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Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

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DESIGN OF TRAFFIC ACCIDENT PREDICTION MODEL IN TOLL ROAD USING A DECISION TREE ALGORITHM

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ABSTRACT

A toll road is a road that the users are obligated to pay, which is held to improve efficient transportation services. Although toll roads have relatively more ideal conditions than highway roads, many traffic accidents still occur on the road. Toll road managers collect operational data on toll roads, including daily traffic, weather, and accident data. One of the solutions to increase the level of toll road safety is to design an accident prediction model through data mining. In this paper, the prediction model was made using attributes according to the framework consisting of day, type of road surface, weather conditions, road surface conditions, time of occurrence, driver sex, and type of vehicle. The prediction model was built to predict certain areas' probability and severity of accidents. The prediction model is built using the decision tree algorithm. The results show that the attributes used can predict the severity of accidents with 39.73% accuracy. The most vulnerable area is in section B on 9 to 10 km, with a total number of accidents of 13.17% of total accidents.

KEYWORDS: Traffic Accidents, Toll Road, Data Mining, Prediction Model, Decision Tree.

1. INTRODUCTION

The toll road is a road that the users are obligated to pay which is held to improve efficient transportation services. Although toll roads have relatively more ideal conditions than the common arterial road, based on data from toll road operator company, there are still many cases of traffic accidents on the toll road. Based on data from toll road operator company and previous research, 501 accidents have occurred on the Semarang toll road from 2007 to 2017 (Budiawan et al., 2019) and 201 accidents have occurred on the Semarang-Batang toll road from 2018 to 2019 (Putri & Widowati, 2021). These traffic accidents are



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

caused by various factors consisting of human factors, vehicles, roads, and environmental factors. In addition, toll road administrators collect current operational data, such as daily traffic and accident data. If this data is not utilized, it will be accumulated and retained as useless data. Several efforts are required to improve traffic safety on toll roads through the utilization of existing data, namely: develop data warehouse (Budiawan et al., 2018), accident severity prediction (Budiawan et al., 2019), road and bridge system evaluation (Sutjahjo et al., 2020).

One of solutions to improve the level of toll road safety is to design accident prediction models through data mining by utilizing data related to accidents on toll roads. Data mining is a process to get information from a set of data that helps in decision making (Budiawan et al., 2018; Han et al., 2011). Several accidents-based Data Mining projects have been conducted previously. (Beshah & Hill, 2010) in the research of Mining Road Traffic Accident Data to Improve Safety: The Role of Integrated Factors on Accident Severity in Ethiopia uses classification methods including Decision Tree, Naive Bayes, and K-Nearest Neighbors. In another study, (Sowmya & Ponmuthuramalingam, 2013) in the research: Analyzing Road Traffic and Accident with Classification Techniques used classification methods including Naive Bayes, AdaBoostM1, Random Forest, Decision tree, and PART. Based on several studies before, the construction of the prediction model can be done by a classification method.

2. METHOD

In this study, the prediction model was designed by identifying the attributes of accident causes. The data was obtained from toll road operator company (2007-2017) and a previous study (2018-2019). Data were analyzed to find vulnerable areas to accidents based on daily cross-data and accident data. Vulnerable areas are analyzed based on the probability of occurrence of accidents in each area. Furthermore, the design of the prediction model was approached using the classification method. The prediction model was designed to predict the severity of accidents on toll roads based on accident attributes. In addition, the prediction model of the current study is a further study of previous studies. The severity level consists of property loss, minor injury, major injury, and fatal (Budiawan et al., 2019). The prediction model was built to predict the probability of accidents in certain areas on toll roads. Current study consisted of five main steps, namely: data collection, data preparation, design of prediction model based on decision tree algorithm, analysis of accuracy, and design of prediction model application.

Data Collection: the data consist of daily traffic and accident data. Data was obtained from toll road operator company period of 2007 to 2017 and previous research period of 2018 to 2019. The main framework for determining the attributes used in this paper is the research: Prediction and Analysis of Injury Severity in Traffic Systems using Data Mining Techniques (Khera & Singh, 2015).



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Moreover, in the data collection step, attributes of previous study are used with adjustments to accident data collected. The all attributes are shown in Table 1.

Attributes	Type of Data	Description
Driver Sex	Text	(Khera & Singh, 2015)
Type of Vehicle	Text	(Khera & Singh, 2015)
Accident Time	Text	(Khera & Singh, 2015)
Accident Location	Text	(Khera & Singh, 2015)
Weather Condition	Text	(Khera & Singh, 2015)
Accident Severity	Text	(Khera & Singh, 2015)
Day	Text	Primary Data
Type of Road	Text	Primary Data
Road Surface	Text	Primary Data

Table 1: Attributes based on the framework

Data Preparation: Data preparation step is several steps that taken before the data mining process, namely:

1. Data Selection

Data selection needs to be done before the data mining process. At this stage, the attributes of the data obtained from sources were selected by adjusting to the research framework (see Table 1). The results of this stage are the research data attributes. The selection data used for mining is stored in a file separate from the operational database.

2. Data Cleaning

Before the data mining process can be carried out, it needs a cleaning process, including removing duplicate data, checking inconsistent data, and correcting errors in data. The results of this stage are data with complete attribute values.

3. Data Transformation

Data transformation is needed so the data set is ready to be processed and produce a better analysis. Accident probability: Accident probability is calculated by dividing the number of accidents from 2007 to 2017 with the number of vehicles traffics from 2007 to 2017 period. The results that obtained from this stage are the probability of accidents for each area on the toll road every one km. The equation for determining the probability of an accident can be written as follows (Han et al., 2011):



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Accident Probability =(Number of Accidents)/(Number of Vehicles crossed)

1)

2)

3)

Prediction Model Design: The data is divided into two parts. They are training data and testing data with a ratio of 0.6 and 0.4. Training data is data that used to build predictive models. While data testing is used to test the model. From existing studies, the classification and design of prediction models in case of accidents can be done using the Decision Tree algorithm. Decision Tree is a classification method to determine the highest attribute information gain to be set as the highest level that affects the data. Information gain will be obtained from the reduction of Entropy. In the Decision Tree, the model is represented in the form of a tree. Entropy values are written as follows (Han et al., 2011):

$$Entropy(S) = \sum_{i}^{C} -p_{i} \log_{2} p_{i}$$

Where c is the number of values contained in the target attribute. While pi states the portion or ratio between the number of samples in class and the number of all samples in the data set.

While the Information Gain value of time attribute (A) is written as follows (Han et al., 2011):

$$Gain(S, A) \equiv Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

The Decision Tree method algorithm is shown in Figure 1.



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

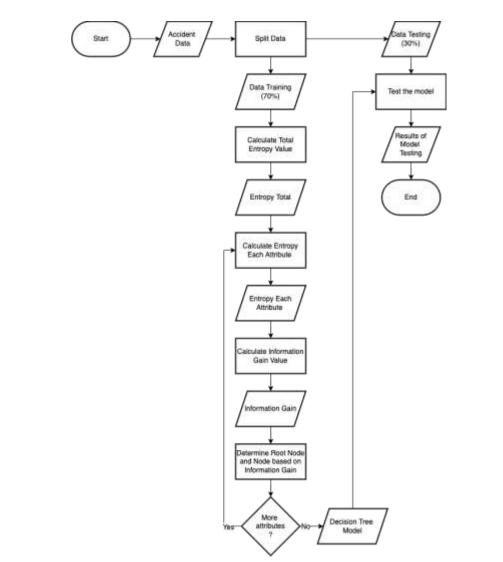


Figure 1: Decision Tree Algorithm

3. RESULT AND DISSCUSION

Results was presented into three parts (data selection, accident probability, and prediction model. In the data selection stage, the data was selected based on attributes needs according to the attributes determined in Table 1. Attributes consist of days of accidents (day), location of kilometers of accidents (km), direction of vehicle driving at the time of occurrence accidents (direction), time of accident (time), type of vehicle (vehicle), weather conditions (weather), type of lane where the accident (road type), driver sex (gender), type of road accident occur (surface), and the severity or type of accident (severity) as in table 2.



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

		Table 2: Data Attribute
Attributes	Type of Data	Description
Day	Text	Monday/ Tuesday/ Wednesday/ Thursday/ Friday/ Saturday/ Sunday
Type of	Text	Flat straight / Descend straight / Ascend straight/ Flat Curve/Descend
Road		Curve/ Ascend Curve
Weather	Text	Sunny/ Cloudy/ Foggy/ Dusty/ Smoky/ Drizzly/ Rainy
Surfaces	Text	Dry/ Wet/ Sandy
Time	Text	Morning/ Noon/ Afternoon/ Night
Driver sex	Text	Male/ Female
Vehicle	Text	Sedan/ Jeep/ Pick Up/ Minibus/ Bus/ Truck
Туре		
Severity	Text	Property Loss/ Minor Injuries/ Major Injuries/ Fatal

1. Data Cleaning: The cleaning process including removing incomplete data and checking inconsistent data. In this paper, the data cleaning process is to eliminate some data without the attributes of time, vehicle, weather, alignment, or direction. From the total operational data as many as 501 data, after the cleaning process became 488 data.

2. Data Transformation: Data transformation is needed so that the data set is ready to be processed and produce a better analysis. Data transformation needs to be done because the operational data has a different format. In addition, the purpose of data transformation is to reduce data diversity so that predictive accuracy is better. Data is transformed into data that is ready to be processed

3.1. Accident Probability Measurement

The Accident Probability is calculated by dividing data on the number of accidents with the total data for vehicle traffic. The probability of an accident can be calculated by equation 1). The probability for each toll road area is obtained as shown as in Table 3.



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

	Г	ab	le 3: Ac	cident Prob	ability	
Section	I	Are	a	Frequency	Probability	%
А	0km	-	1km	18	4.00E-08	3.593
	1km	-	2km	10	2.22E-08	1.996
	2km	-	3km	12	2.66E-08	2.395
	3km	-	4km	18	4.00E-08	3.593
	4km	-	5km	22	4.89E-08	4.391
	5km	-	6km	27	6.00E-08	5.389
	6km	-	7km	10	2.22E-08	1.996
	7km	-	8km	8	1.78E-08	1.597
	8km	-	9km	9	1.55E-08	1.397
В	9km	-	10km	66	1.47E-07	13.174
	10km	-	11km	48	1.07E-07	9.581
	11km	-	12km	28	6.22E-08	5.589
	12km	-	13km	21	4.66E-08	4.192
	13km	-	14km	10	2.22E-08	1.996
	0km	-	1km	20	4.44E-08	3.992
С	1km	-	2km	35	7.77E-08	6.986
	2km	-	3km	27	6.00E-08	5.389
	3km	-	4km	15	3.33E-08	2.994
	4km	-	5km	23	5.11E-08	4.591
	5km	-	6km	12	2.66E-08	2.395
	6km	-	7km	8	1.78E-08	1.597
	7km	-	8km	8	1.78E-08	1.597
	8km	-	9km	1	2.22E-09	0.200
	9km	-	10km	9	2.00E-08	1.796
	10km	-	11km	36	7.99E-08	7.186

3.2. Prediction Model using Decision Tree

3.2.1. Entropy and Information Gain

Information Gain is a value used to determine which attributes are used to be used as a node first. Before determining the value of information gain, it is necessary to calculate the value of information in units of bits from a collection of objects. The way to calculate it is to use the concept of entropy. The entropy value is calculated based on equation (2). While the value of information gain is calculated using equation (3). The results of the Entropy and Information Gain values are shown in Table 4.



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Attributes	Entropy	Information Gain
Time	1.660	0.031
Day	1.613	0.077
Vehicle	1.617	0.073
Driver Sex	1.675	0.016
Weather	1.655	0.035
Type of Road	1.666	0.024
Surface	1.686	0.005

Table 4: Information Gain

From the information gain value, the attribute that specified as the first node or root node as the initial separator is the attribute of day because it has the highest information gain value which is equal to 0.077. To determine the next nodes are carried out with the same steps. In this paper, the node is obtained from the design of the model using RapidMiner.

3.2.2. Model Accuracy

The accuracy of the model is calculated by equation 4 as shown below.

 $Accuracy = \frac{correct \ predictions \ amount}{total \ predictions}$

The results of model accuracy calculation on RapidMiner are shown in Table 5.

	r	Fable 5: Accurac	y of Model		
	True Property_	True Minor_	True Major_	True	Class
	Loss	Injury	Injury	Fatal	precision
pred. Property					
Loss	22	27	19	3	30.99%
pred. Minor_					
Injury	10	23	9	4	50.00%
pred. Major_					
Injury	3	10	13	2	46.43%
pred. Fatal	0	0	1	0	0.00%
class recall	62.86%	38.33%	30.95%	0.00%	

4)



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Accuracy = 39.73%

Information that obtained from these data mining process is a model that can be used to predict accident in the toll road. Based on Table 5, it can be informed that the accuracy of the model is 39.79% to predict the severity of the accident. Based on the design of the traffic accident Prediction model in with decision tree algorithm, the results from the tree as the output of the mining process are summarized in Table 6.

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
							Property
Friday	Bus	Flat Straight					Loss
		Ascend					Minor
	Bus	Straight					Injury
		Descend					Major
	Bus	Straight					Injury
		-					Major
	Bus	Ascend Curve					Injury
							Minor
	Jeep						Injury
	Minib						Minor
	us		Night	Sunny			Injury
	Minib		U	·			Major
	us		Night	Cloudy			Injury
	Minib		U	·			Minor
	us		Morning				Injury
	Minib		e				Minor
	us		Noon				Injury
	Minib		Afterno				Property
	us		on				Loss
	Pick						Minor
	Up	Flat Straight					Injury
	Pick	Ascend					Major
	Up	Straight					Injury
	Pick	Descend					Minor
	Up	Straight					Injury
	Pick	Descend					Property
	Up	Curve					Loss
	- I						Minor
	Sedan	Flat Straight		Sunny			Injury

Table 6: Result of Prediction Model



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
		Ascend			0		Property
	Sedan	Straight		Sunny			Loss
		-		-			Property
	Sedan			Rainny			Loss
				•			Major
	Truck	Flat Straight	Night				Injury
		0	U				Property
	Truck	Flat Straight	Morning				Loss
		0	U				Property
	Truck	Flat Straight	Noon	Sunny			Loss
		U		·			Minor
	Truck	Flat Straight	Noon	Rainny			Injury
		e	Afterno	5			Minor
	Truck	Flat Straight	on				Injury
		Ascend					Minor
	Truck	Straight					Injury
		Descend					Minor
	Truck	Straight	Night	Sunny			Injury
		Descend	U	5			Major
	Truck	Straight	Night	Rainny			Injury
		Descend	U	2			Property
	Truck	Straight	Night	Cloudy			Loss
		Descend	0				Property
	Truck	Straight	Morning				Loss
		Descend	0				Minor
	Truck	Straight	Noon				Injury
		Descend	Afterno				Major
	Truck	Straight	on				Injury
		U					Property
	Truck	Flat Curve					Loss
							Minor
	Truck	Ascend Curve					Injury
		Descend					Major
	Truck	Curve					Injury
							Minor
Thursday	Bus			Sunny			Injury
2				5			Property
	Bus			Rainny			Loss
				2			Property
	Jeep						Loss



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Minib us Minib us Minib us Minib us Minib us Minib us Minib us Di J	Flat Straight Flat Straight Ascend Straight Descend Straight Descend Straight Descend Straight Straight	Night Morning	Sunny Drizzl y	gender	Surface	Minor Injury Property Loss Property Loss Property Loss
Minib us Minib us Minib us Minib us Minib us	Flat Straight Ascend Straight Descend Straight Descend Straight Descend	-	Drizzl			Property Loss Property Loss Property
us Minib us Minib us Minib us Minib us Minib us	Flat Straight Ascend Straight Descend Straight Descend Straight Descend	-	Drizzl			Property Loss Property Loss Property
Minib us Minib us Minib us Minib us Minib	Ascend Straight Descend Straight Descend Straight Descend	-	у			Loss Property Loss Property
Minib us Minib us Minib us Minib us Minib	Ascend Straight Descend Straight Descend Straight Descend	-	5			Property Loss Property
Minib us Minib us Minib us Minib us	Descend Straight Descend Straight Descend	-				Loss Property
us Minib us Minib us Minib us	Descend Straight Descend Straight Descend	-				
Minib us Minib us Minib us	Descend Straight Descend	-				
us Minib us Minib us	Descend Straight Descend	-				
Minib us Minib us	Descend	Morning				Property
us Minib us	Descend	C				Loss
Minib us	Straight					Minor
Minib us	0	Noon				Injury
us						Property
	Flat Curve					Loss
Pick						Minor
	Flat Straight					Injury
	-					Major
						Injury
	U					Minor
						Injury
- 1	8					Property
Sedan	Flat Straight					Loss
	-					Property
Sedan						Loss
	-					Minor
Sedan						Injury
	0					Property
Sedan	Ascend Curve					Loss
						Major
Truck	Flat Straight	Night				Injury
	8					Minor
Truck	Flat Straight	Morning				Injury
	8	8				Major
Truck	Flat Straight	Noon				Injury
IIGOR	i iui stiuigiti					Minor
Truck	Flat Straight					Injury
1100h	-	J 11				Minor
Truck			Sunny			Injury
THUN			•			Major
Truck						Injury
	us Pick Up Pick Up Sedan Sedan Sedan Sedan Truck Truck Truck Truck Truck	Pick Up PickFlat Straight Ascend Up Descend StraightSedanFlat Straight AscendSedanFlat Straight Descend StraightSedanStraight DescendSedanAscend CurveSedanFlat StraightSedanFlat StraightSedanFlat StraightSedanFlat StraightSedanFlat StraightTruckFlat StraightTruckFlat StraightTruckFlat StraightAscendStraight	Pick Up PickFlat Straight Ascend Up Straight Descend StraightImage: Straight Descend StraightSedanFlat Straight Ascend Straight Descend StraightImage: Straight Descend StraightSedanStraight Descend StraightImage: Straight Descend Descend StraightSedanStraight Descend StraightImage: Straight Descend Descend StraightSedanAscend CurveTruckFlat Straight Ascend StraightTruckFlat Straight Ascend Straight AscendTruckFlat Straight AscendTruckStraight AscendTruckStraight Ascend	Pick UpFlat Straight Ascend UpStraight Descend UpPick Pick Descend UpStraight AscendSedan SedanFlat Straight Ascend DescendSedan SedanStraight DescendSedan SedanStraight DescendSedan SedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendStraight DescendNightTruckFlat Straight AscendNoon AfternoTruckFlat Straight AscendTruckFlat Straight AscendTruckStraight AscendTruckStraight AscendTruckStraight AscendTruckStraight Ascend	PickUpFlat StraightPickAscendUpStraightPickDescendUpStraightPickDescendUpStraightSedanFlat Straight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight DescendSedanStraight AscendTruckFlat Straight AscendTruckFlat Straight AscendTruckStraight AscendSunny Drizzl	PickImage: Pick of the second of



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
		Descend			0		Property
	Truck	Straight	Night				Loss
		Descend	U				Minor
	Truck	Straight	Morning				Injury
		Descend	0				Property
	Truck	Straight	Noon				Loss
		Descend	Afterno				Property
	Truck	Straight	on				Loss
		U					Major
	Truck	Flat Curve					Injury
							Property
	Truck	Ascend Curve					Loss
		Descend					Property
	Truck	Curve					Loss
		Descend					Major
Sunday Bus	Bus	Straight	Night				Injury
J		Descend	e				Property
	Bus	Curve	Night				Loss
			U				Major
	Bus		Morning				Injury
			0				Minor
	Bus		Noon				Injury
							Major
	Jeep						Injury
	Minib						Major
	us	Flat Straight	Night	Sunny			Injury
	Minib	0	C	•			Minor
	us	Flat Straight	Night	Cloudy			Injury
	Minib	-	•	•			Minor
	us	Flat Straight	Morning				Injury
	Minib	0	U				Minor
	us	Flat Straight	Noon				Injury
	Minib	Ascend					Minor
	us	Straight					Injury
	Minib	Descend					Minor
	us	Straight					Injury
	Minib	Descend					Major
	us	Curve					Injury
	Pick						Minor
	Up			Sunny			Injury



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
	Pick			Drizzl			Property
	Up			У			Loss
	Pick			•			Minor
	Up			Rainny			Injury
	1			5			Property
	Sedan			Sunny			Loss
	~~~~			Drizzl			Minor
	Sedan	edan		у			Injury
	Soduli		5			Minor	
	Sedan			Cloudy			Injury
	bedan	Scuali		cioudy			Major
	Truck	Flat Straight	Night				Injury
	THUCK	Ascend	i tigitt				Minor
	Truck	Straight	Night				Injury
	TIUCK	Descend	INIgitt				Minor
	Truck		Night	Cuppy			
	TTUCK	Straight	Night	Sunny			Injury Maior
	T1-	Descend	NT: - 1- 4	Classifier			Major
	Truck	Straight	Night	Cloudy			Injury
	<b>T</b> 1	1.0	NT: 1 .				Minor
	Truck	Ascend Curve	Night				Injury
	- 1			ä			Property
	Truck		Morning	Sunny			Loss
							Minor
	Truck		Morning	Cloudy			Injury
							Property
	Truck		Noon				Loss
			Afterno				Minor
	Truck	Flat Straight	on				Injury
		Descend	Afterno				Major
	Truck	Straight	on				Injury
Vednesd							Property
/	Bus		Night	Sunny			Loss
			-	Drizzl			Major
	Bus		Night	у			Injury
			e	2			Major
	Bus		Morning				Injury
	-		0				Major
	Bus		Noon				Injury
	_ •••		Afterno				Property
	Bus		on				Loss
	Dus		011				L033



### ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
					<u> </u>		Minor
	Jeep						Injury
	Minib						Property
	us		Night				Loss
	Minib		U				Minor
	us		Morning	Sunny			Injury
	Minib		U	Drizzl			Property
	us		Morning	у			Loss
	Minib		8	5			Property
	us		Noon				Loss
	Pick		110011				Property
	Up		Night				Loss
	Pick		itight				Major
	Up		Noon	Sunny			Injury
	Pick		NOOII	Drizzl			Minor
	Up		Noon				Injury
	Op		NOOII	У			
	Transla	Elat Straight	Nicht				Property Loss
	Truck	Flat Straight	Night				
	T1.	Ascend	NT: - 1- 4				Property
	Truck	Straight	Night				Loss
	<b>T</b> 1	Descend	NT. 1.	a			Minor
	Truck	Straight	Night	Sunny			Injury
	- ·	Descend		Drizzl			Property
	Truck	Straight	Night	У			Loss
	- ·						Property
	Truck	Flat Curve	Night				Loss
		Descend					Property
	Truck	Curve	Night				Loss
	Truck	Flat Straight	Morning				Fatal
		Ascend					Minor
	Truck	Straight	Morning				Injury
		Descend					Property
	Truck	Straight	Morning				Loss
		-	-				Minor
	Truck	Flat Straight	Noon				Injury
		Descend					Minor
	Truck	Straight	Noon				Injury
							Property
	Truck	Ascend Curve	Noon				Loss
	Truck	Descend	Noon	Sunny			Major
	TIUCK	Descent	TIOOII	Sumy			iviajoi



### ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
		Curve					Injury
		Descend					Minor
	Truck	Curve	Noon	Cloudy			Injury
			Afterno	•			Minor
	Truck		on				Injury
							Minor
Saturday	Bus	Flat Straight					Injury
		Descend					Major
	Bus	Straight					Injury
		-					Major
	Bus	Ascend Curve					Injury
		Descend					Property
	Bus	Curve	Morning				Loss
		Descend	Afterno				
	Bus	Curve	on				Fatal
							Minor
	Jeep						Injury
	Minib						Minor
	us	Flat Straight					Injury
	Minib	Ascend					Major
	us	Straight		Sunny			Injury
	Minib	Ascend					Minor
	us	Straight		Rainny			Injury
	Minib	Descend					Property
	us	Straight		Sunny			Loss
	Minib	Descend		Drizzl			Major
	us	Straight		у			Injury
	Minib	Descend					Major
	us	Straight		Rainny			Injury
	Minib	Descend					
	us	Straight		Cloudy			Fatal
	Minib						Major
	us	Ascend Curve					Injury
	Pick						Minor
	Up		Night				Injury
	Pick		Afterno				Major
	Up		on				Injury
							Minor
	Sedan	Flat Straight	Night	Sunny			Injury
	Sedan	Flat Straight	Morning	Sunny			Major



### ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
							Injury
							Property
	Sedan	Flat Straight		Cloudy			Loss
		Descend		2			Property
	Sedan	Straight					Loss
		Descend					Minor
	Sedan	Curve	Night				Injury
		Descend	-				Minor
	Sedan	Curve	Noon				Injury
		Descend	Afterno				Major
	Sedan	Curve	on				Injury
							Major
	Truck	Flat Straight	Night	Sunny			Injury
		Descend					Minor
	Truck	Straight	Night	Sunny			Injury
		Descend					Minor
	Truck	Curve	Night	Sunny			Injury
							Major
	Truck	Flat Straight	Morning	Sunny			Injury
		Descend					Minor
	Truck	Straight	Morning	Sunny			Injury
							Minor
	Truck	Flat Straight	Noon	Sunny			Injury
		Descend					Minor
	Truck	Straight	Noon	Sunny			Injury
		Descend					Major
	Truck	Curve	Noon	Sunny			Injury
			Afterno				Property
	Truck	Flat Straight	on	Sunny			Loss
		Descend	Afterno				Major
	Truck	Straight	on	Sunny			Injury
		Descend	Afterno				Property
	Truck	Curve	on	Sunny			Loss
				Drizzl			Major
	Truck			У			Injury
							Minor
	Truck			Rainny			Injury
							Minor
	Truck	Flat Straight		Cloudy			Injury
	Truck	Ascend		Cloudy			Property



### ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
		Straight			U		Loss
		Descend					Minor
	Truck	Curve		Cloudy			Injury
				2			Major
Fuesday	Bus		Night				Injury
5			U				Property
	Bus		Noon	Sunny			Loss
				Drizzl			Minor
	Bus		Noon	У			Injury
				•			Property
	Jeep		Noon				Loss
	•		Afterno				Minor
	Jeep		on				Injury
	Minib						Property
	us	Flat Straight	Night				Loss
	Minib	-	•				Minor
	us	Flat Straight	Morning				Injury
	Minib	Ascend	U				Minor
	us	Straight		Sunny			Injury
	Minib	Ascend					Major
	us	Straight		Cloudy			Injury
	Minib	Descend		-			Minor
	us	Straight					Injury
	Minib						Property
	us	Ascend Curve					Loss
	Pick						Major
	Up		Night				Injury
	Pick						Minor
	Up	Flat Straight	Noon				Injury
	Pick	Descend					Major
	Up	Curve	Noon				Injury
							Minor
	Sedan				Male		Injury
							Property
	Sedan				Female		Loss
							Major
	Truck	Flat Straight	Night	Sunny			Injury
		Ascend					Property
		Straight	Night	Sunny			Loss
		Descend	Night	Sunny			Major



### ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
		Straight					Injury
		Ascend		Drizzl			Major
		Straight	Night	У			Injury
		Descend	U	Drizzl			Minor
		Straight	Night	У			Injury
		-	•	•			Minor
			Night	Rainny			Injury
							Minor
			Night	Cloudy			Injury
		Descend					Property
		Straight	Morning				Loss
		Descend					Minor
		Curve	Morning				Injury
							Minor
			Noon				Injury
			Afterno				Major
			on				Injury
	Minib						Property
Monday	us	Flat Straight		Sunny			Loss
	Pick						Minor
	Up	Flat Straight		Sunny			Injury
							Property
	Sedan	Flat Straight		Sunny			Loss
							Property
	Truck	Flat Straight	Night	Sunny			Loss
							Minor
	Truck	Flat Straight	Noon	Sunny			Injury
			Afterno				Property
	Truck	Flat Straight	on	Sunny			Loss
		Ascend					Major
	Bus	Straight	Night	Sunny			Injury
		Ascend					Minor
	Sedan	Straight	Night	Sunny			Injury
		Ascend					Minor
	Truck	Straight	Night	Sunny			Injury
		Ascend		~			Minor
		Straight	Morning	Sunny			Injury
		Ascend		~			Property
		Straight	Noon	Sunny			Loss
		Ascend	Afterno	Sunny			Property



#### ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

Day	Vehicl e	Type of Road	Time	Wheat er	Driver gender	Type of Surface	Prediction
		Straight	on				Loss
		Descend					Major
	Bus	Straight	Night	Sunny			Injury
		Descend					Property
	Bus	Straight	Morning	Sunny			Loss
		Descend					Property
	Bus	Straight	Noon	Sunny			Loss
		Descend					Minor
	Sedan	Straight		Sunny			Injury
		Descend					Property
	Truck	Straight		Sunny			Loss
							Minor
		Flat Curve		Sunny			Injury
		Descend					Property
		Curve		Sunny			Loss
	Minib			Drizzl			Minor
	us			у			Injury
	Pick			Drizzl			Minor
	Up			у			Injury
				Drizzl			Major
	Sedan			у			Injury
				Drizzl			Major
	Truck			у			Injury
							Major
			Night	Rainny			Injury
							Property
			Noon	Rainny			Loss
			Afterno				Property
		Flat Straight	on	Rainny			Loss
		Descend	Afterno				Minor
		Straight	on	Rainny			Injury
		-		-			Minor
				Cloudy			Injury

### 4. CONCLUSION

Based on this research we conclude as follows:

1. The vulnerable areas are identified by calculating the probability of accidents for each point on the Semarang Toll Road per 1 km. The most vulnerable area is in section B on 9 to 10 km which contributes accidents 13.17% of total accident from 2007 to 2017 period.



ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

2. Attributes that take effect on accident severity in this model are time, day, vehicle, gender, weather, alignment or road type, and surface of road.

3. By considering the attributes of time, day, vehicle, gender, weather, alignment or road type, and surface of road, the prediction model that built in this study can predict the severity of accidents on toll roads but with 39.73% of accuracy. At the same time, the prediction model can also predict the probability of accidents at the Semarang toll road in each of 1 km.

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ISSN: 2582-6271

Vol. 3, Issue.6, Nov-Dec 2022, page no. 11-31

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