN architectures. In these studies, Yu et al. [14] and Ren et al. [17] also presented a solution for classification problems such as post-accident traffic prediction using machine learning algorithms. In addition to these two studies, Yuan et al. [16] also preferred CNN models based on LSTM. While the researchers preferred mean square error (*MSE*) and *RMSE* as performance metrics, Yuan et al. [16] also used the cross-entropy metric. Compared to other models, it can be said that CNN-based studies have better predictive performance.

2.1 Research Gaps and Motivation

Although several approaches to predicting the frequency of traffic accidents have been presented, there are some significant challenges in doing so.

1. When examining APMs used in studies to estimate the incidence of traffic accidents, research based on state-of-the-art CNN technique is limited.
2. As far as we know, no model has been proposed to estimate traffic accidents during the tourist season.
3. Scientific studies should be increased for cities where traffic accidents cause great damage. In this way, important findings can be presented to local governments.

2.2 Research Contributions

The main research contributions of this study are as follow:

1. A dataset of information on traffic accidents is examined. In addition, a unique exploratory data analysis is applied to find more information about the dataset.
2. A new hybrid deep learning model based on CNN and LSTM architecture to predict the frequency of traffic accidents during tourist season.
3. The results are compared using accuracy measurement methods such as *RMSE* and *MAPE*. The proposed hybrid model provided better prediction results than SARIMA, Facebook Prophet and LSTM models.

3 MATERIAL AND METHOD

The processes in this study are shown in Fig. 1. First, the time series data containing the daily frequency of traffic accidents were converted into a suitable format for APMs. After separating into training and testing data, experiments were conducted using SARIMA, Prophet, LSTM, and the proposed hybrid CNN-LSTM models. Finally, the results are compared using accuracy measurement methods such as *RMSE* and *MAPE*.

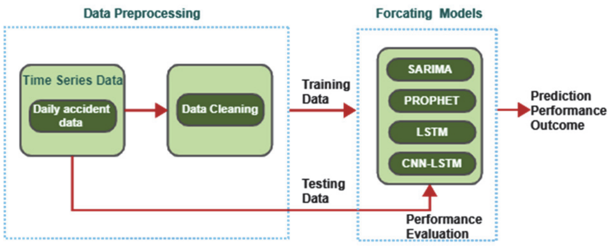

Figure 1 General scheme for predicting traffic accidents

3.1 Data Preprocessing

The dataset used in the study includes the daily frequencies of traffic accidents with fatalities and injuries that occurred in Antalya between January 2012 and December 2017. A total of 36431 traffic accidents (470 fatalities and 35961 injuries) occurred in Antalya, one of the most important tourism centers in Turkey during this 72 month period. The graph in Fig. 2 shows the monthly time series of traffic accidents with injuries and fatalities from 2012 to 2017.

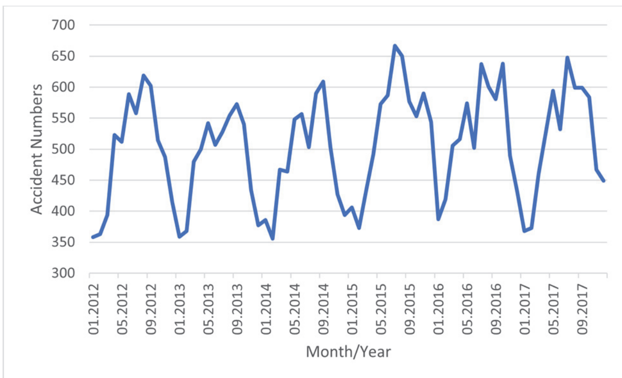

Figure 2 Total number of accidents in Antalya from 2012 to 2017

Especially in the 6 month period between May and October, the number of accidents increases rapidly due to the increasing population density during the tourist season. These data are officially recorded data. The accidents that are not officially recorded and do not cause injury were not included in the data set of this study due to the agreement of the drivers (Fig. 3).

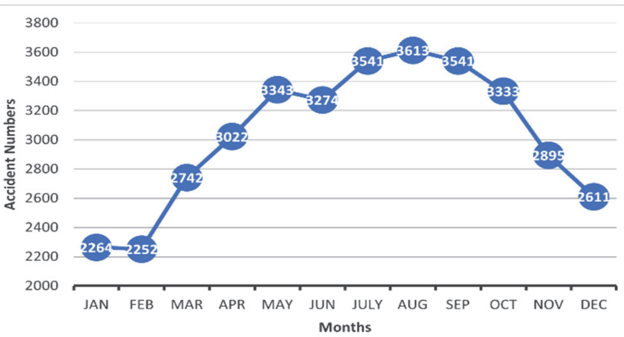

Figure 3 Total number of accidents in Antalya by month

Time series aggregation is used, which significantly reduces computational resources [18] and increases prediction accuracy. Due to the high fluctuation in the numbers of daily traffic accidents prior to the forecasting, in this study the daily data is resampled into monthly frequency. Then, the average values of daily traffic accidents are used.

It is important to test a model created by machine learning with new data unavailable in the dataset to determine the validity of the model. 75% of the dataset was split into training data and 25% into testing data for this purpose, using k-fold cross-validation. This ratio is commonly used in various studies [19-21]. In the experiments conducted, the best k value was found to be 10. Consequently, the analyses in the final model were performed by dividing the data set into 10 parts.

3.2 Performance Evaluation

The performance evaluation criteria in machine learning change depending on the type of application. The evaluation criteria used for regression analysis and those used for applications involving classification or clustering will be different. When conducting a performance evaluation in regression analysis, various regression metrics can be used, including R-squared (Eq. (1)), MAE (Eq. (2)), $RMSE$ (Eq. (3)). These are defined by the following equations:

$$R\text{-square}=\left(y,\widehat{y}\right)=1-\frac{\sum_{i=0}^{n_{\text{samples}}-1}\left(y_i-\widehat{y_i}\right)^2}{\sum_{i=0}^{n_{\text{samples}}-1}\left(y_i-\overline{y}\right)^2} \tag{1}$$

where $\overline{y}=\frac{1}{n_{\text{samples}}}\sum_{i=0}^{n_{\text{samples}}-1} y_{i+}$

$$MAE\left(y,\widehat{y}\right)=\frac{1}{n_{\text{samples}}}\sum_{i=0}^{n_{\text{samples}}-1}\left|\frac{y_i-\widehat{y_i}}{y_i}\right| \tag{2}$$

$$RMSE\left(y,\widehat{y}\right)=\sqrt{\frac{1}{n_{\text{samples}}}\sum_{i=0}^{n_{\text{samples}}-1}\left(y_i-\widehat{y_i}\right)^2} \tag{3}$$

where $\left(\widehat{y_i}\right)$ is the predicted value of the i'th sample, y_i is the corresponding true value and n_{samples} is the number of observations [22, 23].

4 RESULTS
4.1 Classical Time-Series Models

ARIMA models are a method used with stationary series. Therefore, it should first be determined whether the series is stationary or not. In stationary series, the mean, variance, and covariance are constant over time. Stationarity of time series data can be checked using the plot of autocorrelation functions and augmented dickey-fuller (ADF) test. Then, the terms AR and MA are determined using the autocorrelation function (ACF) and partial autocorrelation function (PACF) [24].

In this study, a natural logarithmic transformation of the data set was performed to stabilize the variance of the data set. However, since the autocorrelation coefficients at different lags in the ADF tests and ACF plot were outside the confidence interval, it was determined that the series was not stationary. It can be seen in Tab. 1 that $p > 0.05$ and greater than the critical values of the ADF test statistics.

Table 1 ADF test results

ADF Test Statistic	−0,91381	Critical Values	
p-value	0,78338	1%	−3,54436
# Lags used	11	5%	−2,91107
Number of observations used	60	10%	−2,59190

The results of the ADF test performed after taking the difference of the series are shown in Tab. 2. It can be seen from the results that the series becomes stationary.

Table 2 Differentiated series ADF test results

ADF Test Statistic	−6,64957	Critical Values	
p-value	6,16158e−09	1%	−3,54436
# Lags Used	10	5%	−2,91107
Number of Observations Used	60	10%	−2,59190

As can be seen in Fig. 4, the series includes seasonality. Therefore, the SARIMA model was applied. Fig. 5 shows the ACF and PACF plots obtained when the seasonal difference of the series is taken into account.

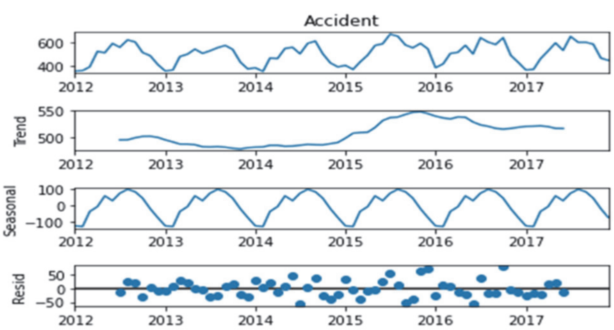

Figure 4 Seasonality and trend analysis of the series

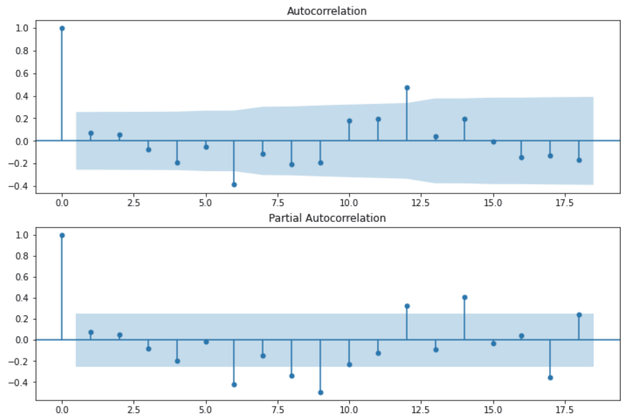

Figure 5 ACF and PACF charts of the seasonally differentiated series

The model with the lowest *AIC* value can be expressed as the best model among the developed models. Tab. 3 shows the best-performed models. Accordingly, it can be said that $(0, 1, 1) \times (2, 2, 1)_{12}$ is the best model.

Table 3 The performance of SARIMA models

$(p, d, q) \times (P, D, Q)_s$	*AIC*	*BIC*
$(0, 1, 1) \times (2, 2, 1)_{12}$	408,6	416,38
$(2, 1, 1) \times (2, 2, 1)_{12}$	409,44	420,33
$(0, 1, 2) \times (2, 2, 1)_{12}$	409,67	419,00

The comparison of the model with the best prediction performance with the actual values can be seen in Fig. 6.

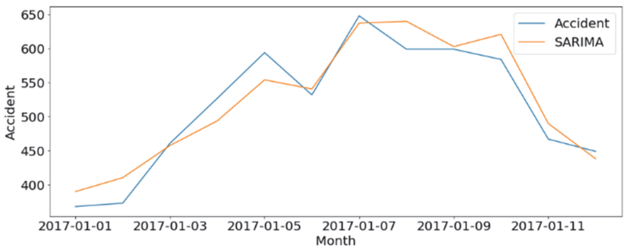

Figure 6 SARIMA prediction results

4.2 Prophet Model

The Prophet model is an open source forecasting application developed by Facebook. The Prophet model tries to predict time series using seasonality, holidays and trends. In this study, the seasonality period was determined as 12, and a 12 month forecast was created for 2017. Some results of the Prophet model for the tourism season can be found in Tab. 4.

Table 4 The results of the Facebook Prophet model

index	*ds*	*yhat*	*yhat_lower*	*yhat_upper*
64	1.05.2017	587.246	543.748	630.679
65	1.06.2017	585.533	541.512	628.049
66	1.07.2017	617.224	577.332	658.233
67	1.08.2017	641.944	599.751	685.445
68	1.09.2017	630.421	587.264	674.191

where *ds* is date. *yhat* is forecast values. *yhat_upper* and *yhat_lower* represent the upper bound and lower bound for the prediction values, respectively.

A comparison of the performance of the prophet model with the actual values can be seen in Fig. 7.

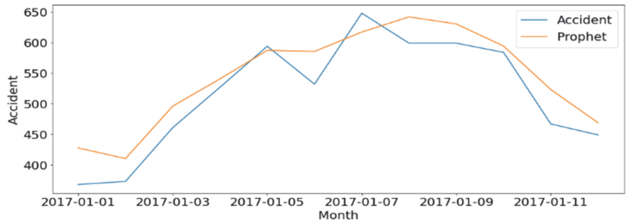

Figure 7 Prophet prediction results

4.3 LSTM Model

The LSTM is a variant of recurrent neural networks (RNN) used in long-term memory networks. The LSTMs were developed to solve the problem of long-term dependence [25]. Before the model was built, data pre-processing was performed with the minmax scalar function. As can be seen in Tab. 5, ReLu was preferred as the activation function. The number of iterations for model training was set to 1000. RMSProp and Adam were preferred as optimization algorithms for model training. The model has two LSTM layers and one dense layer. The first LSTM layer has 21312 and the second 13440 trainable parameters.

Table 5 The structure of LSTM model

Layer (type)	Output Shape	Param #
Lstm(LSTM)	(None, 12, 72)	21312
Lstm_1 (LSTM)	(None, 32)	13440
dense (Dense)	(None, 1)	33
Total params:	34785	

A comparison of the performance of the prophet model with the actual values can be seen in Fig. 8.

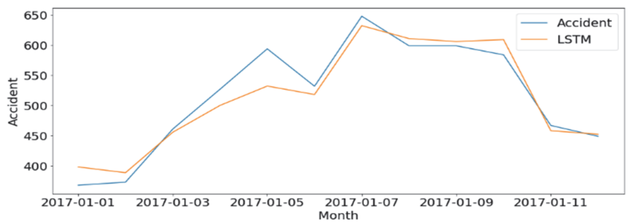

Figure 8 LSTM prediction results

4.4 The Proposed CNN-LSTM Model

CNN is a network model proposed by LeCun et al. in 1998 [26]. It is effectively used for time series estimation. The local perception of CNN and the partitioning of weights can greatly reduce the number of parameters and thus increase the learning efficiency of the model. Thus, CNN can extract useful information and learn the internal representation of time series data.

As can be seen in Fig. 9, a typical CNN model can be divided into two parts as feature learning and classification. The convolution in the feature learning section and the pooling operations applied immediately afterwards can be repeated in different numbers depending on the developed CNN architecture. The performed convolution and pooling operations are revealed the attributes of the input. After the final pooling process, the data is converted into one-dimensional form with the help of flattened operation. The resulting one-dimensional image is given as input to fully connected layers (also called dense layer). Here, classification is performed, in which class scores are determined with classical neural networks processes.

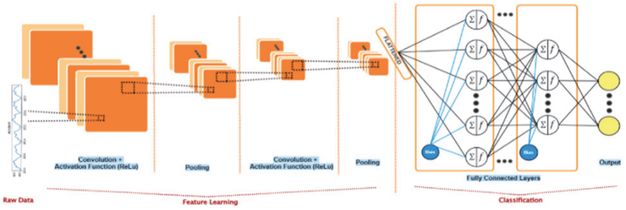

Figure 9 Structure of convolutional neural network

LSTM is an effective technique for detecting short and long term dependencies. The main idea of CNN-LSTM model is to increase the prediction success by combining the successful features of the two methods [27].

Theoretically, hybrid models can achieve more successful results by eliminating the shortcomings of the two models. In the first stage, data features are extracted by convolution and pooling in the CNN layer. In the second stage, the recall problem, which is the main weakness of the CNN model, was tried to be solved thanks to the feedback layers of the LSTM [28].

The layers of the CNN-LSTM model constructed in this study are in Tab. 6. The model has 463393 parameters and softmax activation is used only in the Dense layer at the CNN output. In the other layers, relu is preferred to free the network from the linear structure, reduce the computational cost and achieve success. Convolutional layers transform the input and transfer the result to the next layer. In this study, the accident data for the last 12 months was used as input. The main purpose of the pooling layer is to reduce the size of the feature maps. In this layer, the max pooling method (the cell with the highest value among the cells in the area covered by the filter) was preferred. Then the CNN model is combined with two LSTM layers. The dropout value 0.5 is used to prevent overfitting between LSTM layers. To minimize the loss, the loss function representing the model should be minimized. ADAM optimization algorithms were used to solve this problem. The training was performed with a value of 500 epochs.

Table 6 The structure of the hybrid CNN-LSTM model

Layer (type)	Output Shape	Param #
conv1d_284 (Conv1D)	(None, 12, 192)	768
conv1d_285 (Conv1D)	(None, 12, 192)	110784
max_pooling1d_142 (MaxPooling1D)	(None, 4, 192)	0
conv1d_286 (Conv1D)	(None, 4, 192)	73920
conv1d_287 (Conv1D)	(None, 4, 192)	73920
max_pooling1d_143 (MaxPooling)	(None, 1, 192)	0
dense_284 (Dense)	(None, 1, 96)	18528
lstm_142 (LSTM)	(None, 1, 96)	74112
dropout_71 (Dropout)	(None, 1, 96)	0
lstm_143 (LSTM)	(None, 1, 96)	74112
flatten_71 (Flatten)	(None, 96)	0
dense_285 (Dense)	(None, 192)	18624
dense_286 (Dense)	(None, 96)	18528
dense_287 (Dense)	(None, 1)	97
Total params: 463393 Trainable params: 463393 Non-trainable params: 0		

A comparison of the performance of the proposed hybrid CNN-LSTM model with the actual values can be seen in Fig. 10.

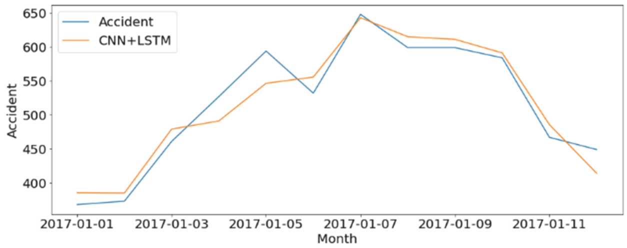

Figure 10 CNN + LSTM prediction results

5 DISCUSSIONS

In this study, SARIMA which is expressed as the traditional time series method, Facebook Prophet and deep learning methods including LSTM and CNN were for predicting traffic accident frequency. In addition, the performance of the models was evaluated using three widely used metrics such as *RMSE*, *MAPE* and R^2.

Tab. 7 summarises and compares the results of the SARIMA, Prophet, LSTM and Hybrid CNN-LSTM models. All three performance metrics show the superiority of Hybrid CNN-LSTM over the other models with the *RMSE* value of 24.076, *MAPE* value of 0.041, and the R^2 value of 0.926. The results show the good performance of Hybrid CNN-LSTM and LSTM models compared to SARIMA and Prophet. The lowest performance among the compared models was obtained with the Prophet model. The focus on financial time series and the importance of holiday data for this model are among the reasons for the poor performance of Prophet.

Table 7 Predictive accuracy for all models.

Models	*RMSE*	*MAPE*	R^2
LSTM	24.262	0.036	0.925
SARIMA	26.556	0.045	0.910
Prophet	37.342	0.069	0.823
Hybrid CNN-LSTM	24.076	0.041	0.926

This study demonstrates well the accuracy of the proposed Hybrid CNN-LSTM model, as it can minimize the error levels. According to the comparison results in Tab. 8, the Hybrid CNN-LSTM model can improve the rate of error and enhance the *R*-squared rate. Therefore, the developed hybrid model is proposed in this study. In particular, Hybrid CNN-LSTM shows lower error than the other models and has the best prediction performance.

Tab. 8 shows the real accident data for the 2017 in the test dataset and the prediction results generated by the models for these values. In addition, the results generated by the models are shown in Fig. 11. According to the results, most traffic accidents occurred between May and September. The average number of accidents in this five-month period is 594. The average of accidents in January and February is 371. The frequency of accidents during the tourist season is directly proportional to the population density of Antalya in this period.

Table 8 Comparison of accident frequency of results with different models for the test dataset

Months	Real accident data	ARIMA	Prophet	LSTM	Hybrid CNN-LSTM
Jan 2017	368	389.957	427.751	398.229	385.453
Feb 2017	373	410.397	410.385	388.689	384.971
Mar 2017	461	457.643	496.077	455.721	479.141
Apr 2017	527	493.862	540.683	500.191	491.099
May 2017	594	554.038	587.246	532.283	546.539
June 2017	532	540.617	585.533	518.245	555.659
July 2017	648	637.323	617.224	632.380	642.999
Aug 2017	599	639.929	641.944	610.951	615.081
Sep 2017	599	602.834	630.421	606.059	611.234
Oct 2017	584	620.875	594.286	609.205	591.260
Nov 2017	467	489.845	523.216	458.288	485.683
Dec 2017	449	438.225	468.807	452.438	414.094

The CNN-LSTM model estimated the actual number of accidents to be 6203, which was 6201 for 2017. In addition, when the predictions of the model for the years 2023 - 2030 (in Tab. 9) are examined, it is predicted that the number of accidents will be between 6187 - 6313 and according to the model, annual change rates vary between 3% and 2.3%.

Table 9 Number of accident prediction in Antalya city from 2023 until 2030

Year	2018	2019	2020	2021	2022	2023
Prediction	6313	6126	6267	6255	6217	6296
Growth Rate / %	1.81	−2.96	2.30	−0.19	−0,61	1.27
Year	2024	2025	2026	2027	2028	2029
Prediction	6224	6260	6306	6187	6294	6291
Growth Rate / %	−1.14	0.58	0.73	−1.89	1.73	−0.05

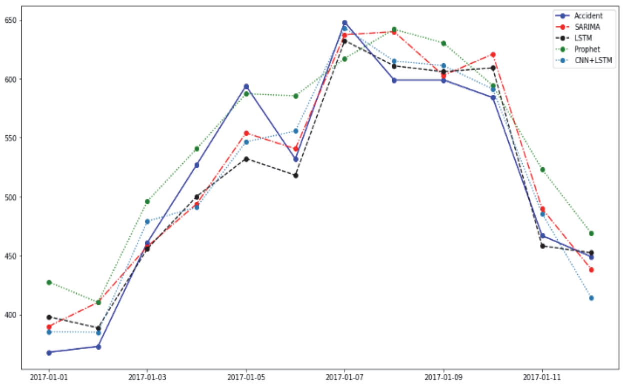

Figure 11 Comparison of accident frequency of results with different models for the test dataset (year 2017)

Antalya is a summer tourism city. The population decreases during the winter months. The number of accidents is at its lowest in January and February. As the weather warms up, the number of accidents begins to increase. The number of accidents reaches the highest levels between the months of May and September, when tourism is at its peak. One of the important results of tourism is the change in the transportation and logistics sectors. The intensity of traffic accidents creates important consequences for many sectors.

Tab. 10 shows the *MAPE* values produced by the models in terms of tourism season, off-season and year. According to the table, the Hybrid CNN-LSTM model produced a more successful result in the tourism season. Accordingly, it can be said that the model is successful in estimating the population fluctuations in the tourism season.

Table 10 The *MAPE* values of the models

Models	Year	Tourism Season	Off Season
LSTM	0.045	0.035	0.052
SARIMA	0.069	0.057	0.078
Prophet	0.036	0.037	0.037
Hybrid CNN-LSTM	0.041	0.036	0.046

6 CONCLUSION

In this study, hybrid deep learning model was developed, based on CNN and LSTM models, to make a forecast of traffic accident frequency during the tourist season. The proposed model has been compared with the SARIMA, Prophet and LSTM models. The dataset used in all models include the daily frequencies of fatal and injury traffic accidents that occurred in Antalya province of Turkey. The best prediction performance among the models was obtained with the proposed hybrid model.

The dataset used in this study covers a 72 month period. The successful performance of the hybrid CNN-LSTM model for this period has shown that the model can also be used for future periods. A limited dataset was used in this study. In future studies, similar results can be obtained with more data for different settlements. In this way, the estimation of traffic accident frequencies in the upcoming tourism seasons is of particular concern to many stakeholders such as local administrators, road users, roadway designers, law enforcement agencies and policy makers. It would be useful in developing strategies that can help to prevent and reduce the number of traffic accident in Antalya, Turkey. One of the limitations of this study is that only the aggregated traffic accident data from the most important tourist city in Turkey are used. It is not recommended to generalize the estimation results for the whole country. However, it can be shown as an example for similar tourism cities. The estimation of the number of accidents is very important in order not to interrupt the transportation. This is a situation that directly affects the number of tourists. This work will have direct benefits to local officials such as transportation to survivors, planning health services, restoring road safety. In addition, there will be benefits such as protection of the supply chain and visitor satisfaction.

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