THE BALTIC JOURNAL OF ROAD AND BRIDGE ENGINEERING
2024/19(2)

ISSN 1822-427X/eISSN 1822-4288
2024 Volume 19 Issue 2: 23–42
https://doi.org/10.7250/bjrbe.2024-19.634

ESTIMATING THE BITUMEN RATIO TO BE USED IN HIGHWAY ASPHALT CONCRETE BY MACHINE LEARNING

MUHAMMED YASIN ÇODUR[1], HALIS BAHADIR KASİL[2], EMRE KUŞKAPAN[2,*]

[1]*College of Engineering and Technology, American University of the Middle East, Egaila, 54200, Kuwait*

[2]*Engineering and Architecture Faculty, Erzurum Technical University, Erzurum, Turkey*

Received 25 July 2023; accepted 11 March 2024

Abstract. Hot mix asphalt, which is frequently used in road pavements, contains bitumen in certain proportions. This bitumen ratio varies according to the layers in the road pavements. The bitumen ratio in each pavement is usually estimated by the Marshall design method. However, this method is costly as well as time-consuming. In this study, the Naive Bayes method, which is a machine learning algorithm, was used to estimate the bitumen ratio practically. In the study, a total of 102 asphalt concrete designs were examined, which were taken from the wearing course, binder course, and asphalt concrete base course and stone mastic asphalt wearing course layers. Each road pavement layer was divided into three different classes according to the bitumen ratios and the algorithm was trained with machine learning. Then the bitumen ratio was estimated for each data set. As a result of this process, the bitumen ratios of the layers were estimated with an accuracy between 75% and 90%. In this study, it was revealed that the bitumen ratio in the road pavement layers could be estimated practically and economically.

* Corresponding author. E-mail: emre.kuskapan@erzurum.edu.tr

Muhammed Yasin ÇODUR (ORCID ID 0000-0001-7647-2424)
Halis Bahadır KASİL (ORCID ID 0000-0002-6678-7868)
Emre KUŞKAPAN (ORCID ID 0000-0003-0711-5567)

Keywords: asphalt concrete, bitumen ratio, highway, road, machine learning, Marshall method.

Introduction

The physical properties of hot mix asphalt (HMA) affect the service life of road pavements under external influences such as cyclic loads and temperature. HMAs are obtained by mixing bitumen, aggregate and additives at different rates at a certain temperature. The properties of HMAs are affected by these components and their ratios. The designs made before the production of HMA cover the determination of the optimal ratio of aggregate and bitumen to meet the technical requirements of the mixture in asphalt pavement application. HMA designs are made using one of the Marshall, Hveem or Superpave design methods in the MS-2 Asphalt Mix Design Method book published by the Asphalt Institute (MS-2 Asphalt Mix Design Methods, 2015). Marshall method is widely used in HMA design in Turkey.

It is possible to list the expected performances of bituminous pavements as stability, fatigue resistance, flexibility, impermeability, durability, friction resistance and workability. When each of them is associated with the percentage of bitumen, an excess of the bitumen ratio makes it difficult to workability and accordingly compaction, while also causing a decrease in stability. A low bitumen ratio causes fatigue resistance to decrease. This situation reduces impermeability and durability. At the same time, a high bitumen ratio increases flexibility and reduces skid resistance (Bituminous Mixtures Laboratory Handbook, 2021).

Optimum bitumen content refers to the amount of bitumen that meets the different mixing properties required for each combination of aggregate type, aggregate gradation, and binder type (Gandhi et al., 2010; Punith et al., 2012; Sanchez-Alonso et al., 2011). In general, in the HMA design method, the optimum binder content and binder types of a given asphalt mixture are determined from the relationships between the volumetric and strength properties of the mixture and the changes in binder content. This method requires a lot of effort. In addition, this method causes significant material consumption and time loss (Hamzah et al., 2013).

Bituminous binders are widely used in road pavement applications where they act as inter-aggregate binders. This situation causes it to be widely used as a binder and waterproofing material. About 95% of the more than 100 million tons of asphalt produced worldwide each year is mainly asphalt concrete. This amount is applied in the road coating industry as a binder (Behnood, 2019; Lesueur, 2009).

HMAs have started to be used at airports to solve the problems of resistance to high pressure that occur during the landing of aircraft wheels (Asorhakt, 1993). HMAs are constructed from multiple layers to transfer loads to the ground without any distortion (Rakaraddi & Gomarsi, 2015). In the design of these mixtures, first the thickness of the flexible pavement layers and then the optimum bitumen ratio are determined (Dias et al., 2014; García et al., 2014; Liu & Wu, 2014; Pasandín & Pérez, 2015; Wang et al., 2017; Zaumanis et al., 2016). Since the optimum bitumen ratio is the most important parameter in the performance of the mixture, it is tried to be determined by conducting the necessary experiments in the laboratories to determine the amount of bitumen (Mousa et al., 2021; Tapkın et al., 2010). Mixtures with low bitumen content may cause durability problems, deformation, drainage and increased air voids, while mixtures with high bitumen ratio may cause rutting, bleeding and insufficient air voids (Kandhal & Cross, 1993).

Currently, the Marshall design method remains the most common way to estimate the optimum amount of bitumen (Barczyszyn et al., 2018; Gomaa, 2014; Leon et al., 2023; Ozturk et al., 2016). In the Marshall method, deviations can be very high since it is determined depending on the average values of the briquette groups obtained with different bitumen ratios. In addition to these deviations, a long time is needed from sample preparation to the conclusion of the design process of the Marshall method (Aljassar et al., 2002; Baldo et al., 2018; Liu et al., 2011). The HMA design of each layer of a road takes approximately seven days. A lot of work is being done to save time in light of this information. Especially thanks to machine learning and deep learning, which are artificial intelligence-based methods, various applications save both workload and time today.

1. Background

Machine learning is a branch of artificial intelligence that imitates the way people learn using data and various algorithms. Methods such as machine learning and deep learning, which are sub-branches of artificial intelligence, are used in many fields today. One of the most common applications of these methods and techniques is civil engineering. These methods are frequently used in transportation, hydraulic, mechanical and geotechnical fields.

In the field of transportation, although most of the studies using machine learning and deep learning have covered topics such as traffic density analysis, transportation planning, accident statistics and intersection designs, there are also studies involving highway superstructure. For example, Othman used deep neural networks to predict the optimum asphalt content in his study. As a result of the study, it has been revealed that the asphalt content is estimated with particular accuracy and the application process is done more practically (Othman, 2022).

In another study, Morova et al. developed an artificial neural network model to predict the Marshall Stability of lightweight asphalt concrete containing expanded clay. As a result, Marshall Stability values of lightweight asphalt concrete containing expanded clay and having various mixing ratios can be estimated without any experiment by using an artificial neural network model (Morova et al., 2012).

Reddy carried out a study that predicts the strength properties of fiber concrete using an artificial neural network. In the study, four input parameters such as fiber percentage, aspect ratio, blend type and blend percentage were determined. Compressive, tensile and bending strengths were used as output parameters. It has been revealed that there is a good correlation between the results in the created model and the experimental results (Reddy, 2018).

Goel et al. used machine learning algorithms to predict the tensile strength ratio of bituminous concrete mixes. As a result of the analysis, it has been revealed that the support vector machine algorithms give successful results in terms of error and accuracy values. A simple linear model is proposed for the estimation of the tensile strength ratio in the created model (Goel et al., 2022).

When the literature is examined, machine learning provides significant advantages in many aspects to accelerate the design process of HMAs and to predict the properties of asphalt mixtures from laboratory test results. In this study, a fast determination method was tried to determine the optimum bitumen ratio by preliminary study without waiting for the completion of the necessary laboratory studies in the regions where road construction works were carried out seasonally. In the study, it is aimed to estimate the bitumen ratios for four different HMA pavement layers in the formation of the highway superstructure by using machine learning.

2. Material and methods

2.1. The study area and data used

In this study, variables such as degree of penetration, specific gravity, bitumen absorption of aggregates and specific gravity, water absorption of HMA mixture were used to determine the bitumen content by a machine learning method. HMA pavements are generally formed by building three different layers on top of each other: asphalt concrete (AC) base course, binder course, and wearing course. In this study, four different asphalt concrete layer designs were considered, with maximum grain sizes of 38.0, 25.0 and 19.0 mm, respectively, asphalt concrete base course, binder course, wearing course and stone mastic asphalt (SMA) wearing course.

84 of these mixtures have dense gradation and 18 of them have gap gradation. While 27 of the dense-graded mixtures consist of asphalt concrete base course, 31 of them are binder course and 26 of them are wearing course, 18 mixtures with gap-gradation consist of SMA wear course layer. A total of 102 asphalt concrete designs were evaluated. The maximum and minimum bitumen ratios, the average bitumen ratios and the standard deviation values of the samples in the four different layers in the study are given in Table 1 below.

In the mixtures prepared for Bitumen Base Course, Binder Course and Wearing Course, the bitumen used for each layer has the same penetration grade and two different aggregate types, basalt and limestone, were used for the aggregates in the mixtures and different basalt and limestone quarries were utilised for each design. In 18 mixtures prepared for SMA wearing course, three basalt and one limestone quarry were used. Each quarry aggregate has different bitumen absorption, water absorption and specific gravity. The bitumen absorptions of the aggregates were determined according to the Laboratory Manual of Bituminous Mixtures. The water absorption and

Table 1. Details of asphalt concrete designs

Layer	Maximum Bitumen Ratio	Minimum Bitumen Ratio	Sample Number	Average Bitumen Ratio	Standard Deviation
AC base course	5.60	3.80	27	4.309	0.408
Binder course	5.65	4,00	31	4.839	0.364
Wearing course	6.30	4.75	26	5.394	0.487
SMA wearing course	6.95	6.45	18	6.683	0.132

specific gravity of the aggregates were determined according to TS EN 1097-6 standard.

B70/100 penetration grade bitumen is used as the binder. It was obtained from Batman Tupras refinery. This bitumen is widely used in the hot mix asphalt industry in Turkey. Bitumen penetration degrees were obtained according to TS EN 1426. The penetration degrees obtained for the B70/100 bituminous binder are given in Tables 2–5. Specific gravity tests were carried out on the bitumen used in the study according to the TS EN 15326 standard.

Table 2. Information about the asphalt concrete base course samples used in the study

Optimum Bitumen Ratio	Bitumen Penetration	Bitumen Specific Gravity	Aggregate Bitumen Absorption	Aggregate Volume Specific Gravity	Aggregate Apparent Specific Gravity	Coarse Aggregate Water Absorption	Fine Aggregate Water Absorption
5.60	82	1.042	0.79	2.531	2.643	1.68	1.87
4.65	92	1.041	0.72	2.543	2.639	1.45	1.57
3.90	80	1.039	0.41	2.660	2.714	0.75	0.84
3.85	75	1.040	0.22	2.694	2.728	0.35	0.70
4.50	72	1.042	0.59	2.601	2.678	1.10	1.24
4.60	90	1.041	0.61	2.706	2.797	1.23	1.30
4.25	81	1.042	0.62	2.679	2.769	1.41	1.05
4.35	86	1.040	0.51	2.549	2.622	1.14	1.14
4.40	88	1.042	0.88	2.736	2.874	1.54	2.28
3.90	71	1.041	0.46	2.709	2.777	0.85	1.08
3.90	87	1.041	0.50	2.634	2.701	0.96	1.01
4.50	74	1.042	0.78	2.637	2.752	1.61	1.71
4.00	72	1.025	0.53	2.707	2.789	1.13	1.15
3.80	82	1.041	0.59	2.631	2.706	1.07	1.12
4.00	79	1.038	0.45	2.620	2.676	0.72	0.99
4.45	76	1.040	0.65	2.583	2.662	1.15	1.26
3.90	74	1.042	0.51	2.665	2.729	0.86	1.01
4.20	74	1.047	0.40	2.815	2.873	0.64	0.90
4.45	77	1.039	0.93	2.579	2.698	1.69	1.91
4.20	70	1.043	0.42	2.675	2.730	0.70	0.97
4.40	71	1.042	0.48	2.545	2.600	0.84	0.90
4.75	73	1.041	0.95	2.551	2.668	1.73	1.88
3.80	77	1.039	0.28	2.672	2.707	0.49	0.53
5.00	73	1.041	1.16	2.539	2.683	2.20	2.32
4.30	71	1.042	0.50	2.794	2.866	0.86	1.08
4.20	71	1.042	0.62	2.791	2.881	1.08	1.31
4.50	76	1.040	0.65	2.730	2.821	1.18	1.31

Table 3. Information about the binder course samples used in the study

Optimum Bitumen Ratio	Bitumen Penetration	Bitumen Specific Gravity	Aggregate Bitumen Absorption	Aggregate Volume Specific Gravity	Aggregate Apparent Specific Gravity	Coarse Aggregate Water Absorption	Fine Aggregate Water Absorption
5.65	82	1.042	0.71	2.528	2.646	2.01	1.64
4.40	80	1.039	0.34	2.667	2.718	0.71	0.81
5.20	91	1.043	0.68	2.753	2.855	1.08	1.81
5.20	83	1.041	0.65	2.596	2.691	1.27	1.64
5.15	90	1.041	0.54	2.734	2.827	1.23	1.33
5.30	80	1.040	0.48	2.554	2.652	1.46	1.56
4.90	76	1.042	0.55	2.727	2.809	1.24	0.91
4.80	85	1.040	0.60	2.543	2.619	1.26	1.08
4.75	86	1.040	0.45	2.680	2.745	0.98	0.84
5.15	71	1.041	0.73	2.668	2.772	1.69	1.11
4.00	81	1.041	0.08	2.698	2.711	0.16	0.22
4.90	74	1.042	0.94	2.631	2.749	1.66	1.74
4.65	78	1.026	0.54	2.704	2.790	1.19	1.20
4.50	85	1.041	0.67	2.618	2.702	1.23	1.26
4.55	79	1.038	0.35	2.619	2.671	0.61	0.99
5.20	76	1.040	0.71	2.533	2.614	1.26	1.33
4.50	74	1.042	0.50	2.674	2.737	0.81	1.06
4.65	74	1.047	0.42	2.827	2.887	0.70	0.91
4.90	77	1.039	0.86	2.605	2.714	1.46	1.90
4.65	70	1.043	0.51	2.678	2.744	0.91	1.00
4.45	75	1.042	0.28	2.676	2.709	0.43	0.56
4.60	71	1.042	0.44	2.552	2.601	0.75	0.80
5.30	73	1.041	0.88	2.562	2.672	1.68	1.70
4.90	71	1.041	0.73	2.794	2.904	1.35	1.53
4.25	77	1.039	0.28	2.671	2.705	0.47	0.56
5.30	73	1.041	1.25	2.547	2.703	2.36	2.44
4.65	71	1.042	0.51	2.795	2.869	0.91	1.06
4.80	71	1.042	0.62	2.796	2.887	1.10	1.31
4.60	71	1.042	0.32	2.832	2.878	0.57	0.60
5.10	75	1.041	0.63	2.501	2.574	1.11	1.34
5.05	76	1.040	0.64	2.738	2.828	1.18	1.27

Table 4. Information about the wearing course samples used in the study

Optimum Bitumen Ratio	Bitumen Penetration	Bitumen Specific Gravity	Aggregate Bitumen Absorption	Aggregate Volume Specific Gravity	Aggregate Apparent Specific Gravity	Coarse Aggregate Water Absorption	Fine Aggregate Water Absorption
5.90	91	1.043	0.57	2.739	2.835	1.09	1.59
4.75	90	1.039	0.23	2.685	2.720	0.47	0.55
6.25	82	1.042	0.69	2.522	2.638	1.90	1.72
6.30	80	1.040	0.81	2.546	2.660	1.74	1.82
5.40	86	1.040	0.54	2.548	2.618	1.14	1.07
5.55	76	1.042	0.61	2.662	2.750	1.27	1.29
5.75	71	1.041	0.74	2.670	2.777	1.56	1.45
4.75	81	1.041	0.19	2.690	2.718	0.29	0.54
5.05	78	1.026	0.48	2.710	2.795	1.15	1.24
5.05	74	1.047	0.43	2.832	2.896	0.77	0.89
5.00	84	1.040	0.54	2.701	2.773	0.97	1.07
5.35	75	1.042	0.56	2.661	2.733	0.92	1.19
5.25	73	1.041	0.61	2.699	2.783	1.61	0.64
5.20	79	1.038	0.28	2.616	2.659	0.55	0.75
5.40	86	1.051	0.60	2.723	2.805	1.08	1.19
4.80	82	1.039	0.25	2.675	2.706	0.38	0.55
5.10	71	1.041	0.37	2.670	2.717	0.63	0.73
5.25	77	1.040	0.56	2.734	2.812	1.04	1.10
5.00	71	1.042	0.43	2.817	2.880	0.80	0.85
5.35	91	1.034	0.62	2.594	2.669	1.03	1.27
4.90	76	1.041	0.28	2.671	2.706	0.45	0.57
5.50	80	1.039	0.69	2.635	2.725	1.24	1.39
6.30	75	1.041	1.17	2.497	2.638	2.48	1.95
6.30	75	1.041	1.14	2.477	2.610	2.49	1.69
5.70	75	1.041	0.78	2.497	2.587	1.42	1.49
5.10	75	1.041	0.30	2.676	2.713	0.48	0.60

In each HMA design, five different bitumen ratios with 0.5% increments were determined for the mixture and three briquette samples were prepared and tested for each bitumen content. In this context, 15 samples were prepared for each design. The standard Marshall method was used to obtain the optimum bitumen content in light of the stability, flow and volumetric properties of 102 asphalt mixtures with B70/100 bitumen penetration and different aggregate gradation. Five design curves were drawn to estimate the optimum bitumen ratio for stability and flow values, density, air void percentage by averaging the values of each triple group obtained, and bitumen ratios were determined. 102 designs were also applied on the road and the results were verified with cores. However, this process took quite a long time, as well as a significant amount of labour was needed and it was not economical. Machine learning was used to determine whether it would be possible to obtain bitumen ratios more practically.

Table 5. Information about the SMA wearing course samples used in the study

Optimum Bitumen Ratio	Bitumen Penetration	Bitumen Specific Gravity	Aggregate Bitumen Absorption	Aggregate Volume Specific Gravity	Aggregate Apparent Specific Gravity	Coarse Aggregate Water Absorption	Fine Aggregate Water Absorption
6.70	72	1.040	0.35	2.628	2.667	0.56	0.74
6.65	72	1.040	0.32	2.635	2.672	0.56	0.62
6.95	72	1.040	0.65	2.749	2.838	1.23	1.35
6.85	72	1.040	0.55	2.717	2.790	1.23	0.62
6.80	72	1.040	0.53	2.668	2.735	0.98	1.12
6.75	72	1.040	0.46	2.668	2.726	0.98	0.62
6.60	74	1.038	0.32	2.628	2.667	0.56	0.74
6.55	74	1.038	0.31	2.635	2.672	0.56	0.62
6.85	74	1.038	0.63	2.749	2.838	1.23	1.35
6.75	74	1.038	0.52	2.717	2.790	1.23	0.62
6.70	74	1.038	0.52	2.668	2.735	0.98	1.12
6.65	74	1.038	0.45	2.668	2.726	0.98	0.62
6.50	74	1.034	0.31	2.628	2.667	0.56	0.74
6.45	74	1.034	0.29	2.635	2.672	0.56	0.62
6.75	74	1.034	0.62	2.749	2.838	1.23	1.35
6.65	74	1.034	0.49	2.717	2.790	1.23	0.62
6.60	74	1.034	0.49	2.668	2.735	0.98	1.12
6.55	74	1.034	0.43	2.668	2.726	0.98	0.62

* The parameters in Table 5 are obtained from Halis Bahadır Kasil's PhD Thesis, which is currently in progress.

2.2. Machine learning

Machine learning is a branch of science that deals with the design and development of algorithms that enable computers to learn based on data types such as sensor data or databases. Machine learning is considered a subset of artificial intelligence. This method uses various algorithms to identify patterns in the data. These patterns are also used to create a predictive data model. The results of machine learning become more accurate as the amount of data and experience increases, just as humans improve with more practice.

Machine learning is an important option when it is not possible to encode data simply. There are various criteria to evaluate the analysis results of machine learning algorithms. Among these criteria, the concepts of MAE, RMSE and Kappa statistics express error rates, while the concepts of precision, recall and f-measure express performance criteria. The fact that the MAE and RMSE concepts are low, and the Kappa statistical value is high, shows that the algorithm is successful. In addition, precision, recall and f-measure values are expected to be high in a successful algorithm. When calculating the values of these criteria, the comparison of the estimated and available data is taken into account. In the comparison process, TP (true positive-right) means TN (true negative-right means false), FP (false positive-false means), and FN (false negative-false means wrong) values are used. The calculation of all these variables is shown in the Equations (1)–(7) below (Zhou, 2016).

$$\text{Precision} = \frac{TP}{TP + FP}. \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{2}$$

$$\text{F-measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}. \tag{3}$$

		Predictive Values	
		Class = 1	Class = 0
Actual Values	Class = 1	TP	FN
	Class = 0	FP	TN

Figure 1. Confusion matrix

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}. \tag{4}$$

$$K = \frac{p_\text{o} - p_\text{e}}{1 - p_\text{e}}, \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|x_{\text{f},i} - x_{\text{o},i}\right|, \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{\text{f},i} - x_{\text{o},i}\right)^2}, \tag{7}$$

where $p_\text{o} = x_{\text{f},i}$ and $p_\text{e} = x_{\text{o},i}$ are expectation and observation, respectively.

In this study, the Naive Bayes algorithm, which is a machine learning algorithm, was used. Naive Bayes is an algorithm that performs transactions based on probability calculations. It processes the found train data according to its formula and extracts a percentage for each case and performs the classification of the test set according to these probabilities. This algorithm is frequently used in solving classification problems. While classifying with Naive Bayes, a certain amount of training data is presented to the system. The given data must have a class. In this way, the algorithm can predict the classes of other data by utilizing the training data. The more the number of training data, the more accurately the class to which the test data belongs can be predicted (Atmaca, 2020; Kuşkapan & Çodur, 2021). The formulation of this algorithm is briefly as follows:

$$P(A \mid B) = \frac{P(B \mid A)\,P(A)}{P(B)}, \tag{8}$$

where $P(A|B)$ is probability of occurrence of event A when event B occurs;
$P(A)$ is probability of event A;
$P(B|A)$ is probability of event B occurring when event A occurs;
$P(B)$ is probability of event B occurring.

4. Results and discussion

To classify the data, the bitumen content in each road pavement layer is divided into three different classes. In this classification process, the minimum, maximum and standard deviation values of the bitumen ratios in the layers have been used. In this way, it is aimed to perform the classification process homogeneously. Thanks to the classification made for each layer, it has become possible to analyse the data with machine learning. Table 6 shows the classification made using the bitumen values of each layer.

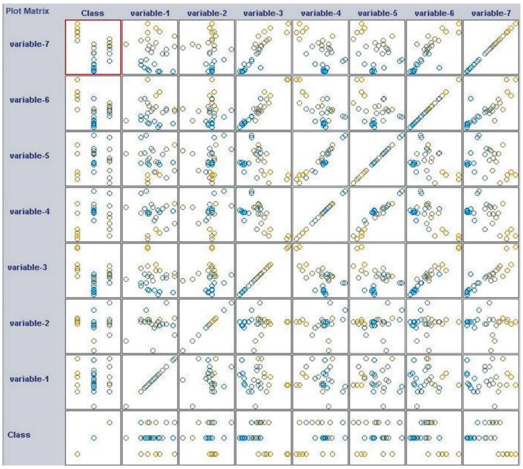
After the classification process is performed, the factors affecting the optimum bitumen rate are defined as a variable. These variables are bitumen penetration, bitumen specific gravity, aggregate bitumen absorption, a bulk specific gravity of aggregate, the apparent specific gravity of aggregate, coarse aggregate water absorption and fine aggregate water absorption. Each of these values has an important place in the classification process as they directly affect the optimum bitumen ratio. Scatter plot matrices of these variables according to each pavement layer are shown in Figure 2.

A scatter plot matrix is a grid (or matrix) of scatter plots used to visualise bivariate relationships between combinations of variables. Each scatter plot in the matrix visualises the relationship between a pair of variables, allowing many relationships to be explored in one chart. After obtaining the distribution matrix for each pavement layer, the error criteria and performance criteria obtained by the Naive Bayes algorithm should be examined. The compatibility of these criteria with each other shows that the data set is suitable for the algorithm. If a successful result is obtained in terms of performance criteria in a pavement layer, but a successful result is not revealed in terms of error criteria, the selected algorithm should be changed. In addition, this incompatibility may be caused by the structure of the dataset. The error criteria calculated for each pavement layer are given in Figure 3.

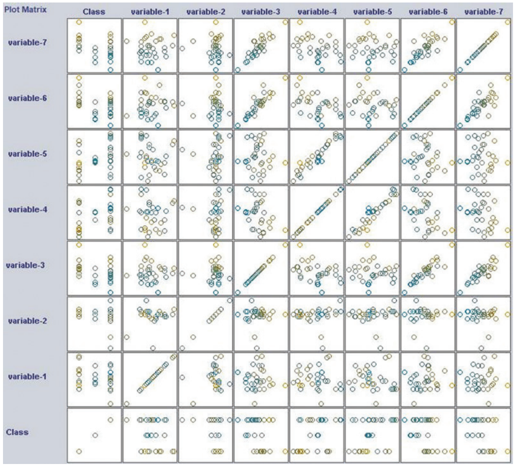
Table 6. Classes created according to bitumen ratios

Pavement layer	Bitumen rate is low, %	Bitumen rate is medium, %	Bitumen rate is high, %
AC base course	3.80–4.30	4.30–4.80	4.80–5.60
Binder course	4.00–4.52	4.52–5.10	5.10–5.65
Wearing course	4.75–5.25	5.25–5.75	5.75–6.30
SMA wearing course	6.45–6.61	6.61–6.78	6.78–6.95

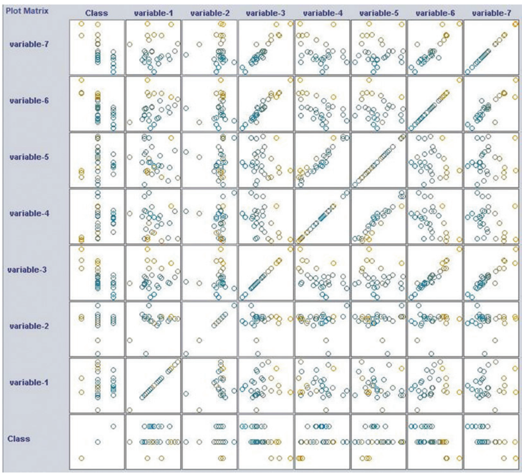
a) AC base course



b) binder course



c) wearing course



d) SMA wearing course

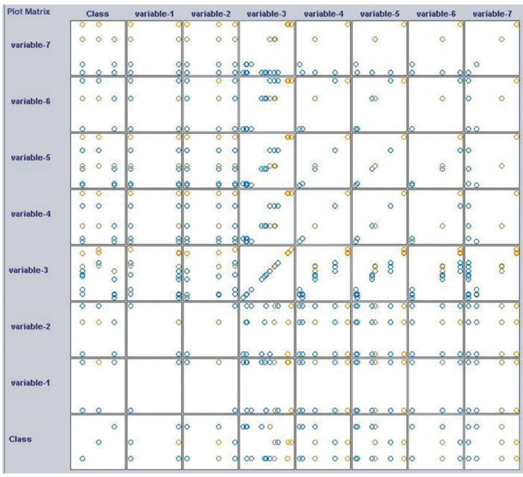


Figure 2. Scatter plot matrices of variables according to each pavement layer

Kappa value is a term expressed to measure the mismatch between observations. The closer this value is to 1, the better the agreement between observations. The kappa statistic is frequently used to test interrater reliability. The importance of rater reliability lies in the fact that it represents the extent to which the data collected in the study are correct representations of the variables measured. MAE is a model evaluation metric used with regression models. MAE error of a model concerning a test set is the mean of the absolute values of the individual prediction errors over all instances in the test set. Each prediction error is the difference between the true value and the predicted value for the instance. RMSE is the square root of mean squared error. RMSE measures the differences between values predicted by a hypothetical model and the observed values. In other words, it measures the quality of the fit between the actual data and the predicted model (Kuskapan et al., 2023; McHugh, 2012). A high Kappa statistic value and a low MAE and RMSE values from the error criteria indicate that the algorithm is successful. When the results according to the road pavement layers are examined in detail, it is seen that the most successful results are in the AC base course, and the least successful results are in the binder course. After examining the error criteria, it is necessary to examine the performance criteria of the algorithm. The performance criteria for each road layer are given in Figure 4.

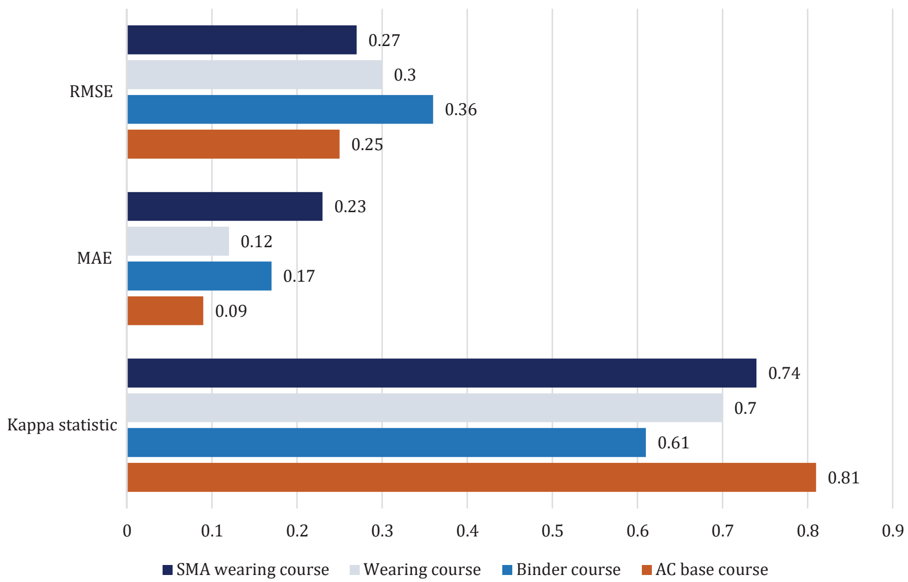
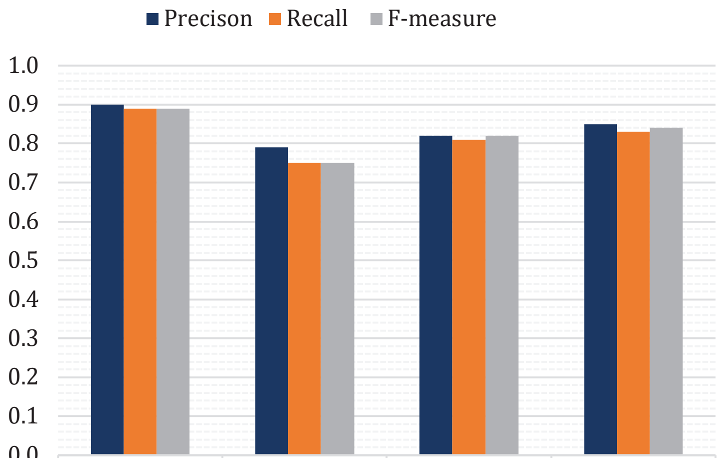


Figure 3. Error criteria of each pavement layer

The recall statement is the ratio of the number of correct and positive samples estimated as class 1 to the number of samples estimated as class 1. Precision is defined as the ratio of the number of correctly classified positive samples to the total number of positive samples. The F-criterion is the harmonic mean of both precision and accuracy expressions. When the performance criteria of the road layers are



	AC base course	Binder course	Wearing course	SMA wearing course
Precison	0.9	0.79	0.82	0.85
Recall	0.89	0.75	0.81	0.83
F-measure	0.89	0.75	0.82	0.84

Figure 4. Performance criteria for each pavement layer

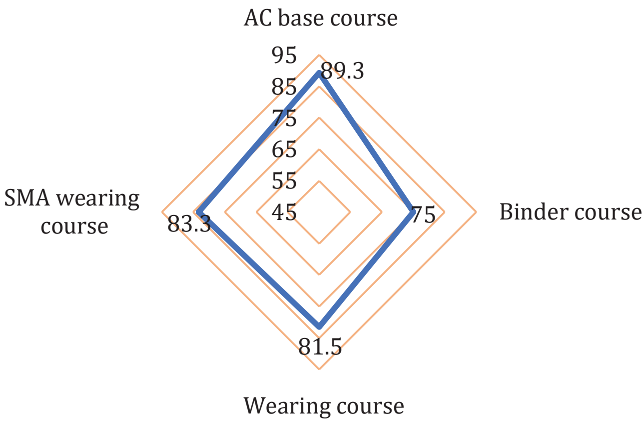


Figure 5. Accuracy values for each road pavement layer

examined, it is seen that the classification gives much more successful results for the AC base course. The performance criteria of the wearing course and the SMA wearing course are closer to each other. On the other hand, it is seen that the results of the binder course are less successful in the performance measures as in the error measures. In line with these results, the accuracy values of each road pavement layer of the classification made with the Naive Bayes algorithm are given in Figure 5.

Accuracy is a metric that measures how often a machine learning model correctly predicts the outcome. It is seen that the classification made with the Naive Bayes algorithm gives accurate results between 90% and 75% according to the road pavement layer. The high accuracy values of these can provide great advantages in the design and application processes of the road.

Today, the Marshall test method is one of the most common application methods used to estimate the optimum bitumen ratio in our country. Depending on the average values of the triple groups obtained at different bitumen ratios by the Marshall test method, too many deviations may occur in the bitumen ratios determined. In addition, the process required to complete the method is very long. The long process makes it difficult for companies with limited time in road construction applications to train their production.

As a result of this study on the determination of bitumen ratio, the high accuracy rates obtained for the AC base course, binder course, wearing course and SMA wearing course will shed light on future studies, and this method will reduce the time and cost required for design by making fast determinations. On the other hand, in order to increase these accuracy values, it is necessary to increase the number of data in the data set. If the number of data is increased, the learning success of the algorithm can be increased by using more data in the training set in machine learning.

Conclusions

In this study, it was intended to estimate the bitumen ratio to be used in HMAs before the application was made. The prediction process used the Naive Bayes algorithm, a machine learning algorithm. As a data set, a total of 102 asphalt samples obtained from the wearing course, binder course, and AC asphalt concrete base course and SMA wearing course design were examined. In the created machine learning model, the factors affecting the bitumen ratio from these samples were assigned as a variable. Based on the distribution of bitumen ratios of each layer, three different classes were formed. As a result of the classes created, the dataset was trained and analysed with the Naive Bayes algorithm. As a result of the analysis processes, bitumen amounts of four different road pavement layers were successfully estimated with low error rates and accuracy between 75% and 90%. As a consequence of these results, it was seen that it was possible to provide significant economic savings by using machine learning in highway road design and application processes, to prevent labour force reduction and time loss. It is foreseen that predictions can be made with higher success rates by increasing the samples in the separate dataset. In this context, it is thought that the current technological developments and artificial intelligence-based methods should be used more in future studies.

ACKNOWLEDGMENT

The authors would like to gratefully acknowledge the General Directorate of Highways (GDH) for providing access to laboratory results of bitumen samples.

REFERENCES

Aljassar, A. H., Ali, M. A., & Alzaabi, A. (2002). Modeling Marshall test results for optimum asphalt-concrete mix design. *Kuwait J Sci Engrg*, *29*(1), 181–195.

Asorhakt, U. (1993). *Mix design methods for asphalt concrete and other hot-mix types*. Asphalt Institute.

Atmaca, K. (2020, January 10). Naive Bayesian algorithm. https://kenanatmaca.com/naive-bayesian-algoritmasi/

Baldo, N., Manthos, E., & Pasetto, M. (2018). Analysis of the mechanical behaviour of asphalt concretes using artificial neural networks. *Advances in Civil Engineering*, *2018*, Article 1650945. https://doi.org/10.1155/2018/1650945

Barczyszyn, G. L., De Camenar, L. M. O., De Do Nascimento, D. F., Kozievitch, N. P., Da Silva, R. D., Almeida, L. D. A., De Santi, J., & Minetto, R. (2018). A collaborative system for suitable wheelchair route planning. *ACM Transactions on Accessible Computing*, *11*(3), Article 18. https://doi.org/10.1145/3237186

Behnood, A. (2019). Application of rejuvenators to improve the rheological and mechanical properties of asphalt binders and mixtures: A review. *Journal of Cleaner Production*, *231*, 171–182. https://doi.org/10.1016/J.JCLEPRO.2019.05.209

Bituminous Mixtures Laboratory Handbook. (2021). https://www.kgm.gov.tr/SiteCollectionDocuments/KGMdocuments/Baskanliklar/BaskanliklarTeknikArastirma/BitumluKarisimlarLaboratuvarElKitabi.pdf

Dias, J. L. F., Picado-Santos, L. G., & Capitão, S. D. (2014). Mechanical performance of dry process fine crumb rubber asphalt mixtures placed on the Portuguese road network. *Construction and Building Materials*, *73*, 247–254. https://doi.org/10.1016/j.conbuildmat.2014.09.110

Gandhi, T., Rogers, W., & Amirkhanian, S. (2010). Laboratory evaluation of warm mix asphalt ageing characteristics. *International Journal of Pavement Engineering*, *11*(2), 133–142. https://doi.org/10.1080/10298430903033339

García, A., Norambuena-Contreras, J., Bueno, M., & Partl, M. N. (2014). *Influence of steel wool fibers on the mechanical, termal, and healing properties of dense asphalt concrete*. ASTM International West Conshohocken, PN, USA.

Goel, G., Sachdeva, S. N., & Pal, M. (2022). Modelling of tensile strength ratio of bituminous concrete mixes using support vector machines and M5 model tree. *International Journal of Pavement Research and Technology*, *15*(1), 86–97. https://doi.org/10.1007/s42947-021-00013-5

Gomaa, A. E. (2014). *Marshall test results prediction using artificial neural network* [MSc thesis, Arab Academy for Science and Technology], Cairo, Egypt.

Hamzah, M. O., Golchin, B., & Tye, C. T. (2013). Determination of the optimum binder content of warm mix asphalt incorporating Rediset using response surface method. *Construction and Building Materials*, *47*, 1328–1336. https://doi.org/10.1016/j.conbuildmat.2013.06.023

Kandhal, P. S., & Cross, S. A. (1993). *Effect of aggregate gradation on measured asphalt content*. National Center for Asphalt Technology, Washington, DC.

Kuşkapan, E., Campisi, T., De Cet, G., Vianello, C., & Çodur, M. Y. (2023). Examination of the effects of the pandemic process on the e-scooter usage behaviours of individuals with machine learning. *Transactions on Transport Sciences*, *14*(3), 25–31. https://doi.org/10.5507/tots.2023.016

Kuşkapan, E., & Çodur, M. Y. (2021). Examination of aircraft accidents that occurred in the last 20 years in the world. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, *9*(1), 174–188. https://doi.org/10.29130/dubited.754339

Leon, L., Smith, J., & Frank, A. (2023). Intermediate temperature fracture resistance of stone matrix asphalt containing untreated recycled concrete aggregate. *The Baltic Journal of Road and Bridge Engineering*, *18*(1), 94–121. https://doi.org/10.7250/bjrbe.2023-18.590

Lesueur, D. (2009). The colloidal structure of bitumen: Consequences on the rheology and on the mechanisms of bitumen modification. *Advances in Colloid and Interface Science*, *145*(1–2), 42–82. https://doi.org/10.1016/J.CIS.2008.08.011

Liu, Q. T., & Wu, S. P. (2014). Effects of steel wool distribution on properties of porous asphalt concrete. *Key Engineering Materials*, *599*, 150–154. https://doi.org/10.4028/www.scientific.net/KEM.599.150

Liu, W. F., Li, H. M., & Tian, B. P. (2011). Research on designing optimum asphalt content of asphalt mixture by calculation and experimental method. *Applied Mechanics and Materials*, *97–98*, 23–27. https://doi.org/10.4028/www.scientific.net/AMM.97-98.23

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia Medica*, *22*(3), 276–282. https://doi.org/10.11613/BM.2012.031

Morova, N., Sargin, Ş., Terzi, S., Saltan, M., & Serin, S. (2012). Modeling Marshall Stability of light asphalt concretes fabricated using expanded clay aggregate with Artificial Neural Networks. *2012 International Symposium on Innovations in Intelligent Systems and Applications*, Trabzon, Turkey, 1–4. https://doi.org/10.1109/INISTA.2012.6246946

Mousa, K. M., Abdelwahab, H. T., & Hozayen, H. A. (2021). Models for estimating optimum asphalt content from aggregate gradation. *Proceedings of the Institution of Civil Engineers-Construction Materials*, *174*(2), 69–74. https://doi.org/10.1680/jcoma.18.00035

MS-2 Asphalt Mix Design Methods. (2015). https://www.researchgate.net/profile/Yasir_Jebur/post/what_are_the_limits_of_thicknesses_of_asphalt_wearing_or_surface_binder_layer_base_materials_asphalt_base_and_the_full_depth_asphalt_layer/attachment/5c13e9eccfe4a76455091d0d/AS:703793855483904@1544808939808/download/Asphalt-Institute-MS2-7th-Edition-Asphalt-Institute-Mix-Design.pdf

Othman, K. (2022). Prediction of the hot asphalt mix properties using deep neural networks. *Beni-Suef University Journal of Basic and Applied Sciences*, *11*(1), Article 40. https://doi.org/10.1186/s43088-022-00221-3

Ozturk, H. I., Saglik, A., Demir, B., & Gungor, A. G. (2016). An artificial neural network base prediction model and sensitivity analysis for marshall mix design. *Proceedings of the 6th Eurasphalt & Eurobitume Congress,* Prague, Czech Republic. https://www.researchgate.net/publication/312336678_An_artificial_neural_network_base_prediction_model_and_sensitivity_analysis_for_marshall_mix_design

Pasandín, A. R., & Pérez, I. (2015). Overview of bituminous mixtures made with recycled concrete aggregates. *Construction and Building Materials*, *74*, 151–161. https://doi.org/10.1016/j.conbuildmat.2014.10.035

Punith, V. S., Xiao, F., Putman, B., & Amirkhanian, S. N. (2012). Effects of long-term aging on moisture sensitivity of foamed WMA mixtures containing moist aggregates. *Materials and Structures*, *45*, 251–264. https://doi.org/10.1617/s11527-011-9763-4

Rakaraddi, P. G., & Gomarsi, V. (2015). Establishing relationship between CBR with different soil properties. *International Journal of Research in Engineering and Technology*, *4*(2), 182–188. https://doi.org/10.15623/ijret.2015.0402023

Reddy, T. C. S. (2018). Predicting the strength properties of slurry infiltrated fibrous concrete using artificial neural network. *Frontiers of Structural and Civil Engineering*, *12*(4), 490–503. https://doi.org/10.1007/s11709-017-0445-3

Sanchez-Alonso, E., Vega-Zamanillo, A., Castro-Fresno, D., & DelRio-Prat, M. (2011). Evaluation of compactability and mechanical properties of bituminous mixes with warm additives. *Construction and Building Materials*, *25*(5), 2304–2311. https://doi.org/10.1016/j.conbuildmat.2010.11.024

Tapkın, S., Çevik, A., & Uşar, Ü. (2010). Prediction of Marshall test results for polypropylene modified dense bituminous mixtures using neural networks. *Expert Systems with Applications*, *37*(6), 4660–4670. https://doi.org/10.1016/j.eswa.2009.12.042

Wang, L., Gong, H., Hou, Y., Shu, X., & Huang, B. (2017). Advances in pavement materials, design, characterisation, and simulation. *Road Materials and Pavement Design*, *18*(sup3), 1–11. https://doi.org/10.1080/14680629.2017.1329856

Zaumanis, M., Mallick, R. B., & Frank, R. (2016). 100% hot mix asphalt recycling: challenges and benefits. *Transportation Research Procedia*, *14*, 3493–3502. https://doi.org/10.1016/j.trpro.2016.05.315

Zhou, Z. H. (2016). Learnware: on the future of machine learning. *Frontiers of Computer Sciences*, *10*, 589–590. https://doi.org/10.1007/s11704-016-6906-3