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Research Article

Machine learning in traffic safety: Techniques for injury severity prediction

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Abstract:

In this research, we look at how deep learning and TL models may be used to forecast how bad traffic crash will be. It is critical to create trustworthy crash severity prediction models since road crash are on the rise and have major social and economic consequences. Research in this area makes use of CAS crash data and employs a number of deep learning and transfer learning models, including ResNet, EfficientNetB4, InceptionV3, Xception, and MobileNet, as well as a number of convolutional neural networks (CNNs), multilayer perceptrons (MLPs), and long short-term memories (LSTMs). MobileNet achieved the highest performance metrics, including an F1-score of 98.9%, a precision of 98.5%, and an accuracy of 98.2%. The model's predictions were further analyzed using SHapley Additive exPlanations (SHAP) to determine the most important components that contributed to the severity of the disaster. Findings show that MobileNet is very effective when it comes to crash severity prediction using transfer learning's strong and generalizable architecture.

1. Introduction

The number of cars on the road has increased dramatically due to the rising living standards in modern civilization. There has been a dramatic rise in the incidence of road crash, which has resulted in enormous financial and human casualties [1]. Countless people all around the world are hurt or killed in car crash every year, and the resulting economic and human costs are huge. Reducing fatalities and losses caused by road traffic crash (RTAs) requires a thorough understanding of their causes and the severity of injuries. As both the number of cars on the road and the complexity of road infrastructure continue to rise, a data-driven strategy is necessary for studying crash patterns and identifying possible risk factors. Reducing the frequency and effects of RTAs requires additional research into their causes [2] and the implementation of appropriate solutions.

According to new research on road safety worldwide, the World Health Organization (WHO) estimates that over 1.19 million people die each year as a result of traffic crash. Among young adults and adolescents, car crash are the leading cause of death. The severity of traffic crash is a strong indicator of the injuries that victims may experience. Road crash can have varying degrees of severity due to a multitude of variables. Injuries and deaths caused by automobile crash have not decreased significantly during the last 20 years. Researchers can improve their understanding of crash risks, save money, and even decrease fatalities by using predictive models. According to Malin, Norros, and Innamaa (2019), the authors discussed the weather on different kinds of roads [3]. The major goal of crash data analysis is to address important road safety concerns by identifying the main elements that impact the frequency of traffic crash. Other critical variables include light levels, the type and quantity of the initial road, and the total number of cars [4]. The main factors that determine the effectiveness of crash prevention programs are the veracity of the data used, both in terms of collected and estimated data, as well as the appropriateness of the analytical methodology [5]. Using a data analysis technique that gets to the heart of the subject is essential if you want to discover why, how often, and to what extent specific types of drivers are safe on the roads in a given research area. Therefore, in order for the research to be of good quality, it is necessary to choose proper methodologies. The authors have made predictions on the probability of traffic crash using machine learning techniques. Using the generalized random forest, Zhang et al. (2022) assessed the effects of heterogeneous treatments on road safety research, with the goals of making speed camera programs more effective and providing lawmakers and local authorities with more thorough information [6]. Researchers used a variety of methods, including statistical analysis, reinforcement learning, hybrid models, and deep learning. Using a deep convolutional neural network and a random forest, the method for crash likelihood prediction proposed by Zhao etal. (2022) is executed [7].

While many studies have focused on crash causes, black box models have gotten far less attention. According to Yang, Zhang, and Feng (2022), the author employed five distinct ML models and also included explainable [8]. The primary goals of this research are to (1) identify the key elements that lead to these injuries in an explainable way and (2) build a model for predicting the severity of injuries in crash using a transfer learning technique. The US accident dataset (2016–2021) is used for the purpose of predicting the seriousness of traffic crash. A system that can automatically categorize the severity of crash is the target of this research.

Problem Statement

An increase in traffic crash has been accompanied by a rise in vehicle density and the complexity of road networks. It is common for conventional models of crash severity prediction to miss the complex interplay of several elements. The fact that many ML models are opaque makes it hard to understand how they arrive at their conclusions. In order to tackle these problems, this project will use transfer learning approaches to make models more accurate predictors and will use SHAP analysis to make them easier to understand and use.

2. Objectives

1. To develop an crash severity prediction model using transfer learning techniques.
2. To compare the performance of deep learning models and transfer learning models.

3. Methodology

The dataset, models (deep learning and transfer learning), and parameters for measuring the effectiveness of these models in predicting the severity of traffic crash are all included in this component of the study. The experimental setup is shown in Fig 1.

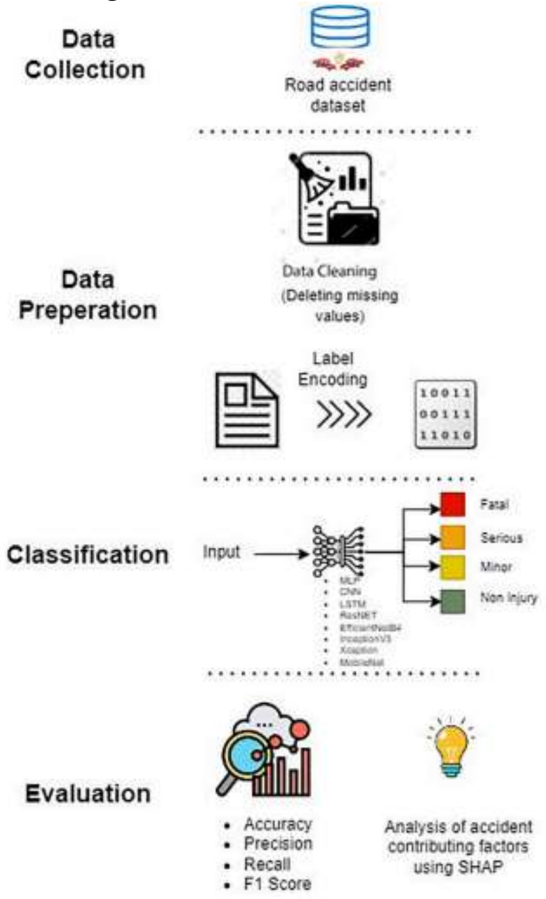

Figure 1. *Proposed Framework*

The crash records utilized for this research span the years 2016-2020 and were obtained from the “Crash Analysis System (CAS)’’ of the Ministry of Transport. The dataset can also be accessed through the open data portal. Information about the crash, the vehicles involved, and the persons involved were retrieved from two databases housed in the CAS system. To better understand what factors, contribute to crash, the 'person' and 'crash' datasets were merged to create a more comprehensive dataset. There are 378,820 rows and 101 columns in the original merged dataset. However, several columns were left out of the analysis because they weren't relevant to the crash causes. A column listing nearby police stations, for example, was deemed superfluous to this study. As a result, 36 traits related to various crash areas were chosen. Variables such as incident type, crash site characteristics, environmental factors, vehicle kinds, and human influences can all have an impact on the severity of an crash. This research categorizes the seriousness of various crash types. Each of the four levels of severity is defined in Table 1.

Table 1. *Security levels description*

Sr. No	Class	Description	No. of
1	Fatal Crash	Deaths caused by a vehicle crash.	1543
2	Serious Injury Crash	A car crash that resulted in the need for medical treatment and the subsequent transportation of one or more injured persons to a hospital.	10582
3	Minor Injury Crash	A car crash when all parties involved had only moderate injuries, such as scrapes and bruises, and no one needed to be taken to the hospital.	42888
4	Non-Injury Crash	It is not necessarily necessary to have law enforcement present in cases of road crash where no injuries have been sustained.	129304

Performance Metrics

This study measures the usefulness of transfer learning models using a variety of criteria, including accuracy, F1 score, recall, and precision. The research also makes use of confusion matrices to measure how well these algorithms perform. One common tabular format for displaying the classifier's performance on test data is an error matrix, also called a confusion matrix. This gives a visual representation of the algorithm's accuracy.

Whereas "True positive (TP)" indicates instances where the model correctly recognized the positive class, "True negative (TN)" indicates instances where the model correctly predicted the negative class. Conversely, "false positive (FP)" describes situations in which the model's prediction of a positive class was at odds with the actual negative class. "False negative (FN)" cases are similar in that they show instances when the model incorrectly classified a positive class as negative.

One way to measure the model's overall performance is to look at the percentage of correct predictions relative to the total number of instances in the dataset. This accuracy measure may be calculated using the following formula:

$$\text{Accuracy } = \frac{TP + TN}{TP + TN + FP + FN} \dots \dots (1.1)$$

A model's precision indicates the percentage of positive cases that were accurately predicted out of all those observed. The major goal of the model is to accurately recognize positive instances; a decrease in false positives will provide insight into this accuracy. To determine the accuracy, one can use this formula:

$$\text{Precision } = \frac{TP}{TP + FP} \dots \dots (1.2)$$

A model's recall is its accuracy in predicting outcomes as a percentage of the dataset's total true positives. The true positive rate is another name for it, along with sensitivity. It is a measure of the model's positive case detection accuracy. Here is the formula for recall:

$$\text{Recall/Sensitivity } /TPR = \frac{TP}{TP + FN} \dots \dots (1.3)$$

By simultaneously considering recall and precision, the F1 score offers a well-rounded assessment of the model's overall performance. The calculation is done using this formula:

$$F1 \text{ score } = 2 \times \frac{\text{Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}} \dots \dots (1.4)$$

3. Results And Discussion

The study's pretrained models were constructed with the help of the open-source frameworks TensorFlow and Keras. The Anaconda platform and the Python programming language were used to conduct a transfer learning analysis of traffic crash severity. The dataset's computing demands were satisfied by a GPU-equipped Dell Poweredge T430 server. The server's eight CPUs and 32 GB of RAM make it quite powerful. The study recommends using transfer learning methods to address the challenge of traffic crash prediction. We will utilize a range of scientific methodologies to evaluate the suggested methodology for its usefulness and efficacy. Results from deep learning-based traffic severity prediction Table 3 displays the outcomes of a test comparing three deep learning models—MLP, CNN, and LSTM—for the purpose of traffic crash severity identification. Among the deep learning models tested, CNN outperformed the competition with an F1 score of 88.7 percent, recall of 89.5 percent, precision of 82.3 percent, and

Table 2. *Results of deep learning models for traffic crash severity detection*

Models	Accuracy	Precision	Recall	F1 score
MLP	87.5	82.3	83.6	82.9
CNN	90	88	89.5	88.7
LSTM	82	80.5	83.2	81.8

accuracy of 90.0 percent. The next one is MLP, which got 87.5% accuracy, 88.0% precision, 89.5% recall, and 88.7% F1.Predictive results of traffic crash using transfer learning models Table .3 displays the outcomes of various transfer learning models that were evaluated in the context of detecting the severity of traffic crash. From this representation, you may observe the performance of ResNET, EfficientNetB4, InceptionV3, Xception, and MobileNet as transfer learning models. The findings show that MobileNet is the top model with a 98.2% accuracy rate, 98.5% precision rate, 98.91% recall rate, and 98.9% F1 score. A lower F1 score (8.35%) and poorer precision (91.4%) indicate that the Xception model could benefit from some improvement. With an accuracy rating of 93.9%, EfficientNetB4 outperforms InceptionV3 by a wide margin. With a 96.5% F1-score, 97.0% recall, 95.5% accuracy, and 96.1% precision, ResNET ranked second. These findings are invaluable for researchers and practitioners seeking to apply transfer learning to the problem of traffic crash severity identification, as MobileNet emerges as a particularly appealing choice for future study and practical application. You can view the overall performance of each model in Table 3.

Table 3. *Results of transfer learning models for traffic crash severity detection.*

Models	**Accuracy**	**Precision**	**Recall**	**F1 score**
ResNet	95.5	96.1	97	96.5
EfficientNetB4	94.3	92.5	93.2	92.8
InceptionV3	92.7	93.9	95	94.4
Xception	91.4	83.5	89.6	86.4
MobileNet	98.2	98.5	98.9	98.7

SHAP explanation

A popular way for explaining the predictions of machine learning models is SHAP (SHapley Additive exPlanations). This is especially true for black-box models used in transfer learning, such as deep neural networks. Classical descriptions of black-box models often use the term "Kernel SHAP" to refer to the primary version of SHAP. Researchers in the field of transportation safety are increasingly tapping into its powerful processing and visualization capabilities. In order to uncover the features' significance in the black-box transfer learning model, this study uses the Python Shap package to compute Shapley values for each feature. The significance of qualities in forecasting water quality is emphasized by SHAP. Although the SHAP feature is more applicable than earlier methods, it does not provide much further insight when used independently. Without a doubt, the road categorization is the most important factor influencing the model's accuracy. Particularly, the model is skewed toward higher values for the left-hand road category, such "Vehicle track" and "Motorway," which is consistent with the fact that most crash occur in both urban and rural areas. It is clear that drug usage is associated with more significant crash. As dosage increases, the Shapley value of the drug-related characteristic increases as well. In a nutshell, the more drugs someone takes, the higher their risk of crash and the more serious their injuries will be.

Table 4. *The class-wise accuracy of all transfer learning for cash severity prediction*

Models	**Fatal**	**Serious Injury**	**Minor Injury**	**Non-Injury**
ResNET	88	96	97	97
EfficientNetB4	87	94	94	95
InceptionV3	86	93	92	95
Xception	87	94	92	93
MobileNet	94	98	99	92

To further evaluate the effectiveness of the proposed technique, K-fold cross-validation is incorporated as an additional performance evaluation step. Shown in Table .4 are the results of the 5-fold cross-validation. The results demonstrate that the proposed approach achieves better results than competing models with respect to F1 score, accuracy, precision, and recall. The low standard deviation values demonstrate constant and stable performance over multiple folds, further bolstering MobileNet's credibility and reliability.

4. Discussion of Results

The study assesses the predictive power of deep learning and transfer learning models for crash severity. With an accuracy of 90.0%, CNN was the top-performing deep learning model. MLP and LSTM came in second and third, respectively, at

Table 5. *Findings of K-fold cross-validation*

MobileNet	**Accuracy**	**Precision**	**Recall**	**F-score**
Fold-1	98.73	99.83	98.73	99.26
Fold-2	97.97	99.56	98.95	99.54
Fold-3	98.79	99.97	99.94	99.86
Fold-4	99.62	99.96	99.96	99.83
Fold-5	99.47	99.95	99.93	99.94
AVG.	98.89	99.83	99.94	99.67

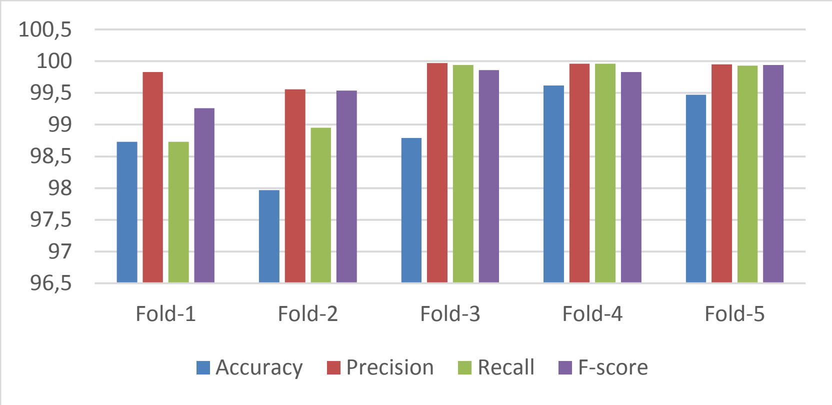

Figure 2. *Comparison of transfer learning model*

87.5% and 82.0%. On the other hand, transfer learning models performed noticeably better than conventional deep learning models. With an accuracy of 98.2%, MobileNet outperformed ResNet, which came in second with 95.5%. With 94% and 98% accuracy in forecasting crashes that resulted in fatalities and serious injuries, respectively, class-wise performance analysis showed that MobileNet performed exceptionally well. The most significant determinants of crash severity, according to SHAP study, were road category, weather, and alcohol use. A 5-fold cross-validation further supported the stability of the model by confirming MobileNet's robustness with an average accuracy of 98.89% and a low standard deviation.

5. Conclusion

This study demonstrates the promise of transfer learning models, and MobileNet in particular, for making very accurate predictions about the seriousness of traffic crash. The results highlight the significance of SHAP analysis, which gives important insights on crash contributing elements, and the importance of explainability in AI-driven models. Integrating real-time crash data and enhancing the scalability of models for practical deployment in intelligent transportation systems should be the focus of future study. According to the research, transfer learning is a good option for enhancing road safety measures since it improves prediction accuracy, guarantees model reliability, and makes the model interpretable.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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