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TrafficNet: A Hybrid CNN-FNN Model for Analysis of Traffic Accidents in Seoul

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Abstract
The escalating global trend of traffic accidents with subsequent loss of lives is a matter of grave concern that requires immediate attention. Extensive efforts have been made to mitigate accidents and develop effective prevention strategies. This research paper focuses on a comprehensive analysis of traffic accidents in Seoul, aiming to identify factors and accident types that contribute to increased severity. To achieve this, we introduced a new approach called "TrafficNet: A Hybrid CNN-FNN Model" to evaluate effects of various parameters on the severity of traffic accidents in Seoul. Our main objective was to classify accidents into four distinct levels of severity: minor injuries, slander, fatalities, and injury reports. To assess the effectiveness of our proposed model, we conducted comprehensive experiments using publicly available traffic accident data provided by Seoul Metropolitan Government. These experiments involved six different models, including five machine learning models (decision tree, random forest, k-nearest neighbor, gradient boosting, and support vector machine) and one deep learning model (multilayer perceptron). The proposed model demonstrated exceptional performance, surpassing all other models and previous research findings using the same dataset. On the test dataset, TrafficNet achieved an impressive accuracy of 93.98% with a precision of 94.31%, a recall of 93.98%, and an F1-score of 93.89%.

Category: Information Retrieval / Web

Keywords: Traffic accidents; Accident severity analysis; Traffic accident factors; CNN-FNN hybrid model; Injury severity levels

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I. INTRODUCTION

In our modern times, traffic accidents have become a significant and worrisome issue. The rapid increase in the number of cars on the road driven by global economic growth and better living standards has brought about this concern [1-3]. The World Health Organization (WHO) in 2018 reported that nearly 1.35 million individuals across the globe lost their lives due to traffic accidents each year [4]. This staggering statistic translates to one person succumbing to a traffic accident every 24 seconds, marking a distressing increase of 100,000 people compared to 2015. Furthermore, according to the Centers for Disease Control and Prevention [5], the monetary toll stemming from medical expenses and productivity losses linked to car accident fatalities exceeds a daunting 63 billion dollars annually.

Given these alarming figures, it is crucial to identify primary factors contributing to these accidents and various types they come in. This knowledge could be pivotal in proactively averting traffic accidents. Notably, recent WHO data from 2020 revealed that in South Korea, road traffic accident-related deaths totaled 4,399, constituting around 1.76% of all reported deaths. When adjusted for age, the death rate stood at 5.76 per 100,000 individuals, ranking South Korea at the 150th position globally in this regard [6].

Similarly, many other countries are conducting various studies and implementing policies related to this issue. However, there is a notable lack of understanding in Seoul regarding main causes and mechanisms of severe traffic accidents. Seoul, the largest city in South Korea, had approximately 3,432,000 registered vehicles as of June 2021. It heavily relies on various transportation methods daily. Consequently, traffic accidents have the potential to result in significant societal and economic losses.

The primary objective of this research was to identify key factors and types of severity significantly impacting the seriousness of traffic accidents, specifically focusing on Seoul. To achieve this goal, we utilized a publicly available traffic accident dataset from Seoul. To facilitate this investigation, we introduced a new approach called "TrafficNet: A Hybrid CNN-FNN Model" for assessing effects of various parameters on severity of traffic accidents in Seoul. The proposed model was then compared with five machine learning models—decision tree (DT), random forest (RF), k-nearest neighbor (KNN), gradient boosting (GBR), and support vector machine (SVM)—and one deep learning model—multilayer perceptron (MLP). Our analysis unveils a significant insight: the severity of traffic accidents in Seoul is primarily driven by variables associated with vehicle types rather than factors related to drivers. This discovery diverges from previous research findings [7-12]. This paper makes the following contributions:

- Comprehensive model comparison: Our research offers an extensive comparative analysis of both established machine learning and deep learning models in the context of assessing the severity of traffic accidents in Seoul. This thorough examination not only highlights strengths and weaknesses of each model, but also equips researchers and practitioners with valuable insights for informed model selection.
- Novel feature extraction: We extracted new features from the existing dataset. This step enhanced the precision and accuracy of our model, enabling more reliable and precise identification and classification of traffic accident severity levels in Seoul.
- Hybrid deep learning model: Our approach introduced a hybrid deep learning model that could amalgamate convolutional neural network (CNN) and feed-forward neural network (FNN) layers. This ensemble of the model demonstrated better performance than previous benchmarks in the classification of traffic accident severity in Seoul.

The remainder of this paper is organized as follows. Section II reviews previous research. Section III describes characteristics of the dataset used for the analysis. Section IV introduces methods adopted in this study. Section V shows findings of this study based on our analyses using these methods. Finally, Section VI concludes this study.

II. LITERATURE REVIEW

A. Analysis of Traffic Accidents Abroad

Zhao [13] conducted a study in China to address severe traffic accidents. The study employed a Bayesian network (BN) crash severity model that was constructed using key factors identified through improved gray correlation analysis. Extensive accident data from China were collected to validate the model. The study demonstrated that the BN model could effectively capture complex relationships among accident factors, making it valuable for understanding and addressing severe traffic accidents. Additionally, the study used BN's junction tree engine to rank factor combinations by severity, providing insights into critical factors and mitigation strategies for these accidents. Feng et al. [14] conducted a study addressing societal challenges posed by road traffic accidents (RTAs) in the UK. They developed a big data analytics platform using machine learning and deep learning techniques. That platform had three components: clustering accident incidents on Google Maps to identify hotspots, visually representing accident attributes to uncover contributing factors, and exploring models for predicting future accidents. Their experimental results showed that the platform was effective in handling large data volumes, providing insights into past and potential accidents, and aiding informed decision-making. Their platform's versatility suggests that it could be applied beyond traffic accident analysis in the field of big data analytics.

De Ona et al. [15] conducted a study assessing the use of BNs to categorize traffic accidents by severity. They recognized that factors such as driver characteristics, road conditions, vehicle features, accident details, and weather could collectively influence injury severity. BNs were chosen due to their predictive capacity and graphical representation capabilities. Using data from 1,536 accidents on rural highways in Spain and 18 relevant variables, they created three BNs classifying severity into slightly injured, killed, and severely injured. Their findings highlighted that key-variables such as accident type, driver age, lighting conditions, and number of injuries were strong indicators of accidents resulting in fatalities or severe injuries. Ahmed [16] conducted a research study to identify significant variables affecting road traffic accident fatalities. The study employed a logistic regression model with the maximum likelihood method to estimate parameters and assess effects of explanatory variables. The dataset included 212 observations from Directorate Traffic-Garmian records, with response variable being accident victims categorized into two groups. The study's key findings highlighted the suitability of logistic regression models for this type of data and identified the following three explanatory variables strongly linked to accident victims: high speed, car type, and location.

Chong et al. [17] conducted a thorough analysis using general estimates system (GES) automobile accident data from 1995 to 2000 to evaluate different machine learning methods for predicting driver injury severity in head-on front impact point collisions. Their results showed that a hybrid approach outperformed other methods, particularly in cases of non-incapacitating injuries, incapacitating injuries, and fatalities. DTs were particularly effective for modeling no-injury and possible injury scenarios. Their study extended previous research by considering various injury levels and emphasizing the importance of predicting both fatal and non-fatal injuries, which could have significant societal implications. However, the absence of vehicle speed data limited the study's scope, suggesting potential areas for future research improvements.

Dong et al. [18] used mixed logit models to analyze detailed crash data from I-25 in Colorado, distinguishing single-vehicle (SV) and multi-vehicle (MV) accident probabilities. They found that factors such as speed gap, segment length, and wet road surfaces affected both SV and MV accidents, while traffic volume, road characteristics, and environmental conditions had unique impacts. These insights are valuable for accident prevention and road design. However, applicability of their study finding to other highways might need caution. This warrants further research on different road types.

Champahom et al. [19] focused on rear-end crashes on Thai highways, a major cause of fatalities. They used classification and regression tree (CART) analysis to identify key factors contributing to these accidents. Two models were created: one for rear-end crash causes and another for fatal crashes. Driver age, number of lanes, and median opening area were crucial for at-fault and not-at-fault drivers, while safety equipment mattered in fatal accidents. These findings can inform public awareness programs and policy changes to reduce rear-end crash severity and guide future research. Obaid et al. [20] conducted a comprehensive study on road pavement conditions' impact on motorist injuries. They analyzed four years (2015–2018) of crash data from South Australia (2015–2018), including 3,812 crashes on sealed pavements and 1,086 on unsealed surfaces. Using a mixed logit model, they considered various factors such as driver attributes, road conditions, and crash types. Their study identified factors such as alcohol involvement, high-speed limits on sealed roads, male drivers, middle-aged drivers, rollover crashes, and straight road accidents on unsealed surfaces that could significantly increase severe driver injuries. Their study recommended tailored safety measures for both pavement types based on these findings.

B. Analysis of Traffic Accidents in Seoul, South Korea

Bhin and Son [21] conducted a research study on factors affecting the severity of traffic accidents involving bus drivers, with a focus on gender differences (male, female). They collected accident data from the Korea Road Traffic Authority's "Traffic Accident Analysis System (TAAS)" involving local and intercity buses in 31 cities within Gyeonggi Province from 2014 to 2016. They used a decision tree model to explore gender-related variables and an ordered logit model to assess accident severity by gender. Their study found that light violations and vehicle-to-vehicle factors were significant factors influencing accident severity for all male drivers. However, no significant variables were identified for female drivers. Their research has implications for designing advanced driver assistance systems tailored to address accident severity with gender-specific considerations.

Lim et al. [22] analyzed factors contributing to traffic accidents on roads with a width of less than 9 m. They employed logistic regression models and discovered that accidents were more likely to occur when drivers were traveling straight. They also found that female and pedestrian cyclists were involved in these incidents.

Meanwhile, Kim et al. [23] investigated effects of driver age and human characteristics on occurrence of traffic accidents. They conducted an in-depth study using Poisson regression analysis to develop severity models for both elderly and non-elderly drivers. Their findings

Table 1. Comparison of previous studies on accidents severity

Study	Objective	Method	Country
Zhao [13]	Severe car accidents in China	Bayesian network	China
Feng et al. [14]	Car accidents in the UK and other things besides accidents	A priori algorithm	UK
De Ona et al. [15]	Accidents on rural highways in Spain and why they are deadly	Bayesian network	Spain
Ahmed [16]	Factors that make car accidents deadly in Iraq	CART and logistic regression	Iraq
Chong et al. [17]	Car accidents in the United States and how bad drivers get hurt	Decision tree, SVM, neural network, and hybrid decision tree	United States
Dong et al. [18]	Differences between accidents with one car and accidents with more than one car	Mixed logit model	Colorado, United States
Champahom et al. [19]	How to reduce crashes on Thai highways	CART and logistic regression	Thailand
Obaid et al. [20]	The effect of road types on how bad drivers get hurt in Australia	Mixed logit model	Australia
Bhin and Son [21]	Factors that make bus accidents worse in South Korea, especially for men and women	Decision tree and ordered logit	South Korea
Lim et al. [22]	Factors in South Korea that make narrow road accidents bad	Logistic regression	South Korea
Kim et al. [23]	How age and other things about people affect car accidents in South Korea	Poisson regression	South Korea

highlighted that elderly drivers faced challenges related to predicting stopping distance, discerning their surroundings, and responding to attention, which affected accident occurrence. Table 1 summarizes related work.

III. DATA COLLECTION

A. Study Area

Seoul, the capital city of South Korea, is a bustling

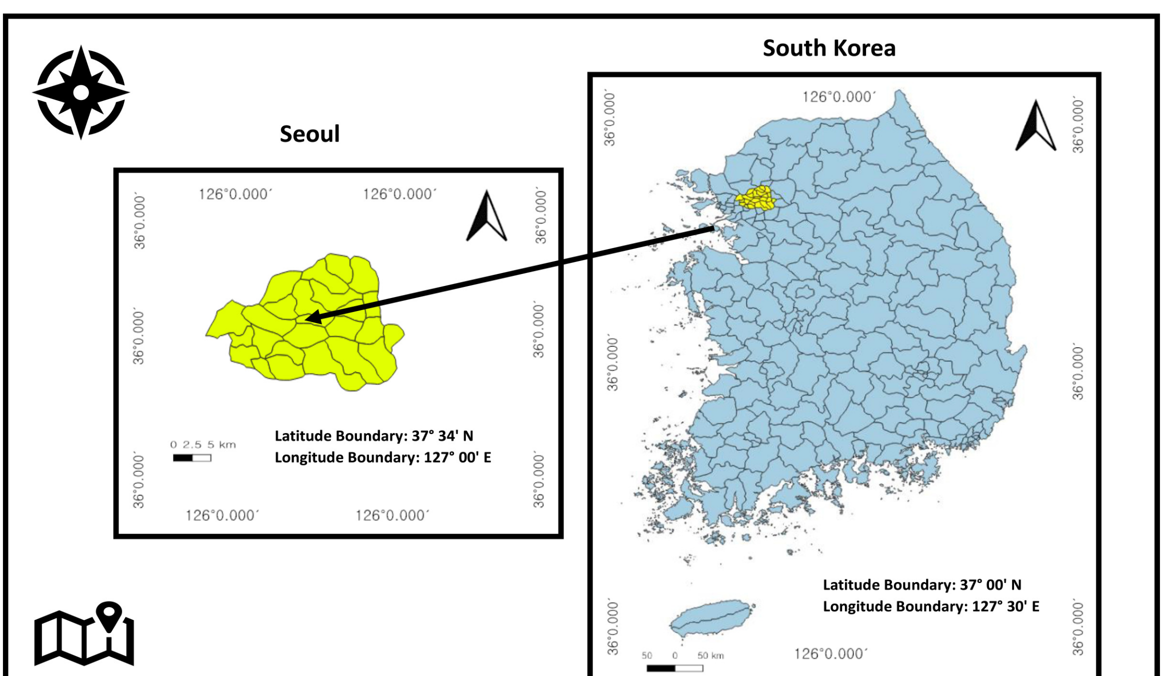

Fig. 1. Study area: Seoul city, South Korea.

metropolis with a population exceeding 10 million. Its rapid growth and density have led to traffic congestion, exacerbated by limited road space and a lack of widespread carpooling. To address this, the Seoul Metropolitan Government has implemented strategies such as efficient public transport, dedicated lanes, and congestion pricing. Accidents on Seoul's roads are common, ranging from minor incidents to severe collisions. Contributing factors include reckless driving, speeding, distractions, and adverse weather. Authorities combat this through strict law enforcement, awareness campaigns, and surveillance systems. Vehicle safety technology has also helped reduce accident severity. The map of Seoul, our study area, is shown in Fig. 1.

B. Dataset Description

In this research, we utilized a publicly available dataset of traffic accidents from Seoul, spanning from year 2010 to year 2018. The dataset was obtained through the Korean government's Public Data Portal [24]. Characteristics of the dataset are summarized in Table 2.

C. Data Preprocessing

During the data preprocessing phase, we executed a series of steps to enhance the quality and suitability of the Seoul traffic accident dataset for subsequent analysis and machine learning model training.

1) Columns removal: The first step involved identification and elimination of redundant columns, specifically "Place dong," "Offender sex," "Offender age," "Holiday," "Victim sex," and "Victim age" columns. By removing these redundant features, we aimed to streamline the dataset, reducing its dimensional and enhancing overall efficiency.
2) Target variable encoding: To make the dataset compatible with machine learning algorithms, we tackled the encoding of the target variable "Y." This involved mapping its classes, which included "minor injuries," "slander," "dead," and "injury report," into corresponding numerical labels. This transformation allowed algorithms to operate on this variable effectively.

Table 2. Description of traffic accident dataset columns

Column name	Description	Example
Occur date	The date when the accident occurred.	1 January 2010 to 31 December 2018
Occur time	The time at which the accident occurred.	00:00 to 23:00
Occur day of the week	The day of the week when the accident took place.	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
Place gu	The administrative district where the accident occurred.	Dobong-gu, Mapo-gu, Guro-gu etc.
Place dong	A more specific location or district (dong).	Seogyo-dong, Daebang-dong, Bangbae-dong, etc.
Accident type A	A category specifying the type of accident involving cars or vehicles.	Side collision, backup collision, head-on collision, etc.
Accident type B	A category specifying the type of accident involving passing through road.	Workpiece collision, on the sidewalk, etc.
Offender violation	Information about the violation committed by the offender.	Such as not maintaining a safe distance or violating traffic signals.
Road surface	Road conditions, indicating whether of the road.	Dry, wet, frozen, snow, flooding, unidentified
Weather status	Information about the weather conditions at the time of the accident.	Sunny, rainy, cloudy, snowy, foggy, unidentified.
Road type A	The type of road where the accident occurred.	At an intersection, near an intersection, on a cross-walk inside a tunnel, over an overpass, in an under-pass, railroad crossing.
Road type B	Further details about the road type.	
Offender vehicle	Information about the vehicle driven by the offender involved in the accident.	Passenger car, lorry, two-wheeler, van, bicycle, etc.
Offender sex	Gender of the offender involved in the accident.	Male, female, unidentified
Offender age	Age of the offender involved in the accident.	1 to 117 years old, unidentified
Victim vehicle	Information about the vehicle(s) affected in the accident.	Passenger car, lorry, two-wheeler, van, bicycle, etc.
Victim age	Age of the victim(s) involved in the accident.	1 to 117 years old, unidentified

3) Handling missing data: Ensuring data consistency was crucial. We carefully examined and removed any rows that contained missing values in the target variable. This process helped maintain the integrity of the dataset and prevented potential issues during analysis.
4) Categorical data transformation: Given that the majority of the dataset comprised categorical data, we employed one-hot encoding. This technique transformed categorical variables into a vector space model, a format compatible with most machine learning algorithms.
5) Time-related feature extraction: To gain insights into time-related patterns, we delved into the "occur time" column. We extracted hour, minute, and second components from this timestamp information. By doing so, we were able to distinguish between peak and non-peak hours, further converting them into Unix timestamps for subsequent analysis.
6) Data splitting: In line with best practices, we divided the dataset into three distinct subsets: a training set, a validation set, and a test set. This division ensured that our model could be trained, validated, and tested independently, preventing overfitting and providing a reliable assessment of its performance.
7) Feature scaling: Lastly, we applied min-max scaling to input features. This step was vital to ensure that all variables were uniformly scaled within a range of 0 and 1. It aids in the convergence and stability of many machine learning algorithms.

D. Chi-square Test for Feature Selection in Machine Learning

Feature selection plays an important role in the process of building machine learning models. It involves identifying and selecting the most relevant features, which are input variables that significantly contribute to the predictive power of the model. One widely used method for feature selection is the chi-square test. It is especially valuable when dealing with categorical data. This method has been proven to be highly effective when features are independent of each other. However, its performance may deteriorate when features demonstrate dependencies. The primary function of a chi-square test is to determine independence between two categorical variables. In the specific context of feature selection, its utility becomes evident as it allows us to assess the relationship between each feature and the target variable. After applying the chi-square test, we found that the most important variables, contrary to common sense, were offender vehicle, victim vehicle, accident type A, accident type B, and offender violation. The chi-square (χ^2) statistic is calculated as follows:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \quad (1)$$

where O is observed frequency (contingency table value) and E is expected frequency (under the assumption of independence).

The chi-square test quantifies the extent to which observed values deviate from what would be expected if the two variables are independent. A higher chi-square value indicates a stronger association between variables. According to the chi-square test, the "Offender Vehicle" had the highest impact on accident severity in Seoul and "Victim Vehicle" had the second highest impact. Detailed results of the chi-square test are illustrated in Fig. 2.

After performing the chi-square test, we excluded the

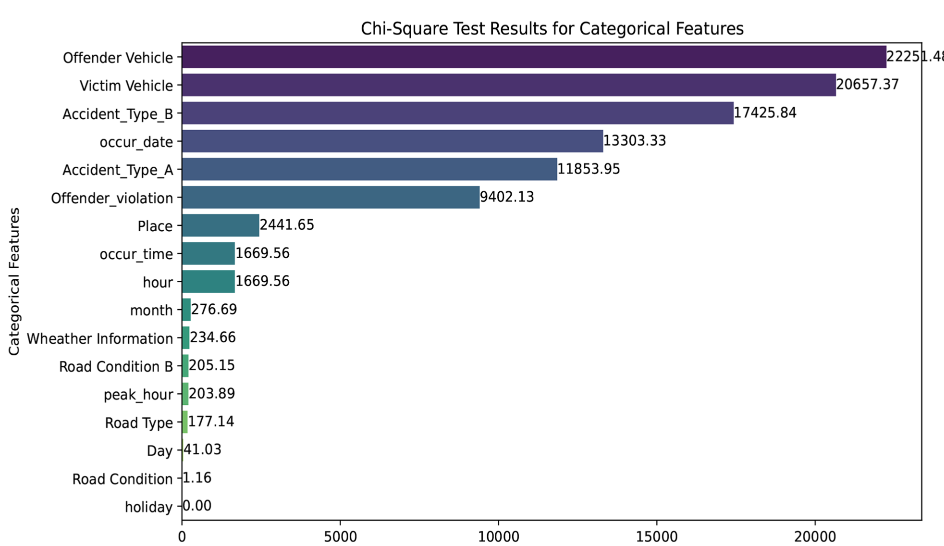

Fig. 2. Feature importance using the chi-square test.

following variables from our analysis: Place-dong, Offender sex, Offender age, Holiday, Victim sex, and Victim age. Our final set of features for the machine learning model was composed of a combination of spatial and sequential variables. Spatial variables included "Place gu," "Road Type A," and "Road Type B." These spatial features provided information about the location and type of road where the accidents occurred. On the other hand, sequential variables encompassed various aspects of the accident's occurrence. These included "Occur Date," "Occur Time," "Occur Day," "Accident Type A," "Accident Type B," "Offender Violation," "Weather Status," "Offender Vehicle," "Victim Vehicle," and "peak hour" (recorded in hours, minutes, and seconds), which we conveniently converted into a Unix timestamp for analysis. Our target prediction variable focused on severity of injury resulting from the accident.

IV. METHODS

We employed four machine-learning models and one deep-learning model to conduct a comprehensive analysis of traffic accidents in Seoul. Descriptions of these models are provided below:

- Decision tree (DT): It recursively splits the dataset into subsets based on the most significant attribute to make classification decisions [25].
- K-nearest neighbor (KNN): It assigns a data point to the class that is the most common among its KNN in the training dataset [26].
- Support vector machine (SVM): It identifies a hyperplane that best separates data points into different classes while maximizing the margin [27].
- Gradient boosting classifier (GBR): Gradient boosting is an ensemble learning method that sequentially builds multiple DTs, with each tree correcting errors of the previous one [28].
- Multilayer perceptron (MLP): MLP is a type of feed-forward neural network comprising multiple layers of nodes (neurons) between input and output layers [29, 30]. It is utilized for a wide range of machine-learning tasks, including classification.

A. TrafficNet Model

TrafficNet, our proposed model, is a hybrid CNN and FNN architecture designed for comprehensive analysis of traffic accidents in Seoul. TrafficNet combines strengths of both CNN and FNN to leverage spatial and sequential patterns present in traffic accident data.

The CNN component of TrafficNet consists of two convolutional layers with 64 and 128 filters, respectively, each having a max-pooling layer to downsample feature maps. These convolutional layers are responsible for capturing spatial features and patterns from the input data, which in this case are the attributes related to traffic accidents. The rectified linear unit (ReLU) activation function is used to introduce nonlinearity into CNN layers, aiding in feature extraction. On the other hand, the FNN component of TrafficNet focuses on capturing sequential patterns and higher-level features. It comprises two dense (fully connected) layers with 64 and 32 neurons, respectively, followed by an output layer with a softmax activation function. These layers are designed to learn complex relationships and patterns in the data that may not be explicitly captured by CNN layers.

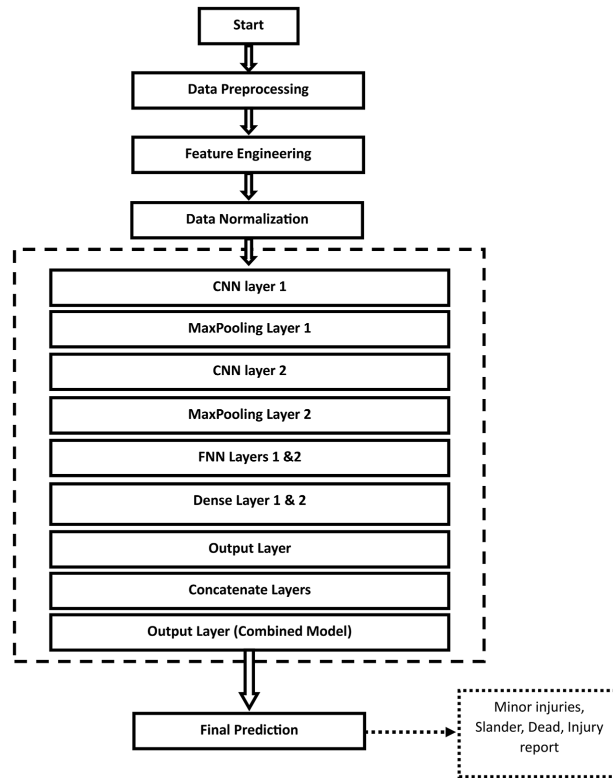

Fig. 3. Overview of TrafficNet model.

To combine information extracted by both CNN and FNN components, the model employs a concatenation layer to merge their outputs. This combined information is then passed through an additional dense layer with four output neurons, each representing one of the accident severity classes.

The softmax activation function in the final layer computes probabilities of each class, allowing TrafficNet to predict accident severity for a given input. A graphical overview of the TrafficNet model is shown in Fig. 3. Hyperparameters employed in all models are detailed in Table 3.

Table 3. Hyperparameters of models

Model No.	Model name	Parameter	Value
1	Decision tree	Criterion	Gini
		Splitter	Best
		Max depth	None
		Min samples split	2
		Min samples leaf	1
		Max features	None
2	Random forest	Number of estimators	100
		Criterion	Gini
		Splitter	Best
		Max depth	None
		Min samples split	2
		Min samples leaf	1
		Max features	'auto'
		Bootstrap	True
3	K-nearest neighbor	Number of neighbors	5
		Weights	'uniform'
		Algorithm	'auto'
		Leaf size	30
		Metric	'minkowski'
		p (for Minkowski distance)	2
4	Gradient boosting	Max depth	3
		Min samples split	2
		Min samples leaf	1
		Min weight fraction leaf	0.0
		Subsample	1.0
		Max features	None
		Random state	1
5	Support vector machine	C	1.0
		Kernel	'rbf'
		Degree	3
		Gamma	'scale'
		Coefficient	0.0
		Shrinking	True
		Probability	False
		Random state	1
6	Multilayer perceptron	Hidden layer sizes	(100,)
		Activation function	'relu'
		Solver	'adam'
		Alpha (L2 regularization)	0.0001
		Batch size	'auto'

Table 3. Continued

Model No.	Model name	Parameter	Value
		Learning rate	‘constant’
		Learning rate, initial	0.001
		Max iterations	200
		Random state	1
7	Our proposed (TrafficNet)	Learning rate	0.001
		Epochs	100
		Batch size	32
		Loss function	Sparse categorical cross-entropy
		Metrics	Accuracy
		CNN layers	2 Conv1D layers with 64 and 128 filters
			ReLU activation
			2 Maxpooling1D layers
		FNN layers	2 Dense layers with 64 and 32 units
			ReLU activation
			Output layer with softmax activation
		Optimizer	Adam

B. Performance Metrics

We utilized the Accuracy metric to assess performances of models on validation sets during the training as described in Eq. (2):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

In all equations, TP represents true positive, FP stands for false positive, TN denotes true negative, and FN indicates false negative. We also considered meaningful metrics such as precision, recall, and F1-score as defined in Eqs. (3), (4), and (5), respectively. These evaluation metrics helped us understand classification performances of our models.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

$$\text{F1}-\text{score} = \frac{2\times\text{Precison}\times\text{Recall}}{\text{Precison}+\text{Recall}} \tag{5}$$

The macro-average is calculated by averaging the F1-scores of all classes, providing a balanced measure when dealing with imbalanced datasets.

$$\text{Macro}-\text{average} = \frac{1}{\text{Number of Classes}}\sum \text{F1}-\text{score}_i \tag{6}$$

V. RESULTS AND DISCUSSION

A. Results of All Models on Test Data

In our study, we conducted a comprehensive comparison of several models, including DT, RF, KNN, GBR, SVM, and MLP, with our proposed model, TrafficNet, for predicting injury severity in traffic accidents in Seoul. Each model's performance was evaluated using key metrics, including accuracy, precision, recall, and F1-score.

Our proposed model, TrafficNet, outperformed all other models, achieving an accuracy of 93.94%, a precision of 94.23%, a recall of 93.94%, and an F1-score of 93.86%. This performance highlights the effectiveness of TrafficNet in accurately predicting the severity of traffic accidents in Seoul. Results obtained with each model are summarized in Table 4. A graphical representation of the model's performance results is shown in Fig. 4.

Comparing strengths and limitations of these models, it was evident that traditional machine learning models such as DT, RF, and KNN exhibited lower accuracy and predictive power than GBR, SVM, and MLP. However, the latter models might have limitations in capturing

Table 4. Results of all models on overall test data (unit: %)

Model No.	Model name	Accuracy	Precision	Recall	F1-score
1	Decision tree	56.07	44.26	44.19	44.21
2	Random forest	58.73	48.94	45.16	46.77
3	K-nearest neighbor	62.54	69.85	40.72	45.61
4	Gradient boosting	66.49	76.67	45.92	52.27
5	Support vector machine	66.70	76.90	46.77	53.35
6	Multilayer perceptron	66.46	76.10	46.50	53.17
7	Our proposed (TrafficNet)	93.94	94.23	93.94	93.86

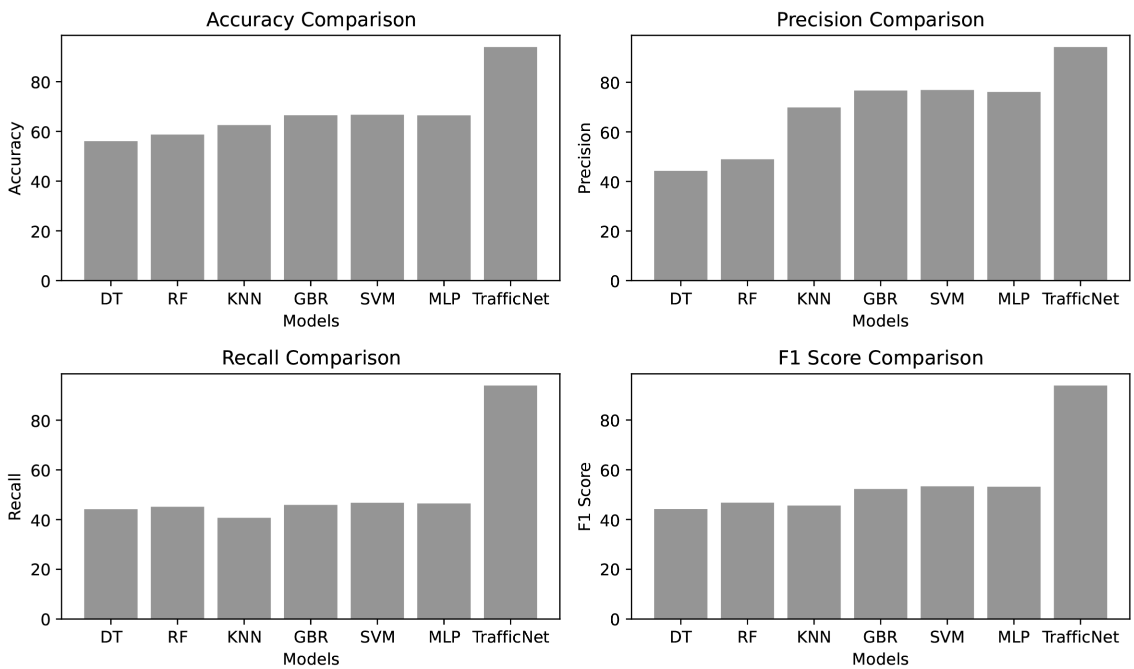

Fig. 4. Graphical representation of models' performances: (a) accuracy, (b) precision, (c) recall, and (d) F1-score.

complex patterns and relationships in the data. In contrast, TrafficNet, as a hybrid deep learning model, could leverage both spatial and sequential information (Occur date, Occur time, and Occur day of the week, Weather status and Road surface, Offender violation, Offender age and Offender sex), enabling it to outperform all other models. Although traditional models are valuable for their interpretability, TrafficNet excels in predictive accuracy. It can provide more precise insights into traffic accident severity, making it a promising choice for practical applications.

B. Effects of Weather and Road Conditions on Results

In an effort to evaluate effects of weather and road conditions on traffic accident severity in Seoul, we conducted an additional experiment removing weather and road conditions. It showed about 1% average degradation on the accuracy. However, our findings suggest that these conditions might have limited influence, consistent with previous research and supporting the work of another researcher [31] as shown in Table 5. We employed various models, including DT, RF, KNN, GBR, SVM, and MLP, which exhibited varying levels of effectiveness but failed to establish strong correlations. Remarkably, our proposed model, TrafficNet, outperformed others with an accuracy of 93.02%, indicating that weather and road conditions might not play a substantial role, while other factors significantly contributed to accident severity.

In our study, we deployed a hybrid CNN-FNN model, TrafficNet, to predict traffic accidents. The performance of TrafficNet was thoroughly evaluated and compared against various other models, as detailed in Tables 4 and 5. These tables present a compelling narrative of the

Table 5. Influence of weather and road conditions on results (unit: %)

Model	Accuracy	Precision	Recall	F1-score
Decision tree	56.16	44.30	44.24	44.26
Random forest	58.21	47.85	45.25	46.42
K-nearest neighbor	62.71	69.94	41.30	46.42
Gradient boosting	66.47	77.04	45.84	52.21
Support vector machine	66.23	76.12	46.22	53.11
Multilayer perceptron	66.17	75.44	46.90	53.67
Our proposed (TrafficNet)	93.02	94.37	93.02	93.93

substantial performance disparity between TrafficNet and other models proposed in this paper.

Table 4 elucidates the superior performance of TrafficNet on overall test data. The hybrid model showed an accuracy of 93.94%, a precision of 94.23%, a recall of 93.94%, and an F1-score of 93.86%. Intriguingly, when compared to results of the other tested models, including DT, RF, KNN, GBR, SVM, and MLP, the performance gap became apparent. TrafficNet outperformed other models by a substantial margin, with differences ranging from 27.24% to 37.87% in accuracy.

In a similar vein, Table 5 shows effects of weather and road conditions on model performance. Even under these challenging conditions, TrafficNet maintained an accuracy of 93.02%, substantially surpassing accuracies achieved by other models. Notably, DT achieved an accuracy of 56.16%, while the accuracy of SVM reached 66.23%. The contrast between TrafficNet and other models revealed a substantial improvement in accuracy, ranging from 26.79% to 36.79%.

These results underscore significant contribution of the hybrid CNN-FNN model, TrafficNet, in predicting traffic accident severity. The observed performance disparities of more than 20% to 30% emphasize unique capabilities of TrafficNet in capturing complex patterns within traffic accident data.

C. Comparison of TrafficNet Model with Machine Learning Model

The better performance of our proposed model, TrafficNet, than other traditional machine learning models can be attributed to the unique architecture of the hybrid CNN-FNN model and its ability to leverage both spatial and sequential information present in the traffic accident dataset. Several factors might have contributed to the success of TrafficNet:

1) Spatial and sequential pattern recognition: TrafficNet incorporates CNN layers, designed to capture spatial patterns in the data. This is crucial in understanding complex relationships between different features such as location (districts, intersections), road conditions, and vehicle types. The inclusion of FNN layers further enabled the model to recognize sequential patterns, considering factors such as date, time, and day of the week.
2) Feature hierarchy and abstraction: The multi-layered architecture of TrafficNet allows the model to automatically learn hierarchical representations of features. This feature hierarchy enables the model to abstract and understand both low-level details and high-level patterns in the data simultaneously.
3) End-to-end learning: The end-to-end learning approach of TrafficNet allows the model to learn complex representations directly from the raw input data. This is especially beneficial for tasks where the relationship between input features and the target variable is intricate and not easily captured by handcrafted features used in traditional models.
4) Deep learning flexibility: The deep learning architecture of TrafficNet is highly flexible and capable of adapting to the inherent complexity of the traffic accident dataset. Deep learning models can automatically learn intricate patterns and relationships from data, making them well-suited for tasks where underlying patterns might be nonlinear and complex.

As for the similar accuracy among traditional models (DT, RF, KNN, GBR, SVM), it is possible that these models, while having their strengths, may struggle to capture nuanced patterns present in the traffic accident dataset. Traditional machine learning models often rely on manually engineered features. They might not be able to effectively handle intricate relationships and spatial dependencies present in the data.

D. Comparison of TrafficNet Model with MLP

Both models share the foundational concept of neural networks. TrafficNet incorporates a hybrid architecture that combines CNN layers with FNN layers. The novelty of TrafficNet lies in its ability to capture and leverage both spatial and sequential patterns inherent in traffic accident data. The additional CNN layer in TrafficNet serves to extract spatial features from attributes such as location (district, specific location), road type, and weather conditions. This spatial awareness is crucial for understanding localized impact of these factors on accident severity. Meanwhile, FNN layers focus on capturing sequential patterns, such as time-related information (date, time, day of the week) and offender characteristics (age, gender, violation).

In contrast, the MLP model, being a standard feedforward neural network, may not be as adept at capturing spatial patterns effectively. The hybrid nature of TrafficNet enables it to overcome this limitation and provide a more comprehensive analysis of traffic accidents than MLP.

VI. CONCLUSION AND FUTURE WORK

Our primary objective was to identify key factors and types of severity that could significantly impact the seriousness of traffic accidents, focusing specifically on the Seoul region. TrafficNet, a hybrid CNN-FNN model, was introduced to assess these factors. Through comprehensive experiments involving various machine learning and deep learning models, TrafficNet outperformed all others, demonstrating an accuracy of 93.98%. Findings of this study have significant implications for understanding traffic accident severity, emphasizing the model's potential to enhance road safety and traffic management.

Despite our impressive results, there are avenues for future research. Further investigation into the intricate relationships among accident factors such as weather and road conditions could provide deeper insights. Additionally, expanding the dataset to include a broader temporal and spatial scope may yield more comprehensive conclusions. Moreover, exploring real-time accident prediction and prevention strategies using TrafficNet could contribute to proactive accident management. Overall, there remains substantial potential for ongoing research to enhance our understanding of traffic accidents and improve safety measures.

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Conflict of Interest(COI)

The authors have declared that no competing interests exist.

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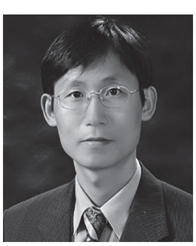

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