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RESEARCH ARTICLE

# Traffic Analysis Model with Bayesian Network and Social Media Data: D100 Highway Travel İnformation System

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**ABSTRACT**
The traffic problem in Intelligent Transportation Systems has recently become a very important issue. Thanks to Intelligent Transportation Systems, the formation of large amounts of traffic data has led to the formation of data-oriented models. There is a growing interest in predicting traffic measures by modeling complex scenarios based on big data with data mining and machine learning methods. In this study, traffic events from Twitter traffic notifications and vehicle density from sensor data were obtained. Traffic density analysis and traffic incident analysis were performed with the machine learning method. In the analysis of traffic incidents, 36627 traffic incidents were digitized. This data was separated into categories including type of accident; day; month; year; season; left, right or middle lane; and vehicle failure, maintenance-repair work and accident notification. Between 2016 and 2020, 1400 daily vehicle data logs were obtained from the sensor data located at 59 points of the D100 highway. Traffic density and parameters affecting traffic incidents on the Anatolian and European sides of the D100 highway in Istanbul were determined. Traffic density and accident event models were designed with the Bayesian network approach. In the sensitivity analysis of the model, it was concluded that the parameter that has the strongest effect on traffic events and density formation on the D100 highway line is the strips. With these models, the infrastructure of the early warning system has been created for region-specific traffic density situations and possible traffic events.

**Keywords:** Traffic management, traffic analysis, machine learning, bayesian networks, big data, twitter

## 1. Introduction

Big data and data mining methods, which have become the focus of attention in many research areas, have become the focus of intelligent transportation systems (ITS). With developing technology, intelligent transportation systems have started to produce big data. Through the big data produced, it will have profound effects on the design and applications of smart transportation systems in terms of making them safer, more efficient, and more profitable. Data mining applications have started to be implemented in intelligent transportation systems as a result of obtaining beneficial results in many areas. Intelligent transportation technologies constantly generate data due to their systemic structure which uses sensor technologies, data transmission technologies and smart card applications. In smart transportation systems, data can be obtained from various sources such as GPS, sensors, video detectors, and social media. Big data obtained through smart cards, GPS, sensors, video detectors, and social media in ITS can move ITS to a more efficient point with accurate and effective data analysis (Shi & Abdel-Aty, 2015). Machine learning algorithms have become increasingly necessary to reveal complex and hidden patterns in the data produced by information processing and communication technologies. Thanks to these algorithms, studies that develop models that can automatically adapt to large and complex data sets and predict scenarios in real-time have become possible. A deep learning method is used in long-term traffic flow prediction (He et al.,2019; Guo et al.,2019; Diao et al.,2019), an artificial neural network in the detection of traffic events (Contreras et al., 2018; Dogru & Subasi, 2018), deep learning in detecting traffic incidents (Zhu et al.,2018; Ren et al.,2018; Fu & Zhou, 2011), traffic accident prediction with a support vector machine (Gu, et al., 2017; Mohamed, 2014), traffic accident analysis with machine learning techniques (Taamneh, et al.,2017; Özbayoğlu, et al., 2016; Vavasi, 2016; Geetha & Shanthi, 2012), traffic accident analysis with the fuzzy logic method (Razzaq et al., 2016), and traffic accident analysis with logistic regression (Agarwal, et al.,2016). These models provide the opportunity to increase the level of safety in ITS by effectively predicting the cause of traffic accidents. Intelligent transportation systems are also gradually becoming integrated based on data. The importance of accurately predicting

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traffic conditions, especially traffic flow density, is increasing. With this data, researchers focus on improving the efficiency of the current transport system of ITS applications by generating traffic flow models in real-time to predict future trends. Thus, it provides both traffic planners and users with accurate and reliable forecasts to help them decide on their plans. In this study, the vehicle density and traffic incidents analysis of the Istanbul D100 highway was carried out. Big data provided by Istanbul Metropolitan Municipality (IMM Data Portal) has been processed and organized. This data consists of instantaneous traffic notifications of users on Twitter. In the analysis of traffic incidents, 36627 traffic incidents were digitized into categories including: accident days, months, years, seasons, left, right, middle lanes, and traffic incidents, including vehicle breakdown, maintenance-repair work, and accident notification. 1400 daily vehicle data logs were obtained from the sensor data located at 59 points of the D100 highway between 2016-2020. With the models created with Bayesian networks, it will lead to the formation of the infrastructure of a warning system based on predicting the traffic density and traffic events on the European Side and the Anatolian Side along the D100 highway line. With these models, the vehicle density and traffic events that will take place on the D100 highway line will be predicted in advance and will make great contributions to taking precautions.

## 2. Literature Search

In the literature, the Bayesian network has been used in many studies in estimating traffic events and in traffic density analysis. The Bayesian network approach was used in traffic flow estimation (Sun, et al., 2006; Kim and Wang, 2016). An analysis of traffic accidents on rural roads was carried out using the Bayesian network approach (De Ona, et al., 2013). A road traffic safety analysis of developing countries was carried out with a bayesian network (Mbakwe, et al., 2016). A factor analysis of traffic accidents in China was carried out with a Bayesian network (Chen, et al., 2020). The analysis of the injury severity of traffic accidents on Spanish highways was carried out using a Bayesian network (De Ona, et al., 2011). The Bayesian network was used to estimate the severity of traffic accidents (Zong, et al., 2013; Zong, et al.,2019). The role of travel purpose of injuries in traffic accidents was analyzed with a Bayesian network (Febres, et al.,2019). The Bayesian network was used in traffic flow estimation (Pascale and Nicoli, 2011). The probabilistic estimation of traffic congestion was performed with a Bayesian network (Afrin and Yodo, 2021). Analysis of the injury severity of traffic accidents on highways with a Bayesian network was performed (Mujalli and De Oña, 2011; Yang, et al., 2022). The analyses of the factors affecting the severity of traffic accidents were performed with a Bayesiann network (Liu, et al., 2022). The severity of traffic accidents were estimated with a multidimensional and layered Bayesian network (Li, et al., 2022). The severity analysis of the accidents of vehicles carrying dangerous goods on highways was carried out with theBayesiann network (Sun, et al., 2022). The Bayesian network approach was used to understand the effects of traffic congestion on the roads (Blackwell, et al., 2022). The analysis of the leading causes of fatal and injury accidents was carried out with the Bayesian network model (Lalika, et al., 2020). In the literature, it has been used in many studies in the analysis of traffic events and traffic density using social media data. Real-time traffic incident detection was performed using Twitter data (Gu, et al., 2016; Paule, et al., 2019). Social media data was used in the detection of traffic accidents (Bao, et al., 2017), a spatial analysis of accidents (Salas, et al., 2017), detection and monitoring of traffic incidents (Nguyen, et al., 2016), detection and situation analysis of traffic accidents (Ali, et al.), 2021; Zhang, et al., 2018; Suat-Rojas, et al., 2022; Alkouz & Al Aghbari, 2022), and social media data was used to detect traffic events (Dabiri, and Heaslip 2019). The studies examining the analysis of traffic accidents in Turkey using the Bayesian method are as follows: 378.800 accident records were examined using the amirik bayesian analysis method, and the areas where there was no traffic safety were clustered (Erdoğan, et al., 2022). The factors causing traffic accidents were analyzed through the Bayesian network (Çinicioğlu, et al., 2013). In order to determine the locations of traffic accident points, a descriptive model has been proposed by using the empirical Bayesian analysis method (Dereli and Erdoğan, 2017).

## 3. Methodology

A structure has been developed that presents traffic information for locations during travel along the D100 highway line. Thanks to this system, traffic analysis for locations is performed and instant information is provided to users. Depending on the input variables such as month, day, time, lane of the locations, density, and traffic events analyses were carried out with Twitter data and the Bayesian Network. An infrastructure has been created that will instantly inform users about the possibility of density and traffic incidents according to input variables such as month, day, time and lane of each location. Especially on the D100 highway line, traffic analyses of the locations where traffic incidents and density occur a lot were carried out. In the traffic analysis model, big data was created by dividing the location, time, day, month, season, lane of the traffic incidents in the messages from Twitter users, accident notification of traffic incidents, vehicle breakdown, maintenance and repair work and density parameters. Traffic incidents and traffic density estimation models were carried out w ith theBayesian network, which is one of the machine learning methods.

### 3.1. Twitter as data source in traffic management

Social media platforms have become an important resource for increasing the efficiency of traffic management systems, thanks to the large data produced, by providing significant opportunities in the generation and dissemination of information. Twitter, one of the social media platforms, also allows users to report events and express their opinions about the events. Information such as traffic incidents, traffic jams, accidents and maintenance and repair works in many countries are shared with passengers in real time via Twitter. The use of Twitter big data in traffic management is increasing day by day. With the Dub STAR (Dublin's Semantic Traffic Annotator and Reasoner) application, the temporal and spatial relationships with traffic events were scanned and their causes were investigated by means of data derived from social media (Daly et al., 2013). Traffic performance analyses of California highways were carried out using Twitter data. Relationships related to the place and time of traffic incidents were revealed (Mai and Hranac, 2013). The SNSJam application has been developed using many social media data sources to predict traffic congestion on the road. It aims to predict future traffic events using current and past posts (Alkouz & Aghbari, 2020 ). According to Gu et al. 2016, they performed automatic detection and analysis of their events using Twitter data. Tweets from Traffic Incidents (TI) are manually labeled as 'TI' or 'no TI'. TI tweets are classified into categories such as accidents, roadworks and incidents (Ribeiro et al). In 2012, the Traffic Observatory established a system and scanned the tweets on Twitter and classified the traffic incidents of Belo Horizonte, one of the big cities of Brazil. In this study, the classification of tweets about the events that took place on the D100 highway line, which has an important place in the traffic flow of Istanbul, was carried out. The D100 Highway Traffic Information System was created. The traffic events and traffic density probabilities that will occur in the locations determined by this system were calculated with the Bayesian Network. The traffic notifications received from Twitter are as follows: 15 Temmuz Şehitler Köprüsü Europe-Anatolia Direction, left lane traffic accident (damaged). 15 Temmuz Şehitler Köprüsü, Europe-Anatolia Direction, 1 lane is closed to traffic due to a right lane traffic accident (with injuries). The accident is being dealt with. D100 Haramidere-Beylikdüzü, vehicle malfunction. The faulty vehicle has been removed. Heavy traffic continues in the area. D100 Acıbadem-Çamlıca Direction, right lane, 1 lane is closed to traffic due to Maintenance-Repair Work. There is heavy traffic in the area. In fig. 1, the classification of tweets has been carried out.

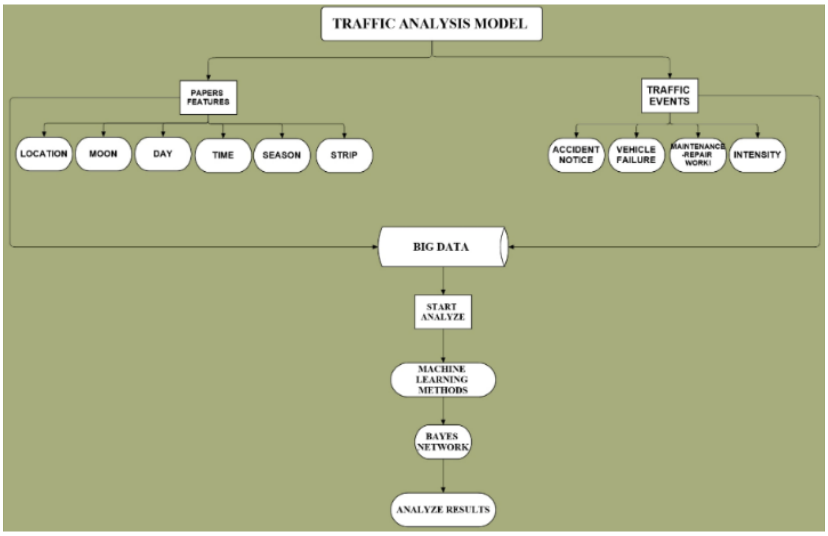


**Figure 1.** Research model flowchart

### 3.2. Research Data

In Table 1, frequencies of vehicle failure, accident notification and maintenance-repair works that occurred in 36627 traffic notification messages on the D100 highway were determined according to time, day, month, lane and season.

The number of vehicles passing 59 different locations on the D100 highway line according to day, month, season and year are given in Table 2. The values are as follows: more than 10 thousand (>=10B), more than 20 thousand (>=20B), more than 40 thousand (>=40B), according to days, months, seasons and years, More than 60 thousand (>=60B), more than 80 thousand (>=80B), more than 100 thousand (>=100B), more than 130 thousand (>=130B), more than 150 thousand ( >=150B), more than 180 thousand (>=180B), and more than 200 thousand days (>=200B).

**Table 1.** Digitization of Traffic Notifications

| **Hours** | **Vehicle failure** | **f** | **Maintenance-Repair Work** | **f** | **Accident Notification** | **f** |
|---|---|---|---|---|---|---|
| Morning | 5808 | 31.67% | 971 | 39,98% | 4482 | 30,02% |
| Noon | 6749 | 36,80% | 715 | 29,44% | 5403 | 36,19% |
| evening | 5276 | 28,77% | 241 | 9,92% | 4025 | 26,96% |
| night | 507 | 2,76% | 502 | 20,67% | 1018 | 6,82% |
| Total | 18340 | 51,38% | 2429 | 6,80% | 14928 | 41,82% |
| **Days** | **Vehicle failure** | **f** | **Maintenance-Repair Work** | **f** | **Accident Notification** | **f** |
| Monday | 3175 | 17,31% | 295 | 12,14% | 2284 | 15,30% |
| Tuesday | 2966 | 16,17% | 383 | 15,77% | 2225 | 14,90% |
| Wednesday | 2956 | 16,12% | 372 | 15,31% | 2261 | 15,15% |
| Thursday | 3036 | 16,55% | 389 | 16,01% | 2297 | 15,39% |
| Friday | 2998 | 16,35% | 358 | 14,74% | 2406 | 16,12% |
| Saturday | 1918 | 10,46% | 325 | 13,38% | 1833 | 12,28% |
| Sunday | 1291 | 7,04% | 307 | 12,64% | 1622 | 10,87% |
| Total | 18340 | 51,38% | 2429 | 6,80% | 14928 | 41,82% |
| **Months** | **Vehicle failure** | **f** | **Maintenance-Repair Work** | **f** | **Accident Notification** | **f** |
| January | 2013 | 10,98% | 246 | 10,13% | 1605 | 10,75% |
| February | 1723 | 9,39% | 228 | 9,39% | 1314 | 8,80% |
| March | 1683 | 9,18% | 220 | 9,06% | 1428 | 9,57% |
| April | 946 | 5,16% | 239 | 9,84% | 961 | 6,44% |
| May | 962 | 5,25% | 128 | 5,27% | 909 | 6,09% |
| June | 1729 | 9,43% | 153 | 6,30% | 1251 | 8,38% |
| July | 1952 | 10,64% | 287 | 11,82% | 1403 | 9,40% |
| August | 1376 | 7,50% | 176 | 7,25% | 1178 | 7,89% |
| September | 1535 | 8,37% | 193 | 7,95% | 1296 | 8,68% |
| October | 1597 | 8,71% | 246 | 10,13% | 1302 | 8,72% |
| November | 1348 | 7,35% | 149 | 6,13% | 1197 | 8,02% |
| December | 1476 | 8,05% | 164 | 6,75% | 1084 | 7,26% |
| Total | 18340 | 51,38% | 2429 | 6,80% | 14928 | 41,82% |
| **Strips** | **Vehicle failure** | **f** | **Maintenance-Repair Work** | **f** | **Accident Notification** | **f** |
| Left | 2172 | 12,41% | 879 | 40,01% | 4959 | 38,05% |
| Middle | 1235 | 7,06% | 11 | 0,50% | 1240 | 9,51% |
| Right | 14094 | 80,53% | 1307 | 59,49% | 6835 | 52,44% |
| Total | 17501 | 53,47% | 2197 | 6,71% | 13034 | 39,82% |
| **Seasons** | **Vehicle failure** | **f** | **Maintenance-Repair Work** | **f** | **Accident Notification** | **f** |
| Spring | 3591 | 19,58% | 587 | 24,17% | 3298 | 22,09% |
| Summer | 5057 | 27,57% | 616 | 25,36% | 3832 | 25,67% |
| Autumn | 4480 | 24,43% | 588 | 24,21% | 3795 | 25,42% |
| Winter | 5212 | 28,42% | 638 | 26,27% | 4003 | 26,82% |
| Total | 18340 | 51,38% | 2429 | 6,80% | 14928 | 41,82% |

Source: https://data.ibb.gov.tr/en/dataset

**Table 2.** Number of Vehicles

| **Days** | **>=10B** | **>=20B** | **>=40B** | **>=60B** | **>=80B** | **>=100B** | **>=130B** | **>=150B** | **>=180B** | **>=200B** |
|---|---|---|---|---|---|---|---|---|---|---|
| Monday | 319 | 866 | 910 | 905 | 1884 | 3292 | 2226 | 1498 | 199 | 46 |
| Tuesday | 337 | 912 | 899 | 767 | 1935 | 3455 | 2344 | 1328 | 177 | 16 |
| Wednesday | 273 | 829 | 933 | 741 | 1800 | 3438 | 2357 | 1578 | 210 | 21 |
| Thursday | 358 | 822 | 920 | 733 | 1754 | 3424 | 2330 | 1612 | 222 | 25 |
| Friday | 349 | 856 | 917 | 670 | 1704 | 3381 | 2315 | 1704 | 238 | 35 |
| Saturday | 778 | 925 | 968 | 654 | 1428 | 2806 | 2332 | 1809 | 236 | 58 |
| Sunday | 873 | 843 | 1101 | 1063 | 1397 | 2702 | 2175 | 1311 | 151 | 5 |
| **Months** | **>=10B** | **>=20B** | **>=40B** | **>=60B** | **>=80B** | **>=100B** | **>=130B** | **>=150B** | **>=180B** | **>=200B** |
| January | 425 | 651 | 804 | 773 | 1088 | 1874 | 1197 | 701 | 87 | 0 |
| February | 274 | 547 | 628 | 531 | 998 | 1758 | 1295 | 870 | 89 | 13 |
| March | 359 | 669 | 669 | 532 | 1101 | 1833 | 1382 | 825 | 81 | 15 |
| April | 512 | 650 | 639 | 517 | 1075 | 1789 | 1209 | 860 | 91 | 10 |
| May | 554 | 834 | 633 | 443 | 863 | 1820 | 1413 | 906 | 131 | 13 |
| June | 171 | 418 | 583 | 381 | 971 | 1887 | 1466 | 1081 | 152 | 33 |
| July | 149 | 390 | 509 | 458 | 947 | 1919 | 1456 | 1152 | 162 | 47 |
| August | 164 | 329 | 466 | 376 | 939 | 2051 | 1426 | 1014 | 145 | 36 |
| September | 125 | 348 | 417 | 350 | 987 | 1998 | 1413 | 1045 | 136 | 20 |
| October | 113 | 368 | 413 | 292 | 1030 | 2088 | 1629 | 1030 | 153 | 8 |
| November | 188 | 441 | 466 | 453 | 1004 | 1880 | 1145 | 721 | 113 | 8 |
| December | 253 | 408 | 421 | 427 | 899 | 1601 | 1048 | 635 | 93 | 3 |
| **Seasons** | **>=10B** | **>=20B** | **>=40B** | **>=60B** | **>=80B** | **>=100B** | **>=130B** | **>=150B** | **>=180B** | **>=200B** |
| Spring | 1425 | 2153 | 1941 | 1492 | 3039 | 5442 | 4004 | 2591 | 303 | 38 |
| Summer | 484 | 1137 | 1558 | 1215 | 2857 | 5857 | 4348 | 3247 | 459 | 116 |
| Autumn | 426 | 1157 | 1296 | 1095 | 3021 | 5966 | 4187 | 2796 | 402 | 36 |
| Winter | 952 | 1606 | 1853 | 1731 | 2985 | 5233 | 3540 | 2206 | 269 | 16 |
| **Years** | **>=10B** | **>=20B** | **>=40B** | **>=60B** | **>=80B** | **>=100B** | **>=130B** | **>=150B** | **>=180B** | **>=200B** |
| 2016 | 653 | 2221 | 2711 | 1684 | 3172 | 4900 | 3503 | 1747 | 124 | 4 |
| 2017 | 602 | 1374 | 1338 | 973 | 2586 | 4917 | 3655 | 2373 | 314 | 77 |
| 2018 | 354 | 662 | 1007 | 792 | 2001 | 3998 | 3822 | 2811 | 353 | 66 |
| 2019 | 784 | 934 | 897 | 1080 | 2344 | 4342 | 2732 | 2174 | 344 | 58 |
| 2020 | 894 | 862 | 695 | 1004 | 1799 | 4341 | 2367 | 1735 | 298 | 1 |

Source:  https://data.ibb.gov.tr/en/dataset

### 3.3. Models of Research

In fig. 2, Bayesian Network traffic events and density probability models are shown. The number of vehicles probability model is shown in fig. 3.

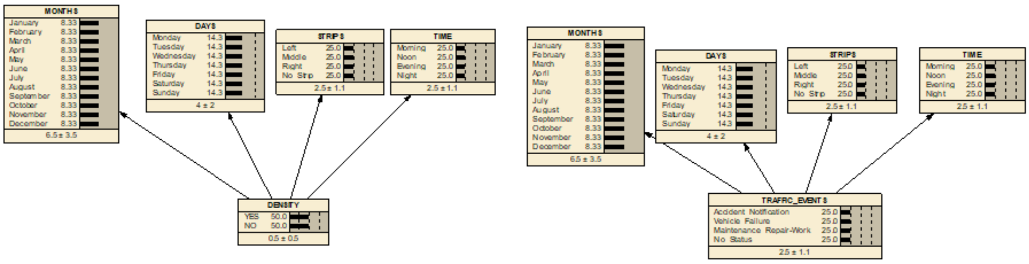


**Figure 2.** Bayesian Network Traffic Event and Density Analysis Models

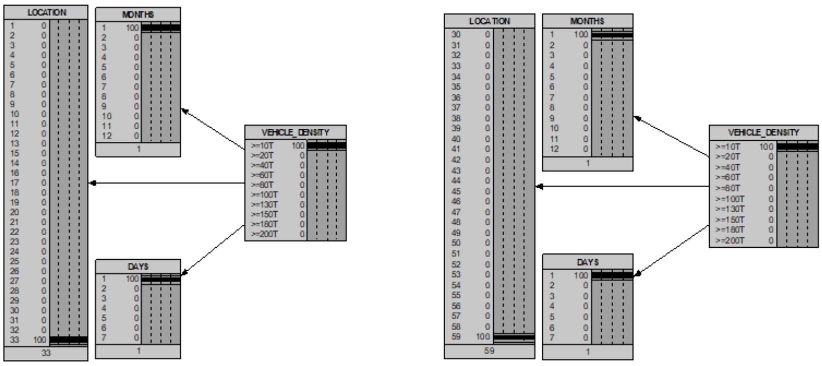


**Figure 3.** Bayesian Network Europe and Anatolian Line Vehicle Density Analysis Model

## 4. Result

Models were created that report the vehicle density of 59 locations along the D100 highway line (in fig.4) and evaluate the density and traffic incident probabilities of important points along the D100 highway line. As a result of the Bayesian Network Traffic Model, the sample information that users will benefit from the traffic information system to be obtained for the locations relates to the following questions:

- What is the probability that congestion will occur in the left lane on Monday morning in January?
- What is the probability of a vehicle breakdown in the left lane on Monday morning in January?
- What is the probability of a traffic incident occurring in the left lane on Monday morning in January?
- What is the probability that an accident will occur in the left lane on Monday morning in January?
- On Monday morning, in the right lane, what is the probability that maintenance repair work will take place in January?
- What is the probability that an accident notification will occur on a Wednesday morning in January, in the right lane?
- What is the probability that a vehicle breakdown in the right lane will occur at noon on a Monday in January?

In fig. 3, the vehicle density model of 59 points on the route of the D100 highway line has been created. In fig. 4, the locations of 59 points of the D100 highway are shown in detail. The points on the D100 highway line are shown on the maps in segments 1, 2, 3, and 4 respectively.

*D100 Selimpaşa (1), D100 Celaliye_2 (2); D100 Celaliye_1 (3); D100 Kumburgaz_2 (4); D100 Kumburgaz_1 (5); D100 Muratbey (6); D100 Güzelce (7); D100Büyükçekmece, (8); D100 S-Rampası (9); D100 Tüyap (10); D100 Ambarlı (11); D100 Avcılar Hacı Şerif (12); D100 Küçükçekmece Gölü_2 (13); D100 Küçükçekmece Gölü_1 (14); D100 Cennet Mah. (15); D100 Florya (16); D100 Sefaköy (17); D100 Sefaköy Havaalanı (18); D100 Çobançeşme_2 (19); D100 Çobançeşme_1 (20); D100 Şirinevler (21); D100 Metroport (22); D100 Türk Böbrek Vakfı Önü (23); D100 Merter (24); D100 Topkapı Haliç Yönü (25); D100 Vatan Metrobüs (26); D100 Edirnekapı (27); D100 Haliç Köprü Çıkışı (28); D100 Okmeydanı (29); D100 Çağlayan (30); D100*

*Zincirlikuyu (31); D100 15 Temmuz Şehitler Köprüsü (32); D100-Altunizade (33); D100 Beylerbeyi (34); D100 Altunizade (35); D100 Acıbadem Köprüsü (36); D100 Uzunçayır (37); D100 Küçük Çamlıca_1 (38); D100 Küçük Çamlıca_2 (39); D100 Göztepe (40); D100 Kozyatağı_1 (41); D100 Kozyatağı_2 (43); D100 Altıntepe (44); D100 Küçükyalı (45); D100 Başıbüyük (46); D100 Maltepe (47); D100 Zümrüt Evler (48); D100 Gülsuyu (49); D100 Soğanlık (50); D100 Kartal Oto Sanayi (51); D100 Kartal Kavşağı (52); D100 Pendik_1 (53); D100 Pendik_2 (54); D100 Kaynarca (55); D100 Pendik Tersane 2 (56); D100 Güzelyalı (57); D100 Tuzla (58); D100 Tuzla Piyade (59).*

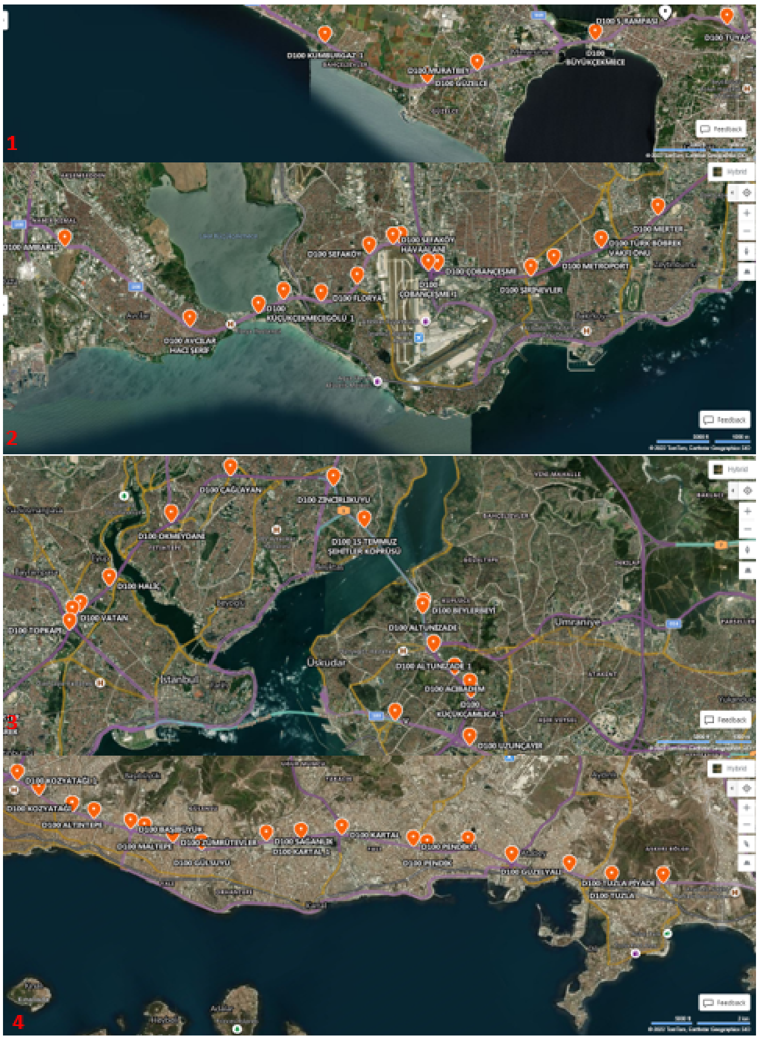

**Figure 4.** D100 Highway

An analysis of 36628 traffic incidents on the D100 highway line was carried out. According to the results obtained:

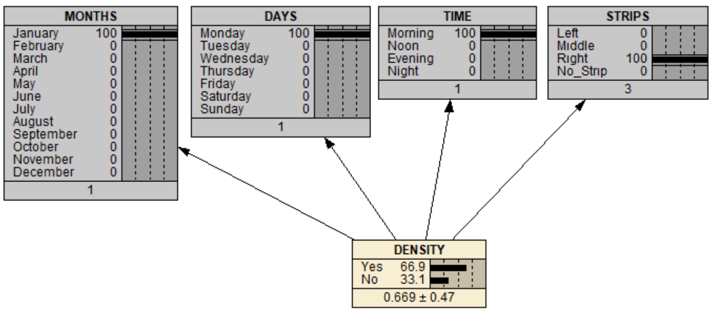


**Figure 5.** Bayesian Network Density Estimation Model

The density data for the traffic incidents that occurred in January, on Monday, in the morning and in the right lane are given in table 3. In January, on Monday morning, the right lane will be crowded with a probability of 66.9% (in fig.5).

**P**(*Density*=***Yes I*** *Months*=***January***, *Days*=***Monday***, *Time*=***Morning***, *Lane*=***Right)=1***

**Table 3.** Traffic Incidents Scenario 1

| Density | Yes | No | Total | %Yes | %No |
|---|---|---|---|---|---|
| | 20552 | 16075 | 36627 | 0.561 | 0,439 |
| January | 2172 | 1791 | 3963 | 0,106 | 0,111 |
| Monday | 3481 | 2390 | 5871 | 0,169 | 0,149 |
| Morning | 6849 | 4701 | 11550 | 0,333 | 0,292 |
| Right Lane | 13818 | 8428 | 22246 | 0,672 | 0,524 |

- *P(Density=""**Yes** " I Months=**January** ",Days= "**Monday** ",Time= "**Morning** ",Strip= "**Right** "")*=0.561*0.106*0.169*0.333*0.672=0.00225
- *P(Density=""**No** " I Months=**January** ",Days= "**Monday** ",Time= "**Morning** ",Strip= "**Right** ""* )=0.439*0.111*0.149*0.292*0.524=0.001115
- *P(Density=""**Yes** " I Months=**January** ",Days= "**Monday** ",Time= "**Morning** ",Lane= "**Right** "*)=0.00225/(0.00225+0.001115 =0.669=66,9%)
- *P(Density=""**No** " I Months=**January** ",Days= "**Monday** ",Time= "**Morning** ",Strip= "**Right** ""*)=0.001115/(0.00225+0.0011 =0.331=33.1%)

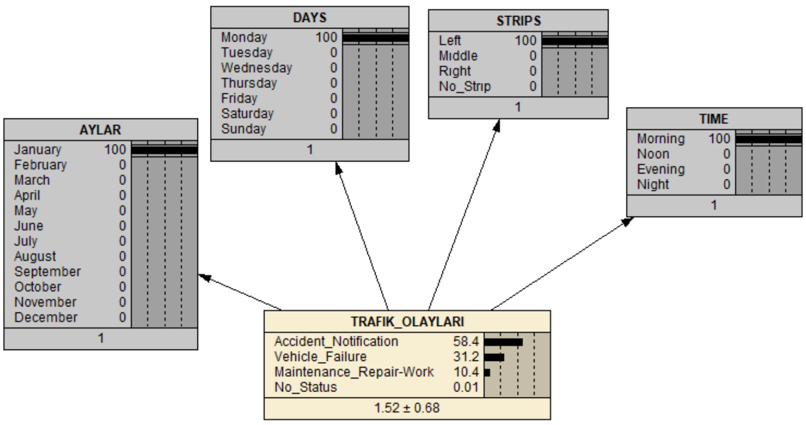


**Figure 6.** Bayesian Network Traffic Event-Based Prediction Model

The traffic events data for the traffic incidents that occurred in January, on Monday, in the morning and in the right lane are given in table 4. In January, on Monday morning, in the left lane, an accident report will occur with a probability of 54.8% (in fig.6).

***P(****Traffic_Events*=***Accident_Notification I*** *Months*=January, *Days*=***Monday***, *Time*=***Morning***, *Lane*=***Left)=1***

**Table 4.** Traffic Incidents Scenario 3

| Traffic_ Event | Accident__ Notification | Vehicle_ failure | Maintenance_ Repair_ Study | No_ Status | Total | % Accident_ Notification | Vehicle_ failure | % Maintenance_ Repair_ Study | % No_ Status |
|---|---|---|---|---|---|---|---|---|---|
| | 14927 | 18337 | 2447 | 916 | 36627 | 0.408 | 0,501 | 0,067 | 0,025 |
| January | 1605 | 2013 | 247 | 98 | 3963 | 0,108 | 0,110 | 0,101 | 0,107 |
| Monday | 2284 | 3175 | 301 | 111 | 5871 | 0,153 | 0,173 | 0,123 | 0,121 |
| Morning | 4481 | 5808 | 977 | 284 | 1155 | 0,300 | 0,317 | 0,399 | 0,310 |
| Left Lane | 4958 | 2170 | 881 | 0 | 8009 | 0,332 | 0,118 | 0,360 | 0,000 |

- P(***Traffic_Events=" "Accident Notification"*** *I Months=**"January"**,Days=**"Monday"**,Time=**"Morning"**,Strip=**"Left" "**)*=0,408*0,108*0,153*0,300*0,332=0,00066885

- P(***Traffic_Events*** *=" "**Vehicle_Failure**" I Months="**January**" ",Days="**Monday**" ",Time=" "**Morning**" ",Strip="**Left**" "*)=0,501*0,110*0,173*0,317*0,118=0,000357
- P(***Traffic_Events*** *=" "**Maintenance_Repair_Study**" I Months="**January**",Days="**Monday**",Time="**Morning**",Strip="**Left**" "*)=0,0607*0,101*0,123*0,399*0,360=0,0001192
- P(***Traffic_Events*** *=" "**No_Status**" I Months="**January**",Days="**Monday**",Time="**Morning**",Strip="**Left**" "*)=0,025*0,107*0,121*0,310*0,000=0,000
- P(***Traffic_Events*** *=" "**Accident Notification**" I Months="**January**",Days="**Monday**",Time="**Morning**",Strip="**Left**" "*)=0,0006685/(0,0006685+0,000357+0,0001192+0,000)=0,584=%58,4
- P(***Traffic_Events*** *=" "**Vehicle_Failure**" I Months="**January**",Days="**Monday**",Time="**Morning**",Strip="**Left**" "*)=0,000357/(0,0006685+0,000357+0,0001192+0,000)=0,312=%31,2
- P(***Traffic_Events*** *=" "**Maintenance_Repair_Study**" I Months="**January**",Days="**Monday**",Time="**Morning**",Strip="**Left**" "*)=0,0001192/(0,0006685+0,000357+0,0001192+0,000)=0,104=%10,4
- P(***Traffic_Events*** *=" "**No_Status**" I Months="**January**",Days="**Monday**",Time="**Morning**",Strip="**Left**" "*)= 0,000/(0,0006685+0,000357+0,0001192+0,000)=0,000=%0,00

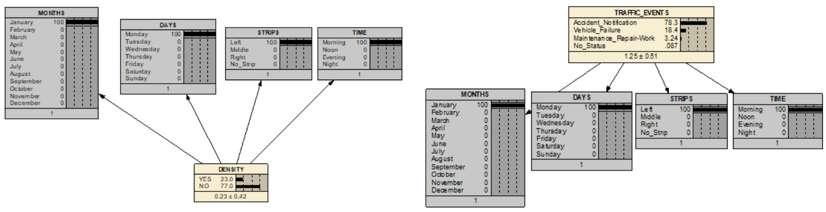

**Figure 7.** Maltepe Location Traffic Analysis

In Maltepe, in January, on Monday mornings, the probability of congestion in the left lane was 23.0%, and the probability of an accident notification from traffic events was 78.3% (fig.7). The probabilities of the traffic incidents that will occur on the D100 15 Temmuz Şehitler Köprüsü were calculated with the Bayesian Network by establishing month, day, time and lane scenarios. In table 5, the probabilities of traffic incidents on Monday are calculated for the 15 Temmuz Şehitler Köprüsü. According to the results, the highest probability of an accident notification on Monday in the morning will occur in the right lane with 71.29% probability, 73.57% probability that vehicle breakdown will occur in the left lane at night, and maintenance-repair work will occur with 30.00% probability in the middle lane at night.

**Table 5.** 15 Temmuz Şehitler Köprüsü Traffic Events On Monday Avg. Probability

| Day | Time | Strips | Accident Notification | Vehicle Failure | Maintenance Repair Work |
|---|---|---|---|---|---|
| Monday | Morning | Left | 62.78% | 26,24% | 10,81% |
| | Noon | | 23,28% | 67,26% | 9,40% |
| | Evening | | 68,21% | 29,54% | 2,01% |
| | Night | | 24,62% | 73,57% | 1,69% |
| | Morning | Right | 71,29% | 27,95% | 0,64% |
| | Noon | | 26,82% | 72,57% | 0,56% |
| | Evening | | 70,87% | 16,23% | 12,59% |
| | Night | | 33,35% | 52,03% | 14,45% |
| | Morning | Middle | 45,47% | 53,68% | 0,48% |
| | Noon | | 47,03% | 52,85% | 30,00% |
| | Evening | | 45,64% | 54,13% | 13,00% |
| | Night | | 67,73% | 30,59% | 1,59% |

As a result of the sensitivity analysis of the model performed on the D100 highway line in Table 6, it was concluded that the biggest factor on traffic events and density is the lane, which has mutual info of 0.1789 and 0.1534, respectively.

**Table 6.** Sensitivity analysis result of the node Traffic Events and Density

| Node | Mutual Info | Percent | Variance of beliefs |
|---|---|---|---|
| ***Traffic Events*** | 1,2573 | 100,0 | 0,2938 |
| Strips | 0,1789 | 14,2 | 0,0308 |
| Months | 0,0103 | 0,8 | 0,0007 |
| Time | 0,0278 | 2,2 | 0,0044 |
| Days | 0,0128 | 1,0 | 0,0015 |
| Node | Mutual Info | Percent | Variance of beliefs |
| ***Density*** | 0,9723 | 100,0 | 0,2405 |
| Strips | 0,1534 | 15,8 | 0,0473 |
| Months | 0,0213 | 2,2 | 0,0072 |
| Time | 0,0094 | 1,0 | 0,0031 |
| Days | 0,0042 | 0,4 | 0,0014 |

Vehicle densities of 59 locations along the D100 Highway line were modeled. The probability of vehicle densities were calculated according to months and days for the 15 Temmuz Şehitler Köprüsü, 29 locations on the European side and 29 locations on the Anatolian side.

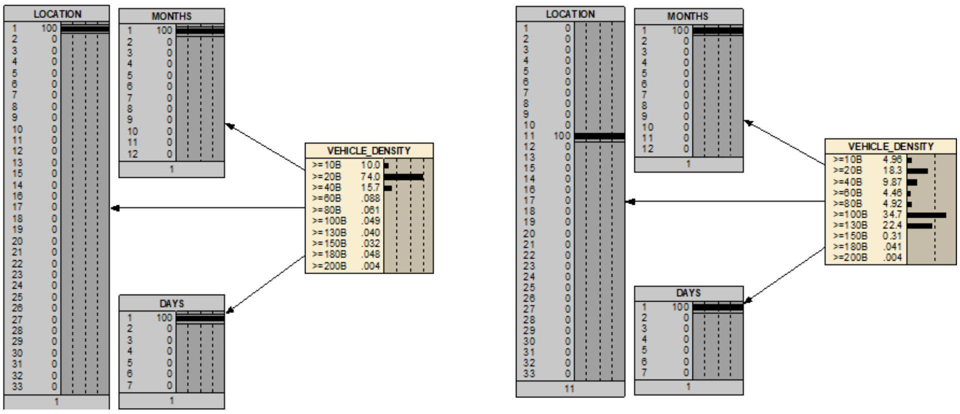


**Figure 8.** D100 Selimpaşa and Ambarlı Location Vehicle Density

On the D100 Highway line in January, on Monday, the vehicle density in Selimpaşa will be more than 20 thousand with a probability of 74.0%. In Küçükçekmece, there is a 34.7% probability that it will be more than 100K (fig.8).

The traffic density probability values of the European side of the D100 highway line for January and Monday are presented in the Table 7. From the places where more than 100 thousand vehicles pass Sefaköy recorded a 58.50% probability , Zincirlikuyu with 54.10% probability, and Florya with 62.00% probability. From the places where more than 130 thousand vehicles pass, Küçükçekmece had a 66.80% probability. From the places where more than 150 thousand vehicles pass, Turkish Kidney Foundation recorded a 47.40% probability. From the locations where more than 180 thousand vehicles passed, Edirnekapı had a probability of 26,60%. It is seen that the density of vehicles on the European side of the D100 highway line is higher on the Küçükçekmece-Florya-Sefaköy-Airport line in January, on Monday.

**Table 7.** European Side, January, Monday, Traffic Density Probability Values

| D100 AVRUPA YAKASI HATTI | >=10B | >=20B | >=40B | >=60B | >=80B | >=100B | >=130B | >=150B | >=180B | >=200B |
|---|---|---|---|---|---|---|---|---|---|---|
| SELİMPAŞA | 10,00% | 74,00% | 15,70% | * | * | * | * | * | * | * |
| CELALİYE_2 | 23,70% | 70,60% | 1,02% | * | * | * | * | * | * | * |
| CELALİYE_1 | 3,41% | 88,00% | 5,95% | * | * | * | * | * | * | * |
| KUMBURGAZ_1 | 6,20% | 79,90% | 10,90% | * | * | * | * | * | * | * |
| KUMBURGAZ_2 | 37,30% | 60,70% | * | * | * | * | * | * | * | - |
| GÜZELCE | 13,40% | 37,40% | 45,70% | * | * | * | * | * | * | * |
| MURATBEY | 3,28% | 18,00% | 57,90% | 20,00% | * | * | * | * | * | * |
| BÜYÜKÇEKMECE | 1,22% | 3,64% | 72,20% | 21,30% | * | * | * | * | * | * |
| S_RAMPASI | 4,71% | 12,90% | 80,40% | * | * | * | * | * | * | * |
| TUYAP | 3,71% | 8,34% | 21,90% | 18,90% | 42,60% | 4,41% | * | * | * | * |
| AMBARLI | 4,96% | 18,30% | 9,87% | 4,46% | 4,92% | 34,70% | 22,40% | * | * | * |
| HACI_ŞERİF | 1,98% | 1,87% | 2,20% | 2,61% | 5,38% | 13,40% | 22,50% | 49,50% | * | * |
| KÜÇÜKÇEKMECE_1 | 2,90% | 2,69% | 2,48% | 2,58% | 3,89% | 7,62% | 9,47% | 66,80% | 1,55% | |
| KÜÇÜKÇEKMECE_2 | 2,98% | 1,79% | 2,08% | 3,64% | 5,17% | 29,70% | 42,40% | 12,10% | * | * |
| CENNET MAH. | 6,58% | 4,50% | 4,17% | 15,70% | 15,40% | 9,02% | 23,80% | 20,80% | * | * |
| FLORYA | 1,50% | 1,90% | 1,19% | 2,30% | 3,72% | 24,00% | 62,00% | 3,26% | * | * |
| SEFAKÖY | 1,77% | 1,85% | 1,80% | 4,98% | 7,39% | 58,50% | 22,30% | 1,34% | * | * |
| SEFAKÖY HAVAALANI | 1,53% | 10,70% | 79,60% | * | * | * | * | * | * | * |
| ÇOBANÇEŞME HAVAALANI | 8,05% | 9,97% | 79,30% | * | * | * | * | * | * | * |
| ÇOBANÇEŞME | 4,79% | 21,60% | 26,60% | 4,38% | 11,50% | 31,10% | * | * | | * |
| ŞİRİNEVLER | 12,00% | 5,02% | 4,05% | 6,85% | 8,75% | 47,50% | 15,40% | * | * | * |
| METROPORT | 25,80% | 2,45% | 14,00% | 2,99% | 6,75% | 27,30% | 20,50% | * | * | * |
| TÜRK BÖBREK VAKFI | 1,70% | 2,13% | 1,09% | 2,47% | 3,45% | 9,18% | 32,40% | 47,40% | | * |
| MERTER | 0,72% | 0,51% | 2,73% | 35,10% | 30,60% | 28,50% | 1,76% | * | * | * |
| TOPKAPI | 4,81% | 2,43% | 3,40% | 8,28% | 11,20% | 38,30% | 21,20% | * | * | * |
| VATAN | 0,87% | 2,45% | 20,50% | 75,60% | * | * | * | * | * | * |
| EDİRNEKAPI | 0,98% | 1,61% | 1,35% | 6,92% | 37,90% | 11,00% | 1,81% | 11,30% | 26,60% | * |
| HALİÇ | 1,89% | 2,17% | 2,08% | 5,49% | 7,31% | 47,30% | 33,00% | * | * | * |
| OKMEYDANI | 2,56% | 1,87% | 2,07% | 3,94% | 7,88% | 43,20% | 37,30% | 1,17% | * | * |
| ÇAĞLAYAN | 2,10% | 53,00% | 43,80% | * | * | * | * | * | * | * |
| HÜRRİYET TEPESİ | 5,01% | 2,44% | 5,09% | 7,79% | 14,20% | 33,60% | 27,30% | 4,43% | * | * |
| MECİDİYEKÖY | 2,59% | 2,25% | 2,31% | 3,87% | 6,28% | 30,80% | 40,20% | 11,60% | * | * |
| ZİNCİRLİKUYU | 3,46% | 2,27% | 9,45% | 9,97% | 11,90% | 54,10% | 8,53% | * | * | * |

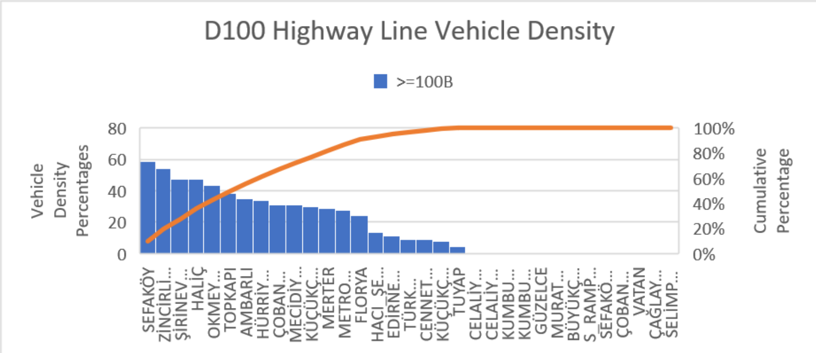


**Figure 9.** D100 Highway European Side Vehicle Density Pareto Analysis

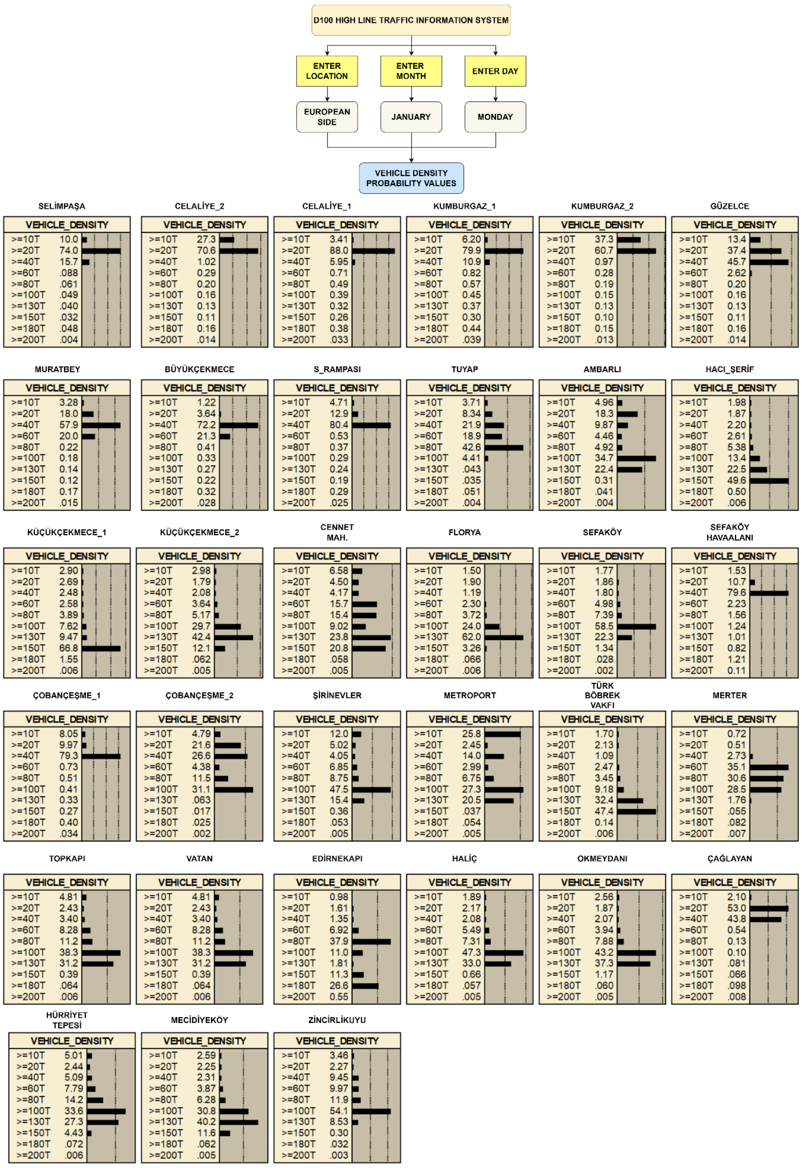


**Figure 10.** D100 Highway European Side Vehicle Density on Monday, January

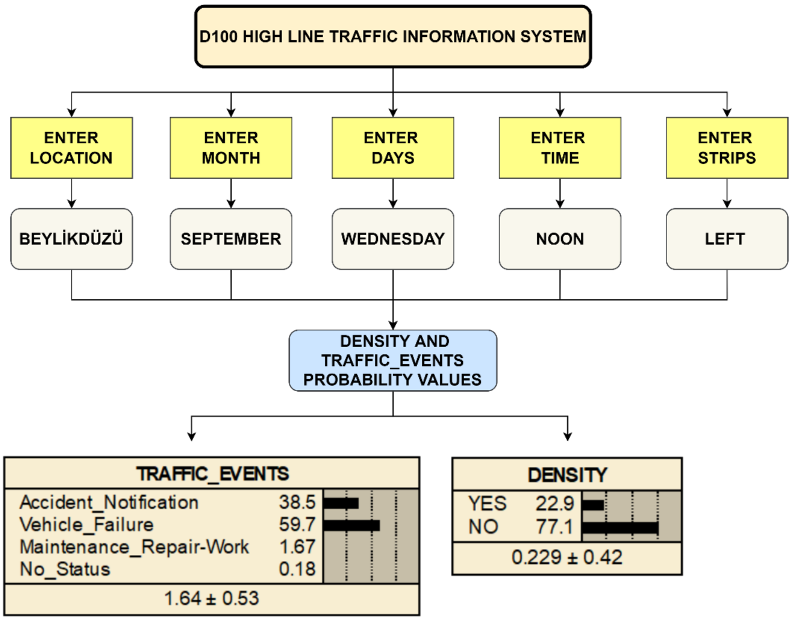


**Figure 11.** Beylikdüzü Location Traffic Information System

## 5. Discussion

It has been emphasized that the measurement and modeling performed with social media data and data mining methods in the analysis of traffic incidents are complementary to the existing methods (Wu, et al., 2022). Suat-Rojas (2022) argued that Twitter data would be effective in detecting traffic incidents and would be an important source of information in traffic management. Salazar et al., (2021) emphasized that social media tools are an important alternative that can be used to collect voluntary geographic information for streets and events taking place on the streets. Yao (2021) offers significant opportunities for transportation research in terms of integrating social media data into traffic forecasts for the detection of traffic incidents and the creation of travel demand models. It has been stated that social media networks are a promising data source for understanding and analyzing the state of metropolitan cities and events occurring in the transportation system (Sumalee and Ho, 2018). In this study, as a result of the processing of Twitter messages, location, month, day, time, lane and season data of traffic notifications were extracted. A Bayesian model was created to predict the traffic events and traffic density that may occur for each region from the traffic notifications obtained from the Twitter social media tool. The main idea of the study is to develop a model proposal on how to use this data in traffic analysis of metropolitan cities by compiling the traffic notification content created by Twitter users with text mining. With the proposed model, it is aimed to create a low-cost model in the realization of traffic analysis. This makes a significant difference to traditional traffic data collection tools, which are costly to maintain and deploy.

## 6. Conclusion

With the density and traffic incident models established with the Bayes Network, the probability of density and traffic incidents to occur according to months, days, time and lane conditions of 59 different locations on the D100 highway line have been obtained. By transforming the designed models into a dynamic structure, data will be transferred as a result of a traffic event that will occur, and an infrastructure will be created that will provide information about the instantaneous density and traffic events of each location. Thanks to this developed model, it is of great importance in preventing traffic congestion and ensuring traffic safety by providing more detailed information about roads to users traveling along the D100 highway.

In the D100 Highway Traffic Information System presented in fig. 10, the probability values of the vehicle density that may occur on the Anatolian and European sides, in which month and on which day, are calculated. Thanks to a dynamic system, the density data is entered every day and the probability value of the vehicle density that will occur the next day is revealed. Thanks to this information system, the vehicle density probability values unique to each region will be revealed. According to the months and days, the vehicle density of each location will be given to users before their journey.

In the D100 Highway Traffic Information System presented in fig. 11, after entering the location, month, day, time and lane, the traffic events and density probability values that may occur in that region are calculated. With this system, users can decide which lane would be more advantageous in terms of safety and cost, thanks to the information they enter into the system, before they travel. During the journey along the D100 Highway line, it provides an opportunity for them to have a better journey by accessing the data in which region bottlenecks will occur and in which regions the traffic incidents are more likely to occur.

The D100 Highway Traffic Information Service, month, day, time and lane conditions will be entered and measures will be taken according to the density situations that will occur along the highway and the probability of traffic events, and it will make a great contribution to the formation of a more reliable traffic. By integrating this system with navigation programs, informing the users about the density and traffic incidents of the location before they reach the next location will prevent traffic incidents that may occur and will naturally prevent traffic density.

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