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An Overview of Machine Learning Approaches for Predicting Marshall Parameters in Modified Asphalt Mixtures (MAM)

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ABSTRACT

Asphalt is a basic material used for pavements and roads construction due to its durability and capacity to endure loads, pressure and stress. To minimize construction cost, asphalt is typically combined with readily available and economically recycled materials. Some of these materials includes glass furnace dross, ashes from municipal waste incineration, crushed bricks, plastic, glass, and crumb rubber, sourced from waste tires. Evaluating Marshall parameters after modification is crucial to maintaining the original capacity of asphalt to withstand enormous stress. There are several Marshall Parameters of modified asphalt mixture (MAM) but Marshall Stability (MS) and Marshall Flow (MF) are the most critical parameters in evaluating the performance of the MAM. Researchers have repeatedly relied on Marshall test in the laboratory to determine the Marshall properties of MAM, which have proved to be expensive, labor-intensive, and tedious. Numerous studies have proposed machine learning (ML) models as an alternative to the traditional evaluation method of Marshall parameters of MAM. The popularity of ML models is largely due to their ability to learn patterns and predictive characteristics from complex data. ML models have been successfully used in the prediction of Marshall parameters of MAM with varying degrees of accuracy, as documented in the literature. Consequently, this paper examines the literature on the use of ML models for predicting Marshall Parameters, particularly MS and MF of MAM. This study identified several ML models, such as support vector machine (SVM), K-nearest neighbor, artificial neural networks, and random forest (RF), previously employed in this domain. The study also looked at various performance metrics used in evaluating the predictive accuracy of MS and MF. Some of the metrics include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). The paper also highlighted the potentials of ML models in reducing costs, time and labour as well as improving prediction accuracy. In addition the study also address challenges such as over fitting and the need for more quality and open source datasets. Recommendations for future research include the development of standardized datasets and the exploration of synthetic data to enhance model reliability and generalizability.

Keywords: Machine Learning, Marshal Parameters, Asphalt Mixtures, pavement construction.

INTRODUCTION

Asphalt is an important material used for pavements and roads construction. This is due to their durability, cost-effectiveness, and ability to withstand heavy traffic and temperature fluctuations. In addition, asphalt offers a smooth surface, reduces noise pollution, and improves driver visibility (Jwaida *et al.,* 2023). However, owing to the high cost of pavement and road construction, research has consistently explored alternative additives that are more economical and locally accessible, which could contribute to reducing the expenses associated with construction cost. One such measures is the use of inexpensive and locally available additives (Cai *et al.,* 2021). These additives not exhaustive, includes glass furnace dross, ashes from the incineration of municipal waste, crushed brick, plastics, glass, and crumb rubber derived from waste tyres. Using one or more of these materials to improve the performance of asphalt is referred to as modified asphalt mixtures (MAM) (Ameri & Ebrahimzadeh Shiraz, 2024; Bilema *et al.,* 2023). The performance, durability, and lifespan of pavements are profoundly affected by the strength and longevity of the bond between the bitumen (asphalt binder) and aggregate (stone or gravel) mixture. A robust bond ensures that the pavement can endure traffic, weather, and other environmental factors, whereas a weak bond may lead to premature failure (Khasawneh *et al.,* 2022). Marshall parameters, include Marshall stability (MS), Marshall flow (MF), air voids, voids in mineral aggregate and void filled with asphalt. These parameters determine the strength and stability of MAM and are usually evaluated before the mixture is used for construction. The Marshall test is often used to assess these characteristics of MAM. Its evaluate the performance and appropriateness of MAM in road and pavement building (Oguntayo *et al.,* 2023).

The traditional technique to determine the Marshall parameter of MAM is often time-consuming, expensive, and labor-intensive. This technique often require manual handling of materials and equipment, as well as intricate laboratory processes from trained individual, which result in increasing the cost of constructions (Awan *et al.,* 2022). Therefore, the need for alternative techniques that can reduce cost, improve efficiency, as well as user-friendly. Several studies have suggested the application of machine learning (ML) models to predict the Marshall parameters of MAM to overcome these challenges (Baldo *et al.,* 2022).

In the last decade, ML emerged as a powerful tool in solving difficult and complicated problems beyond human imagination in various fields, such as civil engineering, material science, healthcare, and marketing, among others. Therefore, the growing interest in the use of ML models to determine the Marshall parameters of MAM. ML techniques can analyze complex datasets and identify patterns that are difficult to discern using statistical methods (Dao *et al.*, 2020). This review critically evaluated several machine learning models used to determine the Marshall parameters of MAM particularly MS and MF of MAM. The rest of the paper is organized as follows. Section 2 provides an analysis of Marshall parameters of asphalt mixture, then Marshall test for asphalt mixture is examined in section 3. Thereafter, Machine Learning Approaches for Predicting Marshall Parameters of Asphalt Mixtures were discussed in section 4, followed by the performance metrics, related literatures and discussion for future studies in section 5, 6 and 7 respectively, before concluding in section 8.

Marshall Parameters of Asphalt Mixture

The properties or parameters of asphalt, known as Marshall parameters, are well defined by their characteristics and are traditionally obtained through a laboratory procedure called the Marshall test. The properties or parameters encompass Marshall stability (MS), Marshall flow (MF), air voids, voids in the mineral aggregate (VMA), voids filled with asphalt (VFA), and the Marshall Quotient, among others (Kaaf & Ibeabuchi, 2023). Asphalt serves as the primary aggregate binding material in the construction of roads and pavements. Consequently, the incorporation of alternative materials will influence performance, such as strength, durability, and resistance to various forms of stress during use (Sumargono *et al.,* 2020). Studies frequently use the Marshall test to evaluate the quality of asphalt mixtures, revealing numerous factors that impact on Marshall attributes. For instance, adding polyethylene to asphalt mixtures improves stability and satisfies surface course requirements (Rahman *et al.,* 2021).

The MS of asphalt mixture is a measure of the load-carrying capacity of the asphalt in use. It measures the maximum load an asphalt specimen can endure prior to failure; this is it resistance to deformation. This parameter indicates the resistance of the road or pavement to permanent deformation under traffic loads (Usanga *et al.,* 2025). The values are interpreted to mean that higher stability values indicate a more durable asphalt mixture and that the pavement can withstand heavy load and resist rust. The MF on the other hand is the measure of the ability to withstand deformation under load. This parameter indicates the flexibility and ability of the road or pavement to withstand traffic-induced stress (Taher & Ismael, 20220). The values are interpreted to mean lower flow values improved the stability. In other words, it is a measure of persistent deformation under load, reflecting plasticity and flexibility. The Air void of an asphalt mixture represents the

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percentage of air voids trapped in the compacted asphalt mixture. In terms of road and pavement construction, adequate air voids are necessary for durability and resistance to moisture (Rasheed *et al.,* 2024). The void mineral aggregate (VMA) of an asphalt mixture is the total void space within the aggregate structure before the asphalt binder is added. This parameter is critical in ensuring that road or pavement contains adequate asphalt content (Elmagarhe *et al.,* 2022). Voids filled with aggregate (VFA) is the percentage of VMA filled with asphalt binders. In road and pavement construction, proper VFA will ensure that there is sufficient asphalt coating of the aggregate which contributes to its durability (Sreedhar *et al.,* 2021). This review paper focuses on the most important properties of asphalt mixture which are the Marshall stability and the flow parameters of the MAM.

Marshall Test of Modified Asphalts Mixture

The Marshall test of MAM is the standard laboratory method design to determine the optimal amount of asphalt binder needed for durable and stable road or pavement construction. The test involves compacting cylindrical asphalt specimens and then subjecting to a compressive load until failure. The test determines the values of the two major parameters of an asphalt mixture Marshall stability and flow (Nada *et al.,* 2025). The Marshall Stability determines the maximum load a compacted sample of asphalt mixture can withstand deformation under a particular load. The test assists the engineer to determine the optimal asphalt binder concentrate needed for a particular mixture (Huang *et al.,* 2020). This exercise guarantee pavement and road constructed from such an asphalt mixture can withstand traffic loads, temperature fluctuations, and environmental stressors (Hamid *et al.,* 2022). The MS and MF are the two most crucial tests to determine the strength and durability of road and pavement resistance to deformation under load (Zhao *et al.,* 2020). These tests evaluate the strength of the asphalt mixture and ability to withstand pressure without deforming, ensuring the creation of durable and long-lasting roads (Dimter et al., 2021). Figure 1 is an E-version of Marshall stability test machine used for this purpose. This review paper provides an overview of machine learning methodologies for predicting Marshall Parameters in modified asphalt mixtures (MAM) and make recommendation for future research work.

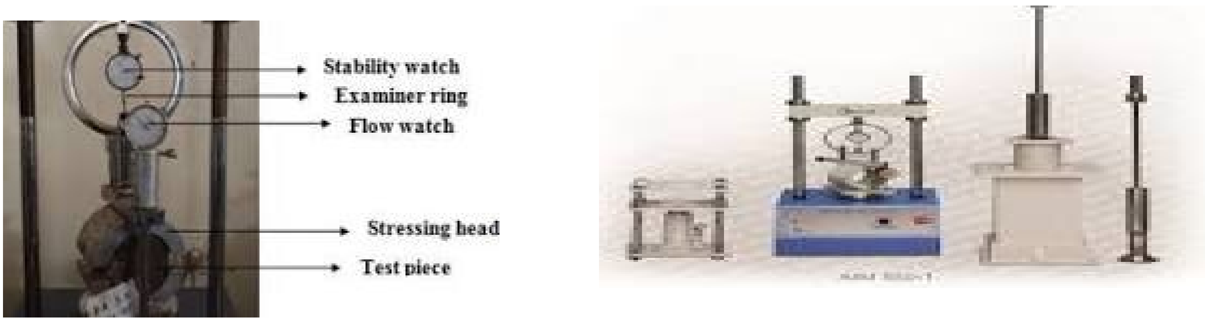

Figure 1: Marshall Stability Test Machine 50kN, Digimatic (E-Version) (Ogundipe, 2016)

Machine Learning Approaches for Predicting Marshall Parameters of Modified Asphalt Mixtures

Machine learning (ML) is a branch of artificial intelligence (AI), focuses on developing algorithms that enable computers to learn from complex data, learning patterns, make decisions or predictions without explicit programming (Mohalder *et al.,* 2024). This implies that the program improves its performance on a given task through experience. The learning process relies on the data used to train the algorithm. The system or model identify patterns and relations between data features and labels to create accurate relationships. ML is typically categorized into three main groups: supervised, unsupervised, and reinforcement learning (Singh *et al.,* 2023)

Supervised ML techniques are trained using labelled datasets, meaning that the correct output for each input is already known (Ali & Mashwani, 2023). The algorithm learns from this relationship between the input features and corresponding output data point. These algorithms are commonly applied in tasks such as image recognition, spam email detection, and the prediction of customer behavior. In contrast, unsupervised machine learning algorithms work with unlabeled datasets, seeking to identify hidden patterns and structures on their

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own, without human intervention. Unlike supervised learning, which relies on labelled data, unsupervised learning operates autonomously, discovering insights through the inherent structure of the data (Naeem *et al.,* 2023). Typical applications include clustering, dimensionality reduction, anomaly detection, and association-rule mining. Reinforcement learning, on the other hand, involves an "agent" that learns to make decisions within an environment by interacting with it and receiving feedback in the form of rewards or penalties. This process, akin to how humans learn through trial and error, enables the agent to improve its decision making over time to maximize its cumulative reward (Wang *et al.,* 2023). Based on typical taxonomies found in machine learning literature, Figure 2 generally illustrates the classification of ML algorithms into three main categories based on how they learn from data

Recent research has investigated the use of machine learning techniques to predict the Marshall design parameters of asphalt mixtures. Several algorithms, such as support vector regression (SVR), k-nearest neighbors (KNN), artificial neural networks (ANN), and random forest (RF), have been utilized on datasets that include material properties and mixture ratios (Nyirandayisabye *et al.,* 2022). This review article assesses existing machine learning prediction models for Marshall parameters of asphalt mixes and offers recommendations for the most effective strategies.

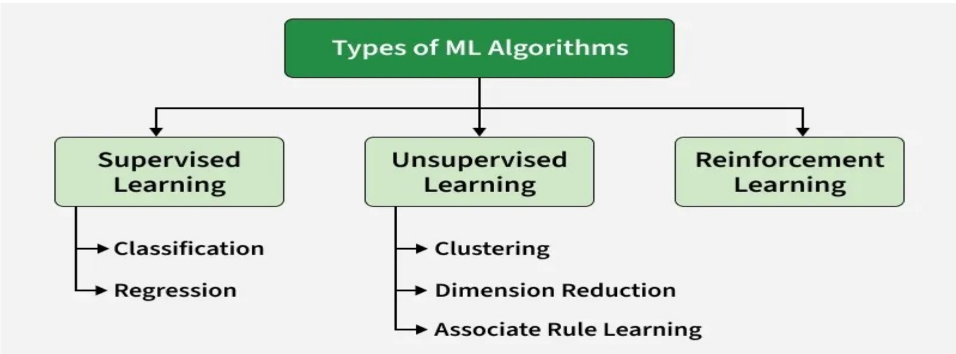

Figure 2: Machine Learning Algorithms

Performance Metrics for Evaluating Machine Learning Algorithms for Prediction of Marshall Parameters of MAM

Performance metrics are essential tools in machine learning used to assess a model's ability to perform a specific task. These metrics allow practitioners to evaluate the model's suitability, reliability, and effectiveness, making it easier to understand its strengths and weaknesses (Schlosser *et al.,* 2024). Choosing and applying the right performance metrics is crucial for validating and accepting a machine learning model. These metrics not only guide the optimization and refinement of algorithms but also influence how results are interpreted across various applications (Plevris *et al.,* 2022). When evaluating machine learning models that predict Marshall parameters—specifically, Marshall stability and flow of asphalt mixtures—metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE) are ideal for gauging prediction accuracy and assessing overall model performance (Asi *et a*l., 2024).

Root Mean Squared Error

Root Mean Squared Error (RMSE) is a statistic that takes the square root of the average squared difference between actual and predicted data points. It is often used to assess the performance of prediction models using continuous dat e squared to guarantee that both positive and negative numbers contribute favorably to th o not cancel out when summed. (Sharma *et al.,* 2022). Equation 1 presents the formula for determining RMSE.

$$RMSE = \sqrt{\frac{\Sigma(y_i - \hat{y}_i)^2}{n}} \qquad \textbf{......................................(1)}$$

In this context, y_i represents the actual values, $\hat{y}_i$ denotes the predicted values, and n is the total number of data points

Mean Absolute Error

The Mean Absolute Error (MAE) is a metric that quantifies the average size of errors between predicted and actual values. It is calculated by summing the absolute differences between the predictions and actual values, then dividing by the total number of samples. A lower MAE signifies better model performance (Schlosser *et al.,* 2024). Mat nula for MAE is as follows

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\textbf{(2)}$$

Here, n represents the number of samples, y_i denotes the actual value of the i^{th} sample, and $\hat{y}_i$ is the predicted value of the i^{th} sample.

Correlation Coefficient or Root squared (R^2)

The coefficient of determination (R^2) is the square of the correlation coefficient (R) between the observed outcomes and the corresponding predictor values. This metric assesses how well the model replicates the observed outcomes by measuring the proportion of the total variation in the outcomes that is explained by the model. Essentially, it quantifies the extent to which the independent variables (input features) can predict the variance in the dependent variable (Marshall parameter). R^2 ranges from 0 to 1, with higher values indicating a better fit of the model (Gao, 2024). Mathematically, R^2 is calculated using the formula in Equation 3.

$$MAE = \frac{\sum|y_i - \hat{y}_i|}{n} \qquad \text{--}\textbf{(3)}$$

SS_{res} refers to the sum of the squared residuals, while SS_{tot} represents the total sum of squares.

Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is a metric that quantifies the average absolute percentage difference between predicted and actual values. It is commonly used as a loss function in regression problems because of its straightforward interpretation, which reflects the relative error between predictions and actual outcomes. MAPE provides insight into the average size of the errors made by a model, essentially showing how far off the predictions are, on average. It is computed by averaging the absolute percentage differences between predicted and actual values. A lower MAPE indicates better model performance. The formula for calculating MAPE is shown in equation 4.

$$MAPE = \frac{\frac{1}{n} * \sum|(y_i - \hat{y}_i)|}{y_i} * 100\% \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\textbf{(4)}$$

In this context, n represents the number of data points, y_i denotes the actual value, $\hat{y}_i$ is the predicted value, and the symbol Σ stands for summation.

Related Literature

The behavior of asphalt concrete mixtures is complex, influenced by various loading conditions and environmental factors, which make predicting the Marshall parameters challenging. Among these parameters, Marshall Stability (MS) and Marshall Flow (MF) are the most crucial for determining the optimal bitumen content in asphalt mixtures. Traditional methods for determining these properties are time-consuming, expensive, and require specialized laboratory skills, creating a demand for more efficient, cost-effective, and accurate prediction models.

Several studies have suggested ML algorithms to address these challenges, and recent advancements have demonstrated the potential of ML models to predict Marshall parameters effectively. The application of ML offers the advantage of reducing the need for extensive laboratory testing, thus improving both the efficiency and sustainability of the asphalt mix design process.

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Zhang *et al.* (2021) emphasizes the importance of selecting appropriate mix design parameters and machine learning models to achieve accurate predictions. Their study employed support vector machines (SVMs) and genetic algorithms to predict the Marshall parameters (stability and flow) of MAM. The study compiled a comprehensive collection of Marshall mix designs, comprising 114 and 145 samples, based on three primary factors: bitumen content, coarse aggregate quantity, and compacted aggregate volume. The model's performance was evaluated using the correlation coefficient, which indicated a correlation of 0.85 for both Marshall stability and flow.

Awan *et al*. (2022) inspired by genetic programming, employed Multi Expression Programming (MEP), ML technique to design a predictive model for MS and MF. The study used Asphalt Base Course (ABC) and Asphalt Wearing Course (AWC) dataset containing 253 and 343 respectively to train and evaluate the model. The MAM includes eight features to predict MS and MF of MAM. The study evaluated the correlation coefficient (R), and external validation to assess model generalization capability. Experimental result show that correlation coefficient, exceeds 90%, consistent with the findings of Zhang *et al.* (2021).

In order to determine the most efficient ML algorithm to predict Marshall parameters of MAM, Upadhya et al. (2022) evaluated five different ML techniques. The techniques include M5P Tree, Random Tree (RT), Gaussian Processes (GP), Artificial Neural Networks (ANN), and Multiple Linear Regression (MLR). The dataset included 164 MAM observations with different bitumen concentrations, fibre diameters, fibre lengths, and combinations of glass and carbon fibres. The models' accuracy was evaluated using statistical metrics including Coefficient of Correlation (CC), R^2, MAE,RMSE, Relative Absolute Error (RAE), and Root Relative Squared Error (RRSE). The study demonstrated that the Artificial Neural Network (ANN) model outperformed alternative models, achieving a Coefficient of Correlation (CC) of 83% and an R-squared (R^2) of 70%. Additionally, it exhibited a lower Mean Absolute Error (MAE) of 1.5 and a Root Mean Square Error (RMSE) of 1.8 in testing. This study provides insights into enhancing MAM designs for better performance through machine learning predictions.

Gul *et al.* (2022) compared three predictive models for the prediction MS and MF in MAM, ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), and MEP. Dataset of 343 data points with nine predictive features were used for the experimental study. Evaluation metrics includes RSE, Nash-Sutcliffe efficiency (NSE), MAE, RMSE, RRMSE, R2, and R. The research demonstrated that the three models ANN, ANFIS, and MEP effectively predicted the Marshall parameters with R^2 values exceeding the acceptable threshold of 0.80 for both MS and MF during validation. However, MEP exhibited superior performance across training, and validation datasets, demonstrating a closer alignment with the ideal 1:1 slope. Results are displayed in Tables 1 and 2.

Althoey *et al.,* (2023) also compared MEP, ANN, ANFIS, and Ensemble Decision Tree Bagging (DT-Bagging) for the prediction of Marshall parameter of MAM. The study utilized a dataset comprising 343 data points. Evaluation metrics used includes RSE, NSE, MAE, RMSE, RRMSE, R^2, and R. The findings demonstrated that ANN, ANFIS, MEP, and DT-Bagging were effective and reliable. However, DT-Bagging model exhibited superior performance relative to other models, attaining 0.971 and 0.980 (R), 16.88 and 0.24 (MAE), 28.27 and 0.36 (RMSE), 0.069 and 0.041 (RSE), 0.020, 0.032 (RRMSE), 0.010 and 0.016 (PI) and 0.931 and 0.959 (NSE) for MS and MF, respectively. The study conclude that ML algorithms can efficiently, and accurately predict MS and MF of MAM with less time and cost, taking into account the resources and time necessary for conducting traditional Marshall tests.

Phung *et al.* (2023) developed predictive ML models Extreme Gradient Boosting (XGB) optimized with metaheuristic algorithms (Sailfish Optimizer and Aquila Optimizer), to predict MS and MF of MAM. Dataset comprises 265 observations collected from existing literature and performance evaluated using R^2 and RMSE metrics. The XGB model showed better prediction accuracy, with R^2 of 0.95 and RMSE of 0.189 for MS, and R^2 of 0.998 and RMSE of 0.189 for MF in the training datasets, which meant there were strong links between the predicted and actual MS values.

Prior research has successfully produced precise predictions for Marshall parameters, including MS and MF. Nevertheless, the models could not be generalized owing to the restricted dataset and input variables. Atakan &

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Yıldız (2024) aim to generalize machine learning (ML) by aggregating 407 data points from six distinct research with shared predictive attributes. The research included four ML techniques for the experiment: linear regression, polynomial regression, k-nearest neighbors (KNN), and SVR. The research findings from k-fold cross validation show that ML accurately predict MS and MF with SVR exhibiting better performance.

Ayazi *et al.,* (2024) In their study, experimented with random tree (RT), M5P, GP, SVM, and RF. The performance of the models in this study was evaluated using , CC, MAE, RMSE among others. Findings reveal that the RF model outperformed other algorithms on both the training and test dataset. The research concludes that ML techniques, particularly Random Forest, are effective tools for predicting the Marshall Stability of MAM.

Asi *et al.*, (2024) used explainable ML techniques, such as CatBoost, LightGBM, XGBoost, and Extra Trees, to predict MS and MF of MAM. The research utilized 721 data points, with predictive features such as aggregate percentage, asphalt content, and specific gravity. The models' performance was evaluated MAE and R^2. Experimental result revealed, CatBoost regression model had superior performance compared to alternative models, attaining R^2 values of 0.835 for MS and 0.845 for MF. The study conclusion was consistent with other study that ML method can efficiently predict MS and MF of MAM.

Due to the limited availability of quality datasets for Marshall parameter prediction research, Asif *et al.* (2025) used Generative Adversarial Networks (GANs) to enhance the existing dataset. This study utilized 184 primary data samples obtained from various construction sites. The primary dataset was used to generate synthetic dataset for data augmentation. Both synthetic and primary dataset were used to train two models: Gene Expression Programming (GEP) and ensemble learning with stacking (ELS). The performance of both synthetic and primary data was compared. The findings indicate that the synthetic dataset generated with GAN model significantly enhanced model accuracy, with GEP and ELS achieving R^2 values exceeding 0.93 in all cases. The study emphasizes the efficacy of advanced ML techniques and data augmentation in creating dependable predictive models for the outcomes of the Marshall design test, thereby enhancing efficient MAM design practices.

Table 1. Machine Learning Model Performance Evaluation for Marshall Stability of MAM

Studies	**ML Model**	R^2	RSE	**RMSE**	**MAE**
Zhang et al. (2021)	SVM	0.90	0.18	157.03	91.8
	GP	0.87	0.26	181.2	108.3
Awan et al. (2022)	MEP	0.96	0.07	46.62	36.30
Gul et al. (2022)	ANN	0.95	-	31.46	24.36
	ANFIS	0.97	-	32.22	23.56
	MEP	0.97	-	27.58	20.89
Upadhya et al. (2022)	SVM	-	-	0.82	0.32
	GP	-	-	2.43	1.97
	RF	-	-	0.90	0.50
	RT	-	-	0.06	0.0322
	M5P	-	-	1.50	1.115
Althoey *et al*., (2023)	ANN	0.97	-	30.95	25.88
	ANFIS	0.97	-	28.34	23.12
	MEP	0.98	-	26.75	21.89
	DT-Bagging	0.98	-	26.78	14.06
Phung et al. (2023)	XGB	0.998	-	0.19	0.05
Ayazi et al. (2024)	RT	-	-	0.04	0.01
	M5P	-	-	1.42	1.13
	GP	-	-	1.29	0.95
	SVM	-	-	0.33	0.15
	RF	-	-	0.40	0.31

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Asi et al. (2024)	CatBoost	0.79	-	128.66	91.81
	ETB	0.73	-	138.79	95.06
	LightGBM	0.69	-	147.41	106.91
	Extra Trees	0.67	-	152.79	106.90
	GBR	0.64	-	159.84	120.81
Asif et al. (2025)	GEP	0.88	0.13	81.87	55.92
	ELS	0.91	0.10	71.80	48.79

Table 2. Machine Learning Model performance Evaluation for Marshall Flow of Modified Asphalt

Studies	**ML Model**	R^2	RSE	**RMSE**	**MAE**
Zhang et al. (2021)	SVM	0.95	0.09	0.85	0.496
	GP	0.921	0.15	1.06	0.78
Gul et al. (2022)	ANN	0.961	-	0.47	0.36
	ANFIS	0.980	-	0.40	0.30
	MP	0.979	-	0.35	0.27
Althoey *et al*. (2023)	ANN	0.947	-	0.44	0.53
	ANFIS	0.963	-	0.47	0.42
	MP	0.973	-	0.42	0.35
	DT-Bagging	0.981	-	0.33	0.23
Phung et al. (2023)	XGB	0.927	-	0.185	0.144
Asif et al., (2025)	GEP	0.89	0.11	0.58	0.38
	ELS	0.88	0.12	0.50	0.33

Discussion and Further Research Directions

The literature examined, clearly shown that MAM behavior is influenced by several conditions and environmental factors, making the prediction of Marshall parameters such as MS and MF very challenging. Traditional methods for determining these parameters are time-consuming, expensive, and require specialized laboratory skills. Multiple studies explored the potential of ML techniques to address the limitations of traditional methods. These techniques aim to improve efficiency, reduce costs, and enhance the accuracy of predicting MS and MF. Various ML models, such as SVM, ANN, MEP, and others, have been successfully applied to predict these parameters. Despite promising results, many models face limitations in generalizing due to small, restricted datasets. Researchers like Atakan & Yıldız (2024) and Asif *et al.* (2025) aim to improve generalization by expanding datasets using techniques like dataset from literature and GANs for dataset augmentation. Newer techniques, such as explainable machine learning (Asi *et al.,* 2024) and ensemble learning (Asif et al., 2025), are used to enhance model accuracy and interpretability. Models like Random Forest and CatBoost show superior predictive performance and offer insights into the variables affecting MS and MF predictions. ML methods not only reduce the reliance on extensive laboratory testing but also contribute to more sustainable asphalt design practices. By using advanced data augmentation techniques and machine learning models, researchers aim to make the prediction process more efficient and applicable to real-world scenarios.

The use of ML for the prediction of MS and MF has made significant progress. However, this paper identified the following areas which are critical to further research directions

Dataset Limitations: While several studies have made significant progress, many models rely on relatively small or region-specific datasets (Awan *et al.,* 2022; Zhang *et al*., 2021). The procedure for obtaining this dataset is tedious, expensive and time consuming. Future research should focus on aggregating data from diverse geographical regions and varying conditions to develop more standardized dataset for the development of a generable model for the prediction of MS and MF of MAM.

Model Interpretability: Although advanced models such as ANN and XGB show high accuracy, their interpretability remains limited. Research into explainable AI (XAI) methods could enhance the understanding of how input variables affect prediction outcomes, aiding in the development of more transparent and reliable models.

Hybrid Models: Further investigation into the combination of multiple ML models or hybrid approaches could offer improved prediction accuracy and robustness, as each model might complement the weaknesses of others.

By addressing these gaps, future research can contribute to the development of more reliable, efficient, and generable ML models for predicting the Marshall parameters in MAM, ultimately lead to improved road and pavement construction and maintenance practices.

CONCLUSION

MAM has proven effective in enhancing the durability of asphalt concrete, particularly in resisting rutting and fatigue, while also offering economic benefits for pavement construction. Traditionally, engineers have relied on laboratory tests to determine the MS and MF of MAM. However, these tests are expensive, labor-intensive, and time-consuming. This study has demonstrated the promising potential of ML models in predicting the Marshall parameters, specifically MS and MF, for MAM. By leveraging ML techniques, it is possible to significantly reduce the time, cost, and labor associated with traditional Marshall testing methods. The review highlights several effective algorithms, such as SVR, ANN, and RF, each offering unique advantages in terms of accuracy and computational efficiency. However, challenges such as data scarcity and over fitting remain significant obstacles to the widespread adoption of ML for asphalt testing. The paper recommends future research into the development of standardized datasets, as well as the use of synthetic data, to address these challenges. Additionally, further refinement of ML models to mitigate bias and improve generalizability will be crucial for their practical implementation in the asphalt industry. Ultimately, ML holds substantial promise for optimizing the design and performance assessment of MAM, contributing to more cost-effective and durable road and pavement solutions.

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