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Predictive Modeling of Urban Traffic Accident Severity in Türkiye's Centennial: Machine Learning Approaches for Sustainable Cities

Türkiye'nin 100. Yılında Kentsel Trafik Kazası Şiddetinin Öngörü Modellemesi: Sürdürülebilir Şehirler İçin Makine Öğrenimi Yaklaşımları

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ÖZ

Halk sağlığı, kentsel gelişim ve toplumsal uyum açısından geniş kapsamlı sonuçlarıyla trafik kazaları küresel bir sorun olmaya devam ediyor. Türkiye Cumhuriyeti'nin 100. yılını kutlarken, trafik kazası şiddetini tahmin etmek, ulusal kentsel yenileme ve sürdürülebilir ilerleme hedefleriyle uyumlu kritik bir öneme sahiptir. Bu araştırma, kazaların şiddetini önceden tahmin etmek için makine öğrenimi yeteneklerini kullanıyor ve belirli sürücü ve araç özelliklerinin kritik rollerini vurgulamaktadır. Random Forest (RF) ve Gaussian Naive Bayes'ten k-NN, CatBoostClassifier, LightGBM ve Decision Trees'a kadar çeşitli ML tekniklerinin derinlemesine değerlendirilmesi yapılmıştır; bu, bir dizi trafik durumunu yansıtan geniş bir veri kümesiyle gerçekleştirilmiştir. RF algoritması, Engine_Capacity_(CC), Age_of_Driver, Age_of_Vehicle, Day_of_Week ve Vehicle_Type gibi belirli değişkenlerin kaza sonuçlarındaki belirleyici faktörler olarak öne çıktığı üstün öngörü yeteneğiyle dikkat çekmektedir. Kazaların şiddetini tahmin etmede RF'nin potansiyelini vurgulamanın ötesinde, çalışma kritik belirleyicilerin önemini vurgulamaktadır. Bu içgörüler, paydaşların özelleştirilmiş müdahaleler tasarlamaları, kamuoyu farkındalık çalışmalarını güçlendirmeleri ve altyapıyı güncellemeleri için bir yol haritası sunar; bu, gelişmiş yol güvenliği vizyonuyla sonuçlanır. Ayrıca, bu araştırma, Türkiye'nin bilgilendirilmiş kentsel ve trafik planlama girişimleri aracılığıyla sürdürülebilir bir kentsel yol çizmesi için bir yol haritası sunar.

Anahtar Kelimeler: Trafik Kazaları, Şiddet Tahmini, Makine Öğrenimi, Özellik Önemi, Sürücü Özellikleri, Yol Güvenliği

ABSTRACT

With their far-reaching implications for public health, urban development, and societal harmony, traffic accidents remain a global challenge. As the Republic of Türkiye marks its 100th year, predicting traffic accident severity assumes critical significance, aligning with the nation's aspirations for urban renewal and sustainable progress. This research harnesses the capabilities of machine learning (ML) to anticipate accident severities, shedding light on the critical roles of specific driver and vehicle characteristics. In-depth evaluation of various ML techniques—spanning from Random Forest (RF) and Gaussian Naive Bayes to k-NN, CatBoostClassifier, LightGBM, and Decision Trees—was undertaken, drawing on an expansive dataset that mirrors a spectrum of traffic situations. The RF algorithm demonstrated superior predictive prowess, with certain variables such as Engine_Capacity_(CC), Age_of_Driver, Age_of_Vehicle, Day_of_Week, and Vehicle_Type emerging as decisive factors in accident outcomes. Beyond highlighting RF's potential in accident severity prediction, the study emphasizes the significance of critical determinants. These insights offer a roadmap for stakeholders to craft specialized interventions, amplify public awareness efforts, and pioneer infrastructural upgrades, culminating in a vision of enhanced road safety. Furthermore, this investigation charts a course for Türkiye to foster a sustainable urban trajectory through informed urban and traffic planning initiatives.

Keywords: Traffic Accidents, Severity Prediction, Machine Learning, Feature Importance, Driver Attributes, Road Safety

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INTRODUCTION:

Road traffic accidents, consistently recognized as a paramount global health issue, have been a significant concern due to their alarming morbidity and mortality rates (World Health Organization, 2018). In the 100th year since the foundation of the Republic of Türkiye, it is essential to seriously address the urban and environmental challenges we face as a nation. The increasing traffic accidents in our rapidly growing cities result in significant costs for individuals and society (Özkan & Lajunen, 2005). In 2022, the road network of our country witnessed a total of 1,232,957 traffic accidents. Of these, 1,035,696 resulted in material damage, while 197,261 were severe or fatal injuries. Among the 321,485 vehicles involved in these accidents, 48.5% were cars, 22.2% motorcycles, 14.2% vans, 2.7% bicycles, 2.5% minibusses, 2.3% trucks with trailers, 2.1% lorries, 1.9% buses, 0.8% tractors, and 2.8% pertained to other vehicle types. Interestingly, fatal and severe injury accidents peaked in August and were most prevalent on Fridays (TUIK, 2022). Delving deep into these accidents' multifaceted causes and underlying factors offers a pathway to forge impactful preventive strategies and sculpt targeted interventions.

In their myriad manifestations, traffic accidents present an escalating challenge to global road safety, underpinning the necessity for an effective accident severity prediction system. Such systems can facilitate improved infrastructure planning, policymaking, and the timely allocation of medical resources. Recent years have witnessed a burgeoning interest in harnessing the predictive power of machine learning (ML) techniques for assessing traffic accident severities. This traction is driven, in part, by the capacity of ML models to decipher intricate relationships within vast datasets, making them potent tools for such predictive tasks (Yassin & Pooja, 2020; Kumeda et al., 2019).

ML is a specialized branch of artificial intelligence that focuses on designing systems that can learn from and interpret data independently, without being explicitly programmed to do so (Goodfellow et al., 2016). This enables computers to 'learn' from data patterns like how humans gain knowledge from experience (Mitchell, 1997). The inherent capability of ML to handle vast amounts of data and discern intricate patterns therein makes it an invaluable tool in tasks loaded with myriad variables, such as predicting the severity of traffic accidents (Mohanty et al., 2016). For urban planners, the implications are profound: with ML, they can swiftly analyze extensive datasets to reveal insights that might be overlooked or impossible to discern through traditional methods (Batty, 2013).

In the domain of traffic safety, the strengths of ML are particularly evident. By enabling the analysis of large and complex datasets, ML provides potent tools for predicting accident severities and understanding the multifaceted factors contributing to them (Jordan & Mitchell, 2015). These predictions can profoundly influence infrastructure planning, policymaking, and the allocation of resources post-accidents (Elvik, 2013). For instance, with the help of ML, urban planners can identify specific road sections with a higher likelihood of accidents or recognize times when accidents are more prevalent, thus facilitating more informed and targeted interventions (Huang et al., 2008).

Prior endeavors in this domain have embraced diverse geographical contexts, datasets, and methodologies. For instance, while some researchers integrated K-means clustering with Random Forest to derive insights from specific road accidents (Yassin & Pooja, 2020), others have examined broad datasets, such as the UK's 2016 traffic accident records (Kumeda et al., 2019) or Bangladesh's traffic accident compendium from 2001–2015 (Labib et al., 2019). The prevalent use of various ML algorithms in these studies, ranging from AdaBoost to Fuzzy-FARCHD, underlines the versatility of ML in decoding complex traffic data.

This investigation seeks to quantify the nature of these accidents, leverage the prowess of contemporary machine-learning techniques, project the severity of these occurrences, and discern the most influential attributes therein (Hastie et al., 2013). The selection of algorithms for this endeavor, including ensemble methods such as Random Forest, gradient boosting mechanisms like CatBoostClassifier and LightGBM, and foundational classifiers like Gaussian Naive Bayes and k-NN, was informed by their provenance in modern literature and their demonstrable efficacy in analogous domains (James et al., 2013; Prokhorenkova et al., 2018).

In the intricate tapestry of urban development, the synchronized orchestration of zoning and transportation plans is paramount. However, when these plans are executed simultaneously without meticulous forethought, the repercussions can be profound, leading to tangible economic and vital societal losses. A notable consequence of such simultaneous planning emerges in the form of roads. These roads envisioned as connectivity and growth arteries often fail to align with the geometric standards requisite for their designated traffic load. Such discrepancies not only impede efficient transportation but also spotlight broader challenges in the realm of urban planning and development (Avşar et al., 2023).

Despite significant advancements in machine learning (ML) for traffic accident severity prediction, existing literature still has unexplored areas, notably the impact of specific features like the vehicle type or driver's age on accident outcomes. Given the diverse ML methodologies and their varying performances across datasets, there is a pressing need for a comprehensive analysis. This research addresses these gaps, delving into feature importance for better accident severity predictions and situating these findings within the broader realm of ML in traffic accident studies. The ultimate goal, rooted in rigorous data analysis, is to offer insights that can inform policymaking, raise public awareness, and enhance infrastructure to enhance road safety (Elvik, 2019).

1. Related Work

Traffic accident severity prediction using machine learning techniques has garnered considerable attention recently, offering a multifaceted exploration into various datasets and methodologies. Yassin and Pooja (2020) proposed a hybrid approach amalgamating K-means clustering and Random Forest to predict the severity of specific road accidents, achieving an impressive accuracy rate of 99.86%. Kumeda et al. (2019) utilized machine learning in the UK's 2016 traffic accident data, with the Fuzzy-FARCHD algorithm delivering the highest accuracy of 85.94% among six tested algorithms.

Meanwhile, Labib et al. (2019) delved into a dataset comprising 43,089 traffic accident records from 2001–2015 in Bangladesh. AdaBoost was the most adept among the evaluated algorithms, boasting an 80% accuracy rate. Kumar et al. (2020) focused on accident type determination based on fundamental vehicle movement parameters, proposing an IoT-based automotive accident detection and classification (ADC) system, with the Naïve Bayes model achieving 95% accuracy.

Chen and Chen (2020) analyzed 9,472 accident records from Taiwan's road traffic accident investigation reports spanning 2015–2019. Their findings indicated that Random Forest outperformed logistic regression and classification and regression tree in determining accident severities. In the UK, Sangare et al. (2021) synergized statistical modeling with machine learning, combining Gaussian Mixture Modeling and Support Vector Classifier to achieve an accuracy of 85.53%.

In an urban context, Qu et al. (2019) explored traffic accidents in a Chinese city from 2006–2016, introducing a genetic algorithm-based actor search, which, when combined with XGBoost, outstripped other models with a 94% accuracy. Further afield in South Africa, Bokaba et al. (2022) scrutinized 46,692 samples of road traffic accidents, with Random Forest outpacing other classifiers in terms of accuracy, precision, recall, and ROC (AUC).

Two other noteworthy studies include Alkheder et al. (2020), who analyzed 5,740 traffic accidents in Abu Dhabi using a Decision Tree, Bayesian Network, and linear Support Vector Machine, with Bayesian Network at 66.18% accuracy. Al Mamlook et al. (2019) utilized a unique dataset based on simulated traffic accidents and found Random Forest as the top-performing model with 82.6% accuracy among six techniques.

2. Purpose of the Study

The primary purpose of this research is to reveal the essential elements of the seriousness of traffic accidents in the 100th anniversary of the Republic of Türkiye. To this end, it is to obtain a standard model by revealing the factors affecting the severity of accidents in the UK covering the period from 2005 to 2015. In this context, the study includes a comprehensive dataset on traffic accidents, with features ranging from driver's age and vehicle type to engine capacity and day of the week. Utilizing a complete dataset encapsulating various attributes, ranging from vehicular specifics to temporal nuances, the study sought to deploy many state-of-the-art machine learning algorithms to predict accident severity. By juxtaposing algorithms such as Random Forest, Gaussian Naive Bayes, k-NN, CatBoostClassifier, LightGBM, and Decision Tree, the research aimed to not only unearth the most efficacious classifier but also elucidate the relative importance of the dataset's attributes in the context of accident severity.

3. Materials and methods

This section presents a detailed description of the dataset that forms the foundation of the study, the data preprocessing steps, and the classification algorithms employed. Specifically, the analysis focuses on a dataset of road traffic accidents that occurred in the UK between 2005 and 2015, emphasizing the ability to predict the severity of the accidents.

3.1. Dataset

This study utilizes a comprehensive dataset encompassing detailed records of UK road traffic accidents from 2005 to 2015. The dataset, with a robust total of 1,534,792 entries, vividly captures an array of factors postulated to influence the outcomes of traffic accidents. These factors range from vehicular specifics, driver demographics, to environmental conditions during the accident. The term "traffic accident severity" in this dataset refers to the seriousness of the outcomes of a traffic accident. Each recorded accident is classified based on its outcomes into one of three predefined categories: Fatal, Serious, or Slight.

Fatal: Accidents that resulted in the death of involved individuals.

Serious: Accidents leading to severe injuries but not resulting in death.

Slight: Accidents causing minor injuries or none at all.

This classification is inherently present in the dataset, which means it was determined and recorded by official sources when the accidents were reported. A dataset analysis reveals that most accidents (1,324,147 or 86.3%) were classified as 'Slight.' In contrast, serious accidents comprised 190,328 (12.4%) of the total, while fatal accidents were the least frequent, with a count of 20,317 (1.3%) (Kaggle, 2023; Data, 2023).

Table 1. Dataset information

Attribute Name	Data Type	Description
Did_Police_Officer_Attend_Scene of Accident	int64	Indicates police attendance at the accident scene.
Age_of_Driver	float64	Age of the driver involved.
Vehicle_Type	float64	Type of vehicle involved.
Age_of_Vehicle	float64	Age of the vehicle during the accident.
Engine_Capacity_(CC)	float64	Engine capacity of the vehicle.
Day_of_Week	int64	Day of the week the accident occurred.
Weather_Conditions	int64	Weather conditions at the accident time.
Road_Surface_Conditions	int64	State of the road surface during the accident.
Light_Conditions	int64	Lighting conditions during the accident.
Sex_of_Driver	float64	Gender of the driver involved.
Speed_limit	int64	The speed limit of the road where the accident happened.
Target Attribute: Accident_Severity	int64	The severity of the accident (Fatal, Serious, Slight).

3.2. Data Preprocessing

Several preprocessing steps were meticulously executed on the dataset to ensure a robust and unbiased analysis.

Normalization: Given our dataset's diverse scales of attributes, normalization was pivotal to bringing all the features to a consistent scale. The Min-Max scaling technique was employed for this purpose. This transformation guarantees that all feature values lie within a similar range, specifically between 0 and 1, facilitating improved convergence and performance of subsequent classification algorithms.

Handling Class Imbalance: An initial examination of the dataset disclosed a pronounced class imbalance in the target attribute, Accident_Severity. A vast majority of accidents, 1,324,147 (86.3%), were cataloged as 'Slight.' In comparison, serious accidents represented 12.4% (190,328) of the data, while fatal accidents were a mere 1.3% (20,317). Such a skewed distribution can bias the training process and diminish the predictive capacity of many machine learning models, particularly for the underrepresented classes.

a. Under-sampling: As an initial step towards addressing this imbalance, under-sampling was applied using the RandomUnderSampler method from the imblearn library. This method randomly discards instances from the over-represented class(es), rendering the class distribution more balanced.

b. Over-sampling: After under-sampling, the Synthetic Minority Over-sampling Technique (SMOTE) from the imblearn library was utilized to balance the dataset. SMOTE works by generating synthetic examples in the feature space. These synthetically generated data points bolster the minority class, creating a more balanced class distribution and enhancing the model's capability to generalize well across all classes.

For all classification algorithms in the study, the data set was divided into 80% training and 20% testing and analysis.

3.3. Modeling and Classification

In this research, various state-of-the-art machine learning algorithms were employed, each chosen due to their prominence in recent literature and relevance to the domain of accident severity prediction. Among the selected algorithms, Random Forest has robust capabilities in handling categorical and continuous features. In contrast, Gaussian Naive Bayes is particularly well-suited for constant variables. The k-NN algorithm can effectively manage categorical and continuous attributes, although feature scaling may be requisite for optimal performance. CatBoostClassifier is renowned for its direct handling capacity for categorical features, while LightGBM exhibits rapid processing on large datasets and supports categorical attributes. Decision Trees are recognized for their versatility in modeling categorical and continuous variables. The rationale behind selecting these algorithms is rooted in their flexibility across diverse feature types and their potential to model the inherent structure of the dataset best.

Random Forest: This ensemble learning method is predominantly used for classification and regression. The Random Forest algorithm operates by constructing a multitude of decision trees during training and outputs the mode of the classes for classification or mean prediction for regression of individual trees when predicting. It introduces randomness in the dataset by bootstrapping samples or selecting a random subset of features at each split, improving the model's generalization and reducing overfitting (Liaw & Wiener, 2002).

Gaussian Naive Bayes (GNB): GNB is a probabilistic classifier based on Bayes' theorem, assuming conditional independence between features given the class variable. GNB assumes a Gaussian distribution of the features for continuous data applications, making it effective in tasks with high-dimensional inputs (Zhang, 2004).

K-NN: The k-NN algorithm, an instance-based and non-parametric method, is primarily employed for classification and regression. Using a predefined distance metric (often Euclidean), k-NN identifies the k-training examples closest to an input instance. The mode of the classes of these k neighbors determines the class label of the input instance, marking its strength in handling multiclass problems (Li et al., 2018).

CatBoostClassifier: Developed by Yandex, the CatBoostClassifier is a gradient-boosting algorithm designed explicitly for categorical features. It employs "ordered boosting" and "oblivious trees" to handle categorical data without extensive preprocessing. These techniques often perform better than gradient-boosting methods (Prokhorenkova et al., 2018).

LightGBM: A gradient boosting framework by Microsoft, LightGBM is recognized for its efficiency and scalability. Techniques such as "gradient-based one-side sampling" (GOSS) and "exclusive feature bundling" (EFB) are incorporated, allowing the framework to train faster and manage large datasets without sacrificing accuracy. Regarding computational efficiency and memory usage, LightGBM has the potential to surpass existing boosting algorithms (Ke et al., 2017).

Decision Tree: The Decision Tree algorithm, suitable for classification and regression tasks, partitions the dataset into subsets based on input feature values, resulting in a tree-like decision model. Decisions at each internal node are based on metrics like entropy, Gini impurity for classification, or variance for regression. One of its strengths is its clear visualization and interpretability for decision-making (James et al., 2013).

4. Results

Table 2. Analysis results of Accuracy and F1 Score

	RF	Gaussian NB	k-NN	CatBoostClassifier	LightGBM	Decision Tree
Accuracy	0,851	0,480	0,742	0,773	0,760	0,744
F1 Score	0,851	0,502	0,751	0,781	0,768	0,744

Two primary evaluation metrics were employed in assessing the performance of various state-of-the-art machine learning algorithms on the dataset: Accuracy and F1 Score. The Random Forest (RF) algorithm exhibited a commendable accuracy of 0.851, complemented by an identical F1 score, emphasizing its balanced classification capabilities. The Gaussian Naive Bayes (Gaussian NB) algorithm's performance metrics are an accuracy of 0.480 and F1 score of 0.502, hinting at stable but moderate outcomes. For k-Nearest Neighbors (k-NN), metrics stand at 0.742 for accuracy and 0.751 for F1, highlighting its robustness in multiclass contexts. CatBoostClassifier shines with metrics at 0.773 (accuracy) and 0.781 (F1), particularly when managing categorical inputs and optimizing between precision and recall. LightGBM efficiently handles vast datasets, evidenced by its 0.760 accuracy and 0.768 F1 score. The Decision Tree's consistent and straightforward nature resulted in a 0.744 accuracy and corresponding F1 score.

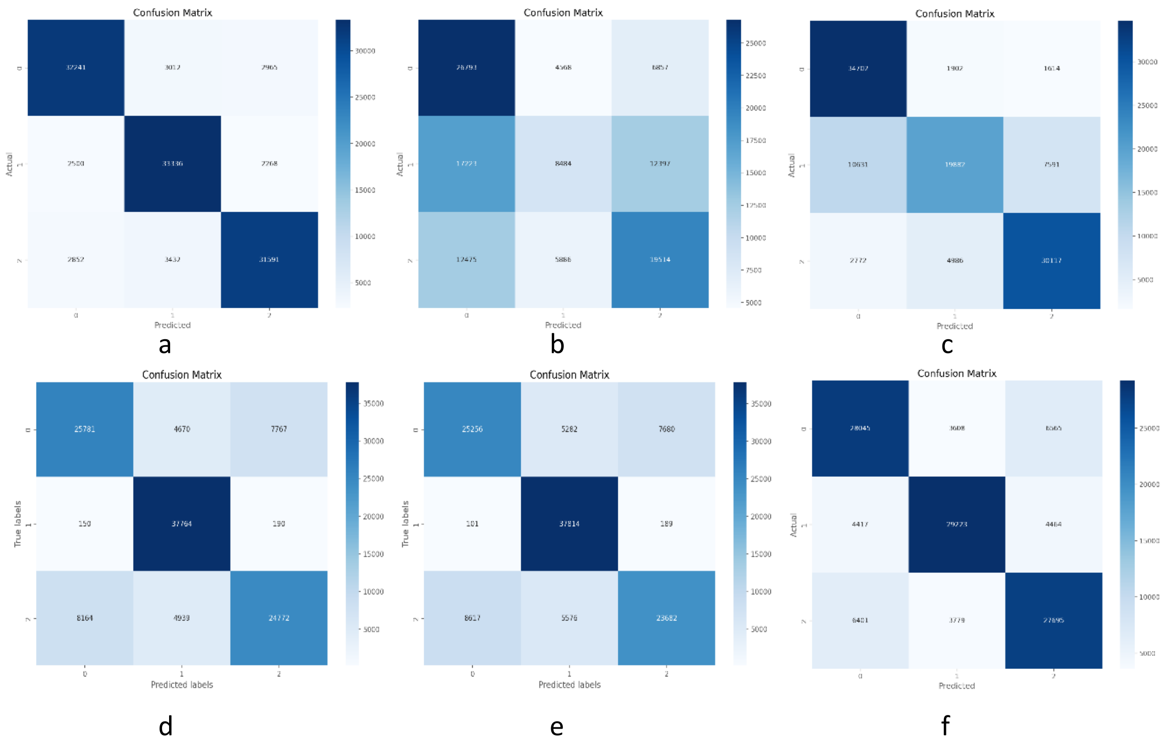

Figure 1. Confusion Matrix Results of RF (a), Gaussian NB (b), k-NN (c), CatBoostClassifier (d), LightGBM (e), and Decision Tree (f)

In analyzing the classifier outcomes via the confusion matrix, the discernment of each model in predicting accident severities became more transparent. The Random Forest (RF) classifier accurately identified 32,241 fatal accidents. However, it misclassified 3,012 and 2,965 as severe and slight accidents, respectively. While accurately classifying 26,793 fatal accidents, the Gaussian Naive Bayes model demonstrated a higher misclassification rate, particularly classifying 6,857 fatal incidents as slight. The k-NN model's robustness was evident with its correct classification of 34,702 fatal accidents, although 3,494 were mistaken for other categories. A distinct feature of the CatBoostClassifier was its unparalleled accuracy in predicting severe accidents, correctly identifying 37,764 instances and only misclassifying a minute proportion as fatal and slight. The LightGBM model, with its correct classifications of 25,256 fatal and 37,814 serious accidents, showcased its strengths, although some misclassifications persisted. Lastly, the Decision Tree algorithm identified 28,045 fatal accidents but, like other classifiers, did not remain immune to misclassifications.

Table 3. Analysis results

	RF			**Gaussian NB**			**k-NN**			
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	support
1	0.86	0.84	0.85	0.47	0.70	0.57	0.72	0.91	0.80	38218
2	0.84	0.87	0.86	0.45	0.22	0.30	0.74	0.52	0.61	38104
3	0.86	0.83	0.85	0.50	0.52	0.51	0.77	0.80	0.78	37875
accuracy			0.85			0.48			0.74	114197
macro avg	0.85	0.85	0.85	0.48	0.48	0.46	0.74	0.74	0.73	114197
weighted avg	0.85	0.85	0.85	0.48	0.48	0.46	0.74	0.74	0.73	114197
	CatBoostClassifier			**LightGBM**			**Decision Tree**			
1	0.76	0.67	0.71	0.74	0.66	0.70	0.72	0.73	0.72	38218
2	0.80	0.99	0.88	0.78	0.99	0.87	0.79	0.76	0.78	38104
3	0.76	0.65	0.70	0.75	0.63	0.68	0.71	0.73	0.72	37875
accuracy			0.77			0.76			0.74	114197
macro avg	0.77	0.77	0.77	0.76	0.76	0.75	0.74	0.74	0.74	114197
weighted avg	0.77	0.77	0.77	0.76	0.76	0.75	0.74	0.74	0.74	114197

Table 3 presents the precision, recall, and f1-score metrics for a range of machine learning models, including RF, Gaussian NB, k-NN, CatBoostClassifier, LightGBM, and Decision Tree, applied to predict three different classes of outcomes. From the results, the RF algorithm exhibits a superior performance, with an accuracy of 0.85 and consistent f1-scores across the three classes. This suggests robustness in its predictive capability irrespective of the class considered. Conversely, the Gaussian NB model underperforms with an overall accuracy of 0.48, indicating limited suitability for this particular dataset. The k-NN, CatBoostClassifier, LightGBM, and Decision Tree models produce comparable results, with accuracy levels clustering around the 0.74 to 0.77 range. Notably, CatBoostClassifier and LightGBM show heightened recall values for the second class, implying a higher propensity for these models to identify true positives in this category correctly. In summation, while Random Forest emerges as the most adept model for this dataset, the relatively close performance metrics across the k-NN, CatBoostClassifier, LightGBM, and Decision Tree models suggest that the choice of algorithm should also consider factors beyond mere accuracy, such as interpretability, training time, and feature importance.

4.1. Feature importance

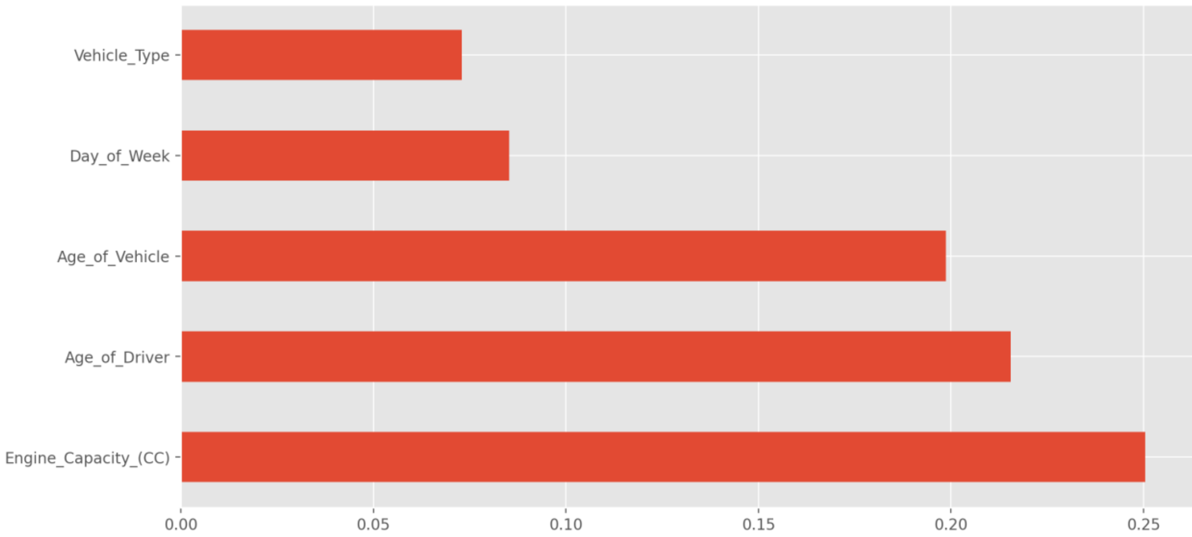

Figure 2. The importance score of the top 5 attributes is derived from the random forest feature importance selection algorithm.

Feature importance is instrumental in comprehending the contributing factors pivotal to prediction accuracy. By deploying the RF model, which emerged as the top-performing classifier in our analyses, we gained significant insights into the relative importance of features vis-à-vis accident severity prediction.

Engine_Capacity_(CC) was significant and surfaced as the most influential feature. This suggests that the engine's capacity, potentially reflective of the vehicle's power and size, might be directly linked to the severity of accidents. Following closely, Age_of_Driver was identified as the following critical determinant. This accentuates the role of age, implying that driving experience or physiological factors associated with age might have a pronounced effect on accident outcomes.

The Age_of_Vehicle, too, was a salient feature, underscoring the possibility that the condition, reliability, or outdated safety features of older vehicles might contribute to the severity of accidents. Furthermore, Day_of_Week emerged as an influential predictor, hinting at temporal patterns of accidents — certain days might witness more severe accidents, possibly due to traffic volume, work-related commutes, or recreational activities.

Lastly, Vehicle_Type was recognized as a significant feature. Given their design and functionality, this aligns with the intuitive understanding that specific vehicle categories might be predisposed to mitigating or exacerbating accident severities.

DISCUSSION AND CONCLUSION:

This research journey, conducted in tandem with the momentous occasion of the Republic of Türkiye's 100th foundation year, sought to shed light on the gravity of road traffic accidents—an issue of global health importance—and its profound implications on our urban landscapes. By navigating through many machine learning models, our analysis pinpointed Random Forest (RF) as an exemplary model for predicting traffic accident severities in the context of Türkiye's evolving urban centers.

Our analysis distinctly highlights that particular attribute such as Engine_Capacity_(CC), Age_of_Driver, Age_of_Vehicle, Day_of_Week, and Vehicle_Type plays a critical role in predicting accident outcomes. According to data from the Turkish Statistical Institute for 2022, fatal accidents predominantly occurred in August and on Fridays. This data corroborates the significance of the "Day_of_Week" attribute in our analysis, indicating the necessity for specific traffic measures on certain days, particularly Fridays.

Furthermore, in 2022 in Turkey, of the vehicles involved in fatal accidents, 48.5% were automobiles, while 22.2% were motorcycles. These statistics affirm the influence of the "Vehicle_Type" attribute in our study, underscoring the imperative for a heightened focus on specialized training programs or awareness campaigns for car and motorcycle drivers. The pronounced representation of motorcycles in these accidents accentuates the elevated risk associated with motorcycle driving.

When contextualizing our research against global benchmarks (Yassin & Pooja, 2020; Kumeda et al., 2019; Labib et al., 2019), a noteworthy observation emerges: the efficacy of machine learning models, though vast, is intricately tied to dataset specifics. Türkiye's unique socio-cultural and infrastructural fabric underscores the importance of a tailored approach to predicting and mitigating traffic accidents.

However, despite the depth of our study, limitations persist. Our insights are anchored to the dataset used, pointing towards the ever-present need for continuous data augmentation, especially as urbanization trends and traffic dynamics evolve.

A striking observation from our research pertains to the ramifications of simultaneous zoning and transportation planning. Roads, often envisaged as lifelines of urban centers, can falter in their role if not aligned with geometric standards commensurate with their traffic load. This observation accentuates the pressing need for synchronized urban development strategies, especially in rapidly urbanizing nations like Türkiye.

Our findings are based on data sourced from the UK. While we believe the results provide valuable insights into the broader trends and patterns of road traffic accidents, one must exercise caution when extrapolating these findings directly to Türkiye due to socio-cultural and infrastructural differences. Reflecting on this centenary year, our findings cannot remain siloed in academic realms. They must permeate through to policymakers, city planners, and Turkish citizens. Only with a collective commitment can we stride towards a future marked by safer roads and sustainable urban environments, ensuring that the echoes of our past guide our steps towards a safer tomorrow.

While roads play a crucial role in urban centers, their design and standards can significantly influence traffic safety. However, in this study, we didn't delve deeply into the implications of geometric standards on accident severity. Future research could more closely examine the interplay between road design and traffic accidents, especially in rapidly urbanizing contexts like Türkiye.

Compliance with Ethical Standards

Ethics Committee Approval: *Ethics committee approval is not required for this study*

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