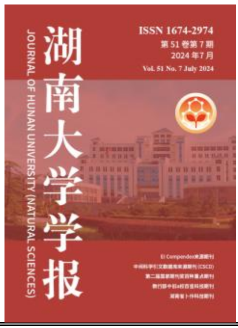

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Performance Prediction of Waste Tire Metal Fiber-Modified Asphalt Mixes Using a Decision Tree Machine Learning Technique

Arsalaan Khan Yousafzai[1,2]*, Muslich Hartadi Sutanto[1], Nasir Khan[1], Mohamed Mubarak Abdul Wahab[1], Muhammad Imran Khan[3], Adamu Sani Abubakar[1], Rania Al-Nawasir[4]

[1] Department of Civil and Environmental Engineering, Universiti Teknologi PETRONAS, Seri Iskandar, 32610, Malaysia

[2] Department of Civil Engineering, University of Engineering and Technology Peshawar, Peshawar, 25120, Pakistan

[3] Department of Civil Engineering, College of Engineering, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, 11564, Saudi Arabia

[4] Roads and Transportation Engineering Department, College of Engineering, University of Al-Qadisiyah, Al-Diwaniyah, 58002, Iraq

* Corresponding author: arsalaan_21002839@utp.edu.my

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Abstract: The Marshall stability and flow of asphalt mixes are important performance indicators of their durability and suitability for application in the pavement industry. The mix design for achieving the optimum levels of bitumen and volumetric properties is critical and depends on the properties of the ingredients used. Recycling waste materials from asphalt is also a key factor in achieving environmental sustainability. The development of machine learning models is crucial for the performance prediction of asphalt mixes. This study investigates the use of a machine learning approach to predict the performance of waste tire metal fiber-modified asphalt mixes. A dataset of 75 experimental data of various mix proportions was compiled to test and train the model. 60/70 penetration grade bitumen was used in conjunction with five modified mixes, each containing varying amounts of waste tire metal fiber at 0%, 0.375%, 0.75%, 1.125%, and 1.5%. Decision tree regression was applied to establish an effective relationship between the input variables. R^2, adjusted R^2, and mean absolute error were used to assess the predictive ability of each model. The input parameters were fiber content, bitumen content, aggregate percentage, and porosity. The study of input variables revealed that the stability decreased while the flow increased with increasing fiber and bitumen contents. With R^2 recorded as 0.901 for training and 0.937 for testing, decision tree regression was found to be an effective model for predicting the performance of the modified mixes. This study fills a gap in machine learning applications by predicting the stability and flow performance of modified asphalt mixes using decision tree algorithms. Using waste tires and promoting recycling also enhances environmental sustainability in the pavement industry.

Keywords: Marshall stability, Marshall flow, metal fiber, asphalt mixes, decision tree.

使用决策树机器学习技术预测废轮胎金属纤维改性沥青混合料的性能

摘要：沥青混合料的马歇尔稳定度和流动性是其耐久性和在路面行业应用适用性的重要性能指标。混合料设计对于实现最佳沥青水平和体积特性至关重要，并且取决于所用成分的特性。回收沥青废料也是实现环境可持续性的关键因素。机器学习模型的开发对于沥青混合料的性能预测至关重要。本研究调查了使用机器学习方法预测废轮胎金属纤维改性沥青混合

料的性能。编制了一个包含75个不同混合比例的实验数据的数据集来测试和训练该模型。60/70渗透级沥青与五种改性混合料一起使用，每种混合料含有不同量的废轮胎金属纤维，分别为0%、0.375%、0.75%、1.125%和1.5%。应用决策树回归来建立输入变量之间的有效关系。使用R2、调整后的R2和平均绝对误差来评估每个模型的预测能力。输入参数包括纤维含量、沥青含量、骨料百分比和孔隙率。对输入变量的研究表明，随着纤维和沥青含量的增加，稳定性降低而流动性增加。训练时的R2为0.901，测试时的R2为0.937，决策树回归被发现是预测改性混合料性能的有效模型。本研究通过使用决策树算法预测改性沥青混合料的稳定性和流动性能，填补了机器学习应用的空白。利用废旧轮胎和促进回收也提高了路面行业的环境可持续性。

关键词：马歇尔稳定性、马歇尔流动、金属纤维、沥青混合料、决策树。

1. Introduction

Asphalt is the oldest and most commonly used composite material for constructing pavements [1-3]. Rapid innovations are being introduced to meet society's sustainability goals in green construction, diverse service demands, and global price hikes [4-7]. Since plain asphalt behaves as an insulator material by nature, it exhibits high resistance to the flow of electric current [8-11]. Such ordinary pavements can perform smart functions by incorporating various additives into traditional asphalt mixes to prepare multifunctional asphalt concrete [12]. Hence, additives are used to improve its non-structural applications by manipulating its electrical properties in addition to asphalt's fundamental role of offering resistance to mechanical loads [13]. Such piezoresistive asphalt facilitates the real-time monitoring of loads and the resulting defects in pavements. Several smart applications and multifunctional benefits of electrically conductive asphalt mixtures/concrete (ECAM/ECAC) have been reported in recent literature [12-21]. These can broadly be classified as self-sensing of strain for early damage detection, traffic monitoring, guidance of autonomous vehicles, pavement damage sensing, truck weigh-in-motion, structural health monitoring, non-destructive testing, in-situ self-healing of asphalt microcracks, self-snow melting (deicing) for winter road and runway maintenance, fast patching of potholes, noise reduction, and piezoelectric energy harvesting. These potential applications of self-sensing asphalt provide great encouragement for future research and development in the field [22].

Identifying an appropriate additive for fostering asphalt conductivity is a significant factor [23]. The conductivity of asphalt depends on the conductive network in the mixture, which indirectly depends on the geometry, composition, and content of the additive. Since the recycling of industrial and household waste is a pressing issue, it is envisioned to be utilized in asphalt pavements to make them electrically conductive while offering substantial environmental sustainability benefits in pavement engineering [24-27]. Fiber-based, binder-based, and granule-based additives along with their combinations have been used by researchers aiming to increase the electrical conductivity that leads to self- or induced healing of asphalt mixes [28, 29]. Another classification is based on material type, dividing them into carbonic (non-metallic) and metallic materials [29-31]. The third classification is based on their size, i.e., nano-, micrometer-, and centimeter-level [32]. This classification was also performed for powders, fibers, and solid particles by Chen et al. [31]. The fourth classification divides modifiers and additives into four groups: polymer modifiers, chemical modifiers, adhesion/anti-stripping agents, and fiber additives [33]. Independent of the above classifications, previous studies have used several types of additives for imparting electrical conductivity into asphalt. The most commonly used ones are carbon fiber, steel fiber, aluminum fiber, steel wool [34], carbon nanotubes [28, 35], graphene (nanometer-level) [32], graphite powder (micrometer-level), carbon black, nickel powder, ITA [36], copper slag [37], coke [22], and metal and steel shaving [30, 36-40].

According to [41], steel fiber enhances the mechanical performance of asphalt mixes. These modified mixes can also provide increased damage resistance with reduced cracking potential in pavements. Moreover, using waste metal fibers for producing modified asphalt also brings about environmental sustainability by making wise use of recyclable materials [42].

Hence, for predicting the performance of asphalt mixes associated with the Marshall stability (MS) and Marshall flow (MF), waste tire metal fiber in various proportions (0%, 0.375%, 0.75%, 1.125%, and 1.5%) as a modifier, along with varying proportions of bitumen (4%, 4.5%, 5%, 5.5%, and 6%), was studied. The proportions of metal fibers were selected according to Luana et al. [43], Hanwen et al. [32], Ying-Yuan et al. [44], Lusheng Wang et al. [45], Shafi Ullah et al. [14], Messaoud et al. [39], Zhenxia Li et al. [23], Jia-Liang Le et al. [46], Cahit Gürer et al. [20, 47], Zejiao Dong et al. [19], and Liping Cao et al. [48]. The aim of this study was to develop a computer-based model to predict the Marshall mix parameters based on a dataset composed of 75 Marshall tests performed with combinations of the fiber and bitumen contents. The model was used to optimize the amount of waste tire metal fiber and characterize its performance in a modified asphalt mixture. Fiber content, bitumen content, aggregate percentage, and porosity were used as input variables to develop a decision tree (DT). Statistical tools like coefficient of determination (R^2), adjusted coefficient of determination ($\overline{R}^2$), and mean absolute error (MAE) were used to assess the model performance. The hypothesis is that incorporating metal fibers into asphalt mixtures may significantly enhance pavement performance and provide high piezoresistivity, which could ultimately be used for self-sensing applications.

2. Literature Review

2.1. Metallic Additives in Asphalt

Several metallic additives have been studied for the modification of asphalt mixes. These additives include iron tailing, steel, magnetite, carbonyl iron powder, copper wire, aluminum metal fiber, and steel slag [14, 15, 47, 49-51]. Additives belonging to this group are observed to have electro-mechanical damage-sensing capabilities even after the first cracking (i.e., in the linear elastic range) [28]. Steel fiber is one of the most commonly used asphalt additives [31]. A single steel fiber is found to have tensile strength > 500 MPa; it is much higher than that of asphalt concrete [33]. Its electrical conductivity is very high, i.e., $7.0x10^{-5}$ Ω-m, but its conductivity improvement potential is lower than that of carbonaceous materials [49]. Moreover, this additive has been reported to experience uneven heating, and the resulting asphalt is of poor durability [31]. Metal fibers extracted from waste tires are also found to increase the air voids (AV) content and reduce the bulk density of asphalt mixtures [25]. It is also exposed to easy oxidation (i.e., less corrosion resistant), and are chemically incompatible with asphalt materials [15]. These disadvantages make metallic materials less desirable than carbon-based additives. Conductive additives made of steel can be of various sizes. Their length may vary from 1 to 9 mm and diameter from 6 to 20 mm [49]. Steel wool fiber (SWF) is one of its common forms, which is prepared from virgin materials, and used to make asphalt electrically conductive and enhance its crack-healing capability [34, 52]. On the other hand, metal shavings, which are waste materials obtained from metal industries, can be used to replace SWF [53]. In a study, the use of centimeter-level SWFs has been shown to result in lower mechanical performance with localized electrical conductivity [38]. However, Hanwen et al. [32] reported SWF-modified asphalt mixtures to have good electrical conductivity and hence self-healing ability. Heopeng et al. [33] reported that they achieved significantly increased MS, tensile strength, and rutting resistance of asphalt specimens modified with SWF due to the fact that well-distributed steel fibers form a complex 3D structure that makes asphalt capable of transferring more stress. Iron tailings are a form of common yet less frequently utilized solid waste that is generated during extracting iron ore, which is referred to as beneficiation [54]. Tailings are the parts with low content of the target component in the selected mineral product, whereas iron tailings are by-products of iron ore [48]. Partial or full replacement of natural aggregates with iron tailing aggregates is widely utilized in the building materials industry of China and has been observed to have improved mechanical and thermal properties, along with deicing characteristics, when used in asphalt [36, 48]. In an economic feasibility comparison, Cao et al. [48] found iron tailing aggregates (ITA) to be approximately 4.5 times cheaper than limestone and basalt natural aggregates. In addition to ITAs, magnetite (Fe_3O_2) is a rock mineral with a strong magnetic field and electrical resistivity of around $4.0x10^{-3}$ Ω-m and can also be considered as a good candidate for replacing natural aggregates in conductive asphalt since it has been reported to effectively improve its microwave absorption [49].

Nevertheless, previous research has mainly focused on improving the piezoresistive behavior while maintaining the required mechanical performance parameters of asphalt mixes. Moreover, the complex relationships between the Marshall parameters, asphalt ingredients, and different types of additives complicate understanding and prediction. With advancements in high-tech computing, machine learning algorithms are becoming more trustworthy and robust and can accurately predict outcomes. These machine learning algorithms can prove to be more fruitful if its application is extended to sustainable smart asphalt manufacturing. Hence, this study focuses on machine learning algorithms for predicting the Marhsall parameters of modified asphalt mixes containing varying contents of optimized bitumen, aggregates, and waste tire metal fiber at different mix ratios.

2.2. Modeling Techniques

Several machine learning algorithms have been used to predict various key civil engineering parameters. Leon et al. [55] used GEP to assess the effect of aggregate angularity on asphalt's permanent deformation. A total of 98 laboratory-prepared samples with varying percentages of angular, sub-angular, rounded, and sub-rounded aggregates were used in the study. Awan et al. [56] adopted multi-expression programing to assess the Marshall parameters based on a dataset comprising 253 and 343 samples for asphaltic base coarse and asphaltic wearing coarse, respectively. Khan et al. [57] utilized an artificial neural network (ANN) to develop the relationship between water-cement ratio, superplasticizer, flow, and 1-day and 7-day compressive strengths for predicting the 28-day compressive strength of semi-flexible pavement. Upadhya et al. [58] adopted an ANN, random tree (RT), RF, and the adaptive neuro-fuzzy inference system (ANFIS) for predicting the MS of glass fiber-modified asphalt. An ANN and least squares support vector machines (LS-SVM) were adopted by Khuntia et al. [59] to predict the air voids (AV), MS, and MF of waste polyethylene (PE)-modified bituminous mixtures. Nyirandayisabye et al. [60] used SVR, linear regression (LR), KNN, RF, a light gradient boosting machine (LGBM), gradient boosting regressor (GBR), DT regressor, and stacking regressor to evaluate the quality of pavement damage and distress. Pal et al. [61] utilized ridge regression, lasso regression, LR, SVR, KNN, ANN, DT, RF, AdaBoost, voting regressor, XGBoost, gradient boost, and cat-boost, to predict the compressive strength of rubber and recycled aggregate-modified fiber-reinforced concrete.

A classification strategy for a dataset is the DT, which is one of the most commonly used regression approaches. DTs are primarily composed of leaves, branches, and roots [62]. The DT model is simple to understand, interpret, and visualize and one of the simplest methods for determining the linkages between variables and the most essential variable [63]. DTs come in numerous varieties, including basic, thorny, and intermediate varieties. The difference between them is determined by the size of the smallest leaf. A DT is composed of branches, nodes, leaves, and other components, as presented in Fig. 1. DT regression separates nodes into sub-nodes depending on all factors and then selects the split with the most homogenous sub-nodes. The prediction result of the tree is taken from the leaf at the path's end. DT regression has been employed effectively by researchers in a range of fields [64-66].

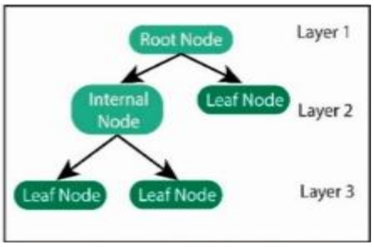


Fig. 1 General representation of DT [67]

3. Materials and Methodology

The aim of this study was to determine the optimal quantity of waste tire metal fiber (WTMF) and bitumen in a modified asphalt mixture and evaluate its performance using the DT machine learning algorithm. The criteria for selecting the research objects were based on the need to optimize modified asphalt mixes, utilize waste materials to promote environmental sustainability, and explore the application of these modified mixes for smart pavement materials, including electrical conductivity. The experimental process was segmented into several stages, each focused on achieving a specific milestone. The first step involved determining the optimum bitumen content (OBC) of both the control samples and each type of modified mixture containing a specified amount of WTMF. The input parameters were fiber content, bitumen content, aggregate percentage, and porosity. The next step was to develop an algorithm capable of optimizing the mix parameters. Finally, different statistical tools were applied to assess the performance of the developed models.

3.1. Materials and Sample Preparation

The study utilized locally sourced construction materials from Perak, Malaysia. Aggregates were acquired from Sunway Quarry Industries Sdn Bhd. The bitumen was selected to be 60/70 penetration grade, keeping in view its current usage in Malaysia. WTMF was employed as the primary electrically conductive additive in this study, as illustrated in Fig. 2. The dimensions of the WTMF used were 3-9 mm in length and 0.1 mm in diameter. The content of the metal fiber was selected to reinforce previous studies and address agglomeration, improper mixing, and compaction in high contents. Moreover, the Marshall mix design adopted in this study conforms to JKR standard specifications [68]. Asphaltic concrete with a maximum nominal aggregate size of 14 mm (AC-14) was used for the aggregate gradation and preparation of asphalt mixture samples, representing the wearing course of pavement. The aggregates were initially sieved to obtain the necessary size combinations according to particle dimensions. Fig. 3 shows JKR's specified aggregate gradation limits and the gradation envelope followed in this research.

Fig. 2 Waste tire metal fiber used in this study (Developed by the authors)

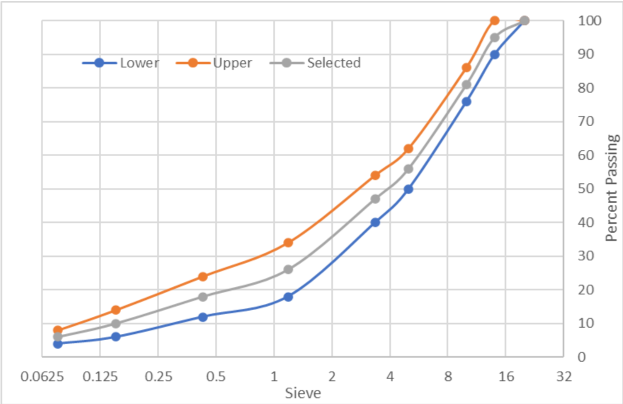


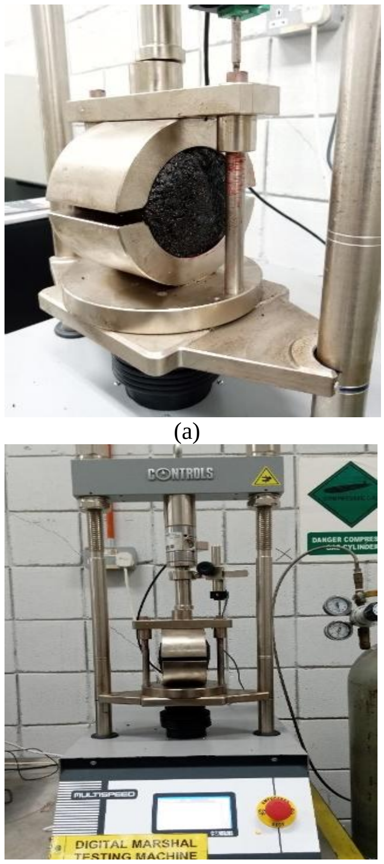
Fig. 3 JKR's aggregate gradation limits (Developed by the authors)

The Marshall mix design procedure is adopted to determine the optimum mix proportions for this study. First, the OBC is determined. The aim of determining the OBC is to maximize the durability of mix compositions by finding the ideal amount of bitumen for a specific type of mix. The OBC was determined for both the controlled mix and the WTMF-modified mixes following the Asphalt Institute procedure [69]. The OBC of each series differed from the other due to the varying WTMF content in each mix series.

The Marshall specimens, which measure 100 mm in diameter and 65 mm, were manufactured in compliance with ASTM D6926-20 [70]. 1200 grams of blended aggregates were incorporated into the formulation of each Marshall specimen, which consisted of a blend of bitumen and a specific amount of WTMF additive. Each mixture was composed of 44% coarse aggregates, 50% fine aggregates, and 6% mineral filler. The aggregates were first kept in an oven at 140-160°C to completely remove moisture. To ensure a seamless blending process, the fibers were incorporated in minor amounts during the dry mixing of the oven-dried aggregates with the pre-determined optimal bitumen content. The mix was then shifted to pre-heated specimen molds with a diameter of 100 mm and height of 63.5 mm to maintain the mixture temperature. The molds were internally lubricated and fitted with paper filters on both the top and bottom surfaces to prevent the compacted mix from adhering to the mold's surface. The filled molds were subsequently moved to a Marshall compactor, where they received 75 blows on each face of the specimen for compaction. The specimen was extruded from the mold and permitted to cool down to room temperature during the night. These samples were further tested for Marshall stability, flow, and volumetric properties.

3.2. Marshall Stability and Flow

The MS and flow tests are crucial for evaluating the ability of bituminous mixtures to withstand deformation and endure continuous traffic loads. Marshall stability represents the tensile strength of the asphalt mixture as its ability to resist rutting at high service temperatures, whereas the Marshall flow correlates the rutting resistance of the mixture, which shows the permanent strain that occurs at failure during a Marshall test. A total of 75 Marshall samples were prepared, including both the control and WTMF-modified series (Series A-D). This was achieved by combining JKR-graded aggregate with 60/70 penetration grade bitumen and the specified quantity of WTM fiber. The aggregate-bitumen mixture was directly inoculated with fiber during the dry mixing phase of the process. For compaction, all samples were given 75 blows per diametrical face using a standard Marshall compaction hammer. The equipment used in this study is shown in Fig. 4, where the test was performed at a continuous loading/deformation rate of 50.8 mm/min at 60°C. The maximum load at failure was recorded at the MS (kN). The specimens were placed in a water bath at the designated testing temperature for 25-30 minutes to simulate operational temperatures.



(a)

(b)

Fig. 4 Sample placement in a digital Marshall testing machine (Developed by the authors)

3.3. Model Development

In recent times, machine learning has become indispensable for automating simulations, allowing researchers to minimize the dependence on extensive laboratory testing. Several approaches are available that can be adopted to map the relationship between inputs and predict target outputs based on real-life data. This research employs a DT regressor, programmed in Python, to forecast the MS and MF of fiber-modified mixtures created in the laboratory. The performance of this model was evaluated using certain statistical tools based on which the best performing model was selected. This model was used to evaluate the importance of each input variable in the prediction of the output variables. Furthermore, this model was used to assess the output based on combinations that were not evaluated directly in the laboratory.

The MS and MF models were developed based on 75 datapoints divided into 80% of the training data and 20% of the testing data. The DT regressor was used to develop the model with input variables, aggregate percentage, asphalt content, fiber content, and porosity. Assessment of the model was performed using R-Square, Adjusted R-Square, and Mean Absolute Error (MAE) (Eq. 1-3). The best-performing model in terms of training data was deployed and used to calculate the optimal combination of input variables and the importance of each input variable in output prediction. The performance of the model is detailed in Table 1.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})}{\sum_{i=1}^{n}(y_i - \bar{y})} \quad (1)$$

$$Adj.R^2 = 1 - \left(\frac{\left(1 - \frac{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})}{\sum_{i=1}^{n}(y_i - \bar{y})}\right)(n-1)}{(n-p-1)}\right) \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{Y}_i\right| \quad (3)$$

where:

y_i, $\hat{Y}_i$ - actual and predicted output

$\bar{y}$, $\bar{Y}$ - mean values of actual and predicted outputs

n and p - number of observation and input variables, respectively

Table 1 Model's performance in both training and testing (Developed by the authors)

DT Model	Training	Testing
MAE	0.421	0.259
R-Square	0.901	0.937
Adj. R-Square	0.897	0.927

4. Results and Discussion

From the experimental data, it was decided to use bitumen content, aggregate percentage, fiber content, and porosity as input variables and MS and MF as output variables using DT regressor using Python programing. To guarantee that the dataset was devoid of any missing values, the k-nearest neighbor method was employed to replace any missing value in any variable with the closest value from among 5 values to either side. Fig. 5 and 6 show the distributions of the MS and MF for fiber contents at five different percentages, which includes the control. Every subplot in these figures presents one proportion of fiber content, where the mean, first quartile, third quartile, and lower and upper limits of both MS and MF can be observed. The datapoints are distributed evenly around the mean value of each percentage of fiber content. To make sure the data are normally distributed, an outlier check was performed, and it was concluded that two datapoints in the case of the MS were above the upper limit and ultimately discarded from the dataset. The details of the outlier check are given in Table 2 and Fig. 7.

Table 2 Outlier check (Developed by the authors)

	Q1*	Q2*	Q3*	IQR**	Lower limit	Upper Limit	Outliers
MS (kN)	10.609	12.525	14.535	3.925	4.721	20.423	23.044, 22.190
MF (mm)	3.134	3.637	4.301	1.167	1.383	6.052	None

* 1st, 2nd, and 3rd quartiles

** Interquartile range

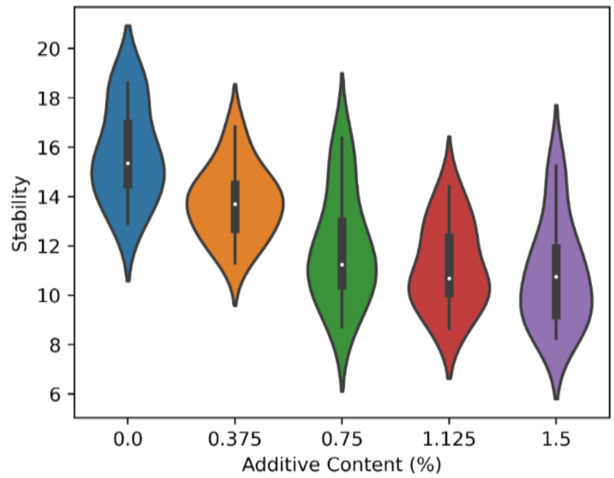


Fig. 5 MS distribution as a function of the additive content (Developed by the authors)

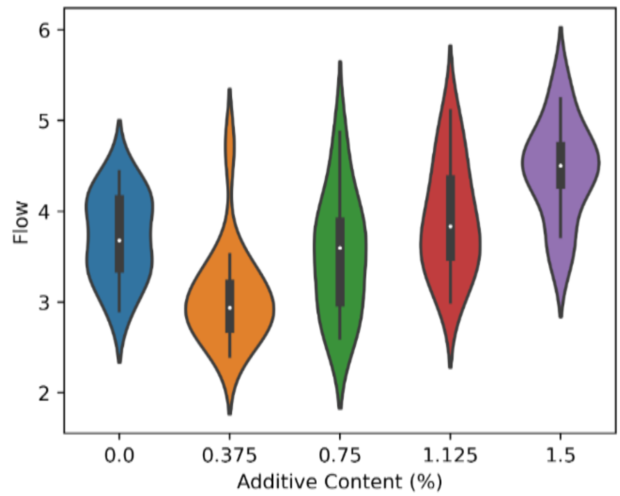


Fig. 6 MF distribution as a function of the additive content (Developed by the authors)

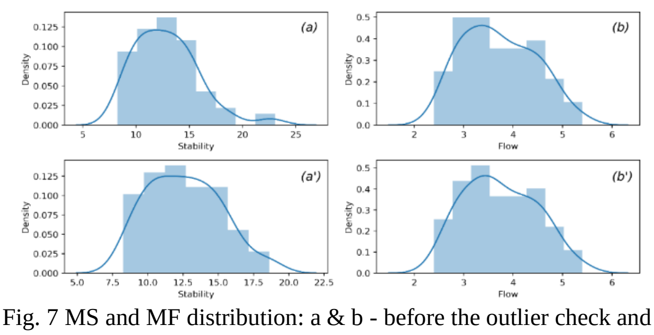


Fig. 7 MS and MF distribution: a & b - before the outlier check and a' & b' - after the outlier check (Developed by the authors)

The Pearson correlation coefficient was then computed between the input and output variables using Equation 4. According to Table 3, the skewness of all the variables falls within the normal distribution range of -0.5-0.5, with the exception of stability, which has a value of 0.95, indicating that the values of the MS are slightly positively skewed. Based on kurtosis, all the variables have significant peaks that are close to normal distribution. The details of the data distribution and correlation are presented in Table 3 and Fig. 8. In this figure, intense colors represent strong correlations, whether positive or negative, whereas lighter colors represent weak correlations.

$$C_{J-K} = \frac{\Sigma(J_i - \bar{J})(K_i - \bar{K})}{\sqrt{\Sigma(J_i - \bar{J})^2}\sqrt{\Sigma(K_i - \bar{K})^2}} \tag{4}$$

where:

$C_{J\text{-}K}$ - correlation of variable J with variable K

J_i, K_i - i^{th} entry of variables J and K

$\bar{J}$, $\bar{K}$ - mean value of variables J and K

Table 3 Descriptive statistics of the dataset (Developed by the authors)

	Additive Content (%)	Aggregate (%)	Binder Content (%)	Porosity (%)	Stability (kN)	Flow (mm)
Count	75	75	75	75	75	75
Mean	0.75	95.00	5.00	4.29	12.86	3.72
St. Dev.	0.53	0.71	0.71	1.63	3.03	0.73
Min.	0.00	94.00	4.00	0.63	8.25	2.40
Max.	1.50	96.00	6.00	7.99	23.04	5.40
Skewness	0.00	0.00	0.00	-0.32	0.95	0.29
Kurtosis	-1.31	-1.31	-1.31	-0.32	1.36	-0.83

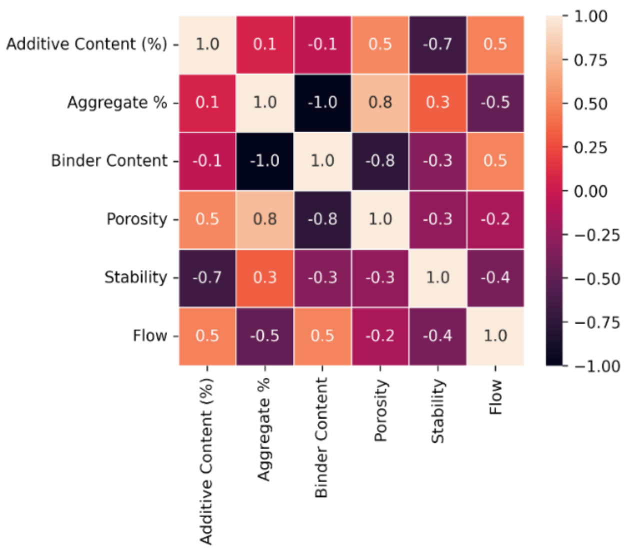


Fig. 8 Variable correlation matrix (Developed by the authors)

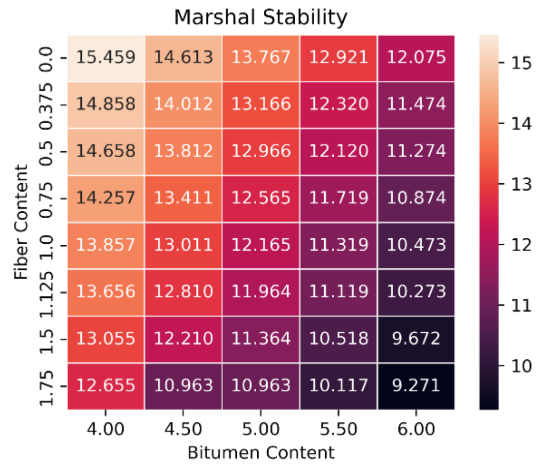


Fig. 9 Effects of fiber and bitumen contents on stability (Developed by the authors)

The DT model was used to map different values of input variables to assess the MS and MF. The direct results of the MS and MF in this study are limited to specific combinations. This machine learning model was used to calculate values that were not directly estimated in the laboratory. In this regard, the MS and MF values were predicted against 0.5%, 1%, and 1.75% fiber content while varying the bitumen content from 4% to 6%. The MS decreases with increasing fiber and bitumen contents, whereas the MF increases with increasing fiber and bitumen contents. The sensitivity of the MS to both fiber and bitumen contents remained almost constant, whereas the MF reacted differently to variations in bitumen and fiber contents. The effect of bitumen content on MF was smaller for lower fiber content, whereas the effect was observed to be greater with higher fiber content. The detailed predictions of the model are shown in Fig. 9 and 10.

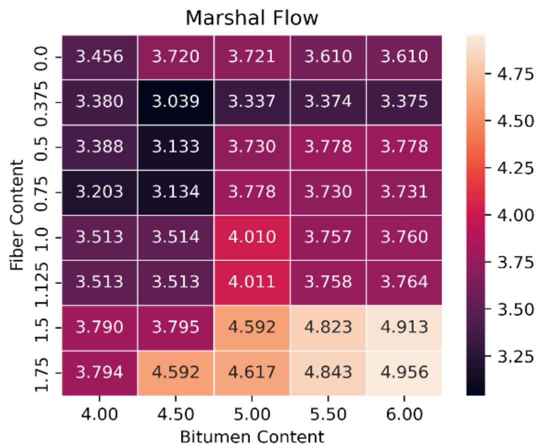


Fig. 10 Effects of fiber and bitumen contents on flow (Developed by the authors)

5. Conclusions and Recommendations for Future Research

This study makes a significant academic contribution by addressing the gap in machine learning applications for predicting the stability and flow performance of modified asphalt mixes. It introduces an innovative approach by incorporating waste tire metal fibers to enhance environmental sustainability and self-sensing behavior in asphalt. By exploring the application of DT machine learning algorithms on an extensive database, this study provides a deeper understanding of the complex relationships among modified asphalt ingredients.

This study explores the use of the DT algorithm for developing relationships between four input variables (fiber content, bitumen content, aggregate percentage, and porosity) to predict the MS and MF based on a dataset consisting of the results of 75 laboratory experiments. The relationship between input variables was successfully mapped using a DT regressor. The predictive power of the model was assessed using R-Square, Adjusted R-Square, and MAE. R^2 recorded for the model was 0.937 for testing data. The established correlation underscores the possibility of using this machine learning model to successfully predict the performance parameters of the modified mixes. Based on the model's predictions, the effect of bitumen content on flow values is stronger at higher percentages of fiber content than at lower fiber content. In conclusion, this research explores an innovative method for evaluating and forecasting the stability and flow performance of WTMF-modified mixes.

The results aid in the advancement of sustainable pavement design and offer valuable insights for both academic researchers and industry professionals in the field of asphalt technology. Such modified mixes can also contribute to the recycling and reuse of waste materials to reduce environmental impact. Further research and validation can be performed in the future to refine and expand the findings, which would ultimately advance machine-learning predictive practices in the pavement industry. A larger and more diverse dataset can be used to enhance the model's robustness and applicability across different scenarios. Other machine learning algorithms, such as neural networks, support vector machines, and ensemble methods, can also be used to compare their predictive accuracy and efficiency against the existing models.

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