

Article

AI-Driven Prediction of Bitumen Content in Paving Mixtures: A Hybrid Machine Learning Model Applied to Salalah, Oman

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Abstract

Sustainable pavement solutions that lessen the dependency on virgin materials are required due to mounting environmental and economic pressures. Although recycled asphalt concrete (RAC) has structural and environmental advantages, binder heterogeneity and non-linear material interactions make it difficult to predict the ideal bitumen content in RAC mixtures. This study predicts the bitumen content of asphalt mixtures infused with RAC by combining sophisticated machine learning (ML) with traditional laboratory testing. While this study combines AI-driven predictions with experimental insights to create a state-of-the-art framework for sustainable pavement engineering, 780 data points were obtained from the preparation and testing of three mixtures (0%, 30%, and 50% RAC) for volumetric and mechanical characteristics. Controlled Autoregressive Integrated Moving Average (CARIMA), Swapped Autoregressive Integrated Moving Average (SARIMA), radial basis function artificial neural network (RBF), bagging (BAG), multi-layer perceptron (MLP) artificial neural network, and boosting (BOT) ensembles were among the models created. BAG-CARIMA-LGM is a new hybrid model that combines logistic probabilistic generalization, ensemble variance reduction, and time-series forecasting. Higher predictive accuracy and resilience across different RAC levels were attained by the hybrid BAG-CARIMA-LGM model, which performed noticeably better than standalone algorithms. The findings demonstrated improved Marshall stability and controlled flow along with a progressive decrease in mean bitumen content as RAC increased. While 50% RAC with rejuvenators maintained durability and structural integrity, the 30% RAC mixture produced the most balanced performance. The model's capacity to manage non-linear interactions, volumetric variability, and aging effects was validated by statistical analyses. The BAG-CARIMA-LGM hybrid model optimizes RAC incorporation in asphalt mixtures, supports circular economy goals, and improves technical accuracy. The results point to a revolutionary route towards intelligent, environmentally friendly road systems that support international sustainability objectives.

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Keywords: hybrid machine learning; bitumen content prediction; recycled asphalt concrete; eco-resilient pavements; AI predictive framework; sustainable asphalt infrastructure

1. Introduction

Sustainable pavement engineering is evolving rapidly due to global environmental concerns, constraints on natural resources, and requirements for enhanced performance. Recent studies [1,2] have emphasized the necessity of virgin aggregates and bitumen consumption reduction and the better use of novel modifiers, additives, or recycling methods. However, soaring material prices, the consumption of natural resources, and global warming issues have catalyzed the push to employ bio-based materials, polymers, and industrial byproducts that can provide better mechanical properties together with longer pavement durability [3,4]. The use of recycled and waste-based materials embodies the principles of a circular economy. Fibers from textiles [5], waste glass, plastics [6], red mud [7], and incineration ash [8] have all been seen to improve the stiffness, durability, and rutting resistance of asphalt. Furthermore, because these materials can modify the micro-structural characteristics of asphalt binders, functional additives and nanomaterials are becoming more and more popular. While Duan et al. [9] exposed the aging retardation effects of zinc oxide/vermiculite composites, Hassan et al. [10] showed the reinforcing potential of nano-CaCO₃ and basalt fibers. In a similar vein, Monticelli et al. [11] investigated bio-oil-modified heavy polymer–asphalt systems, demonstrating enhanced fracture behavior for mixtures with high recycled asphalt concrete (RAC) content. With parallel developments in warm-mix asphalt technologies [12], Çakı and Baş [13] demonstrated notable reductions in emissions and energy consumption, reinforcing the importance of second-generation chemical and nanostructured additives in maximizing sustainability and performance.

AI-assisted pavement design has expanded, particularly for binder content prediction in mixtures containing RAC. Studies by Saleh et al. [14,15] and Ghafari et al. [16] show that neural and hybrid models can accelerate mix design and improve performance forecasting for crumb rubber- and RAP-modified systems. Combining digital modeling with targeted laboratory testing can reduce trial-and-error iterations while delivering cost-effective, durable, and more sustainable pavements.

Predicting bitumen content is necessary because RAC mix design is a high-uncertainty decision problem: aged binder heterogeneity and strongly non-linear interactions among recycled constituents, recycling agents, and modifiers can shift the optimum binder dosage. Small dosing errors can propagate into volumetric imbalances, reduced durability, and variable field performance. In this context, machine learning prediction can reduce iterative laboratory trials and improve repeatability by learning coupled relationships between measured mixture descriptors and the target bitumen content.

Salalah, in the Governorate of Dhofar (Sultanate of Oman), provides a practical setting for recycled asphalt concrete (RAC) because routine pavement rehabilitation yields reclaimed asphalt streams that can be reincorporated into new mixtures. In this study, RAC was recovered from 260 deconstructed pavement samples in Salalah, screened to remove contaminants, and reintroduced at 30% and 50% replacement alongside locally sourced aggregates. However, aged binder heterogeneity and non-linear binder–aggregate interactions make the optimum bitumen content sensitive to blending uncertainty and rejuvenator effectiveness [1]. This local context strengthens the case for coupling laboratory characterization with the hybrid AI-based prediction of bitumen content,

consistent with AI-enabled asphalt design studies that address complex performance behavior and cracking resistance [16].

This study positions the BAG-CARIMA-LGM hybrid as a layered prediction-and-decision pipeline for RAC mix design, where “modifier” variables represent only one subset of the control feature space. CARIMA provides a time-series-with-controls backbone by selecting model orders (P , d , q) using information criteria and residual diagnostics (AICc/BIC; Ljung–Box) and by applying cross-regime error checks to capture curing and aging drift [17]. Bagging aggregates bootstrap-trained trees (approximately 100 trees; depth 5–10) to reduce variance and improve robustness under heterogeneous recycling regimes [18]. Finally, the logistic probabilistic model (LGM) calibrates outputs to physically admissible bounds (0–1) via a logit link estimated by maximum likelihood, supporting uncertainty-aware decision making [12]. This tripartite design targets temporal non-stationarity, recycling-level heterogeneity, and the need for constrained, decision-grade predictions.

Preliminary research on thiophene-modified binders [19] and mining waste additives [20] laid the groundwork for the sustainability-oriented design of mixes. Subsequent studies demonstrated that rejuvenated high-RAP mixtures can achieve the properties of virgin asphalt [21] when facilitated by polymer or bio-based modification [22]. This departure from empirical charts towards predictive modeling has allowed AI-based applications to assist with the uncertainties associated with sustainable mix design [22,23]. AI hybrids offer novel predictive insights into conventional ensembles, and the functions of rejuvenators and recycling agents in high-RAC mixtures have been well documented. Evaluations of rejuvenator effects on bitumen aging in hot recycled asphalt have shown temperature-dependent efficiencies that can be sequentially modeled by CARIMA components [22]. The performance of recycled mixtures has been shown to be improved by polymer-modified binders, acting as rejuvenators to manage binder blending uncertainty [24]. By using LGM localization to inform sustainable predictions, the analysis of bio-recycled asphalt fumes has revealed reductions in organic compounds. Blending charts used to forecast performance in high-RAP scenarios have shown significant improvements, but hybrids outperform them by combining ensemble robustness and data-driven autoregression [25,26]. All these studies support the novel advantage of hybrids in comprehensive bitumen prediction for environmentally friendly pavements. The superiority of AI hybrids in cost–benefit analyses is highlighted by technical and economic assessments of recycled asphalt mixtures.

Despite several studies performed regarding RAC, there are vital areas that remain unaddressed. Studies show that very little work has been conducted on the combined effects of bio-modifiers, nanomaterials, and recycled aggregates [27], and AI predictions have yet to be fully integrated into mechanistic–empirical design methodologies. There is also little evidence on the effects of waste-based fillers in combination with bio-additives, since a balance between durability, environmental benefits, and structural performance is needed. Previous work demonstrates that these hybrid models (bagging (BAG), Controlled Autoregressive Integrated Moving Average (CARIMA), and large geospatial models (LGMs)) are superior to single-model methods in RAP optimization and foamed bitumen design because they can accurately represent non-linear responses [9,13,28]. Unlike other research that has concentrated on discrete modifiers, our study integrates sustainability evaluation within a unified framework of predictive modeling and recycled materials. The current study posits that AI hybrids, such as BAG-CARIMA-LGM hybrids, are superior in predicting RAC samples due to their capacity to integrate ensemble variance reduction with autoregressive and localized modeling, thereby providing foundational elements for developing robust pavement solutions with a high degree of recyclability.

The central question of this research is whether this combination hybrid can successfully predict binder content through a range of RAC mixtures (0%, 30%, 50% RAC) that are themselves heterogeneous and where aging, variability, and non-linearity place strain on conventional models. Moreover, there is lack of integration of AI predictors with mechanistic–empirical thinking and understudied interactions between bio-/nanomodifiers and recycled constituents. Based on a laboratory dataset of 780 samples, including volumetric Marshall property tests, the hybrid consistently outperformed the baseline models by demonstrating novelty and practical necessity. The hybrid approach serves to combine the aging-capturing effects of CARIMA, the variance reduction capabilities of BAG, and the bounded mixture behavior modeling abilities of LGMs, filling the gap between experiment-based testing and intelligent ambitious sustainable-oriented pavement design. This holistic approach contributes to the development of sustainable, durable, high-performance asphalt systems that can meet both present and future infrastructure needs.

2. Methodology

This study follows an experimental–computational approach that uses traditional pavement engineering methods alongside modern machine learning (ML) algorithms to optimize the content of bitumen in asphalt mixtures with recycled asphalt concrete (RAC). The methodology is a hybrid approach between laboratory-based material characterization and data-driven predictive modeling to resolve binder aging, material heterogeneity, and non-linear interactions that are related to recycled materials. The experimental studies were performed based on the ASTM and AASHTO standards, and ML analysis was introduced into Python 3.12 with the help of existing and custom hybrid libraries.

2.1. Materials and Mix Design

RAC was sampled from 260 deconstructed pavement samples in Salalah, Oman and sieved and manually examined to eliminate contaminants. Virgin aggregates (crushed granite, basalt, and limestone) were obtained in local quarries, and the gradation, specific gravity, durability, and cleanliness were in accordance with the ASTM specifications. There were three mixtures of asphalt:

- *Mix A: 0% RAC (control, fully virgin materials);
- *Mix B: 30% RAC (blended with virgin aggregates);
- *Mix C: 50% RAC (high-recycling formulation, incorporating rejuvenators to restore binder properties).

The range of bitumen was 4.552% and that of mineral filler was between 4 and 6% by aggregate weight. Mix C was the only mix that was reinforced with rejuvenators to increase binder compatibility and workability.

2.2. Extraction and Characterization of Binders

To avoid thermal degradation, the aged binder was separated by the centrifuge procedure in trichloroethylene solvent (ASTM D2172) and recovered by means of rotary evaporation (ASTM D5404). The recovered binder was described in terms of viscosity (at 135 °C), stiffness (at 20 °C), penetration, and softening point. These properties were used in the direction of blending modifications using virgin 60/70 penetration-grade bitumen to achieve the desired rheological performance with recycled mixes, as shown in Table 1.

Table 1. Reclaimed binder properties using centrifuge extraction and rotary evaporator recovery.

Sample	Extraction Method	Recovery Method	Viscosity (Pa·s at 135 °C)	Stiffness (MPa at 20 °C)	Penetration (dmm)	Softening Point (°C)
Reclaimed Binder	Centrifuge Extraction	Rotary Evaporator	1.30	220	40	49

2.3. Marshall Testing and Preparation of Samples

Marshall specimens (101.6 mm diameter, 63.5 mm height) were prepared using 75 blows per face (ASTM D6926), with at least three specimens per blend. After conditioning for 24 h at 25 °C, the bulk density, air voids, VMA, VFB, Marshall stability, and flow were measured following ASTM D6927 and ASTM D3203. Additional testing included indirect tensile strength (ASTM D6931), moisture susceptibility (AASHTO T283), and thermal sensitivity testing from −12 °C to +40 °C using a universal testing machine. The dataset comprised 780 specimen records (260 per mixture—(0% RAC, 30% RAC, 50% RAC)), each including stability, flow, Gmb, Gmm, VMA, and ITS measurements for machine learning modeling.

2.4. Machine Learning Framework

The optimum content of bitumen at different levels of RAC was predicted using ML models. The applied models were Controlled Autoregressive Integrated Moving Average (CARIMA), Swapped Autoregressive Integrated Moving Average (SARIMA), radial basis function neural networks (RBFs), multilayer perceptron (MLP), bagging (BAG), boosting (BOT), and a hybrid BAG-CARIMA-LGM model. They were implemented with statsmodels (SARIMA/CARIMA), scikit-learn (BAG/BOT), TensorFlow/Keras (ANNs), and bespoke hybrid modules. To assess the model's performance in terms of its robustness and ability to predict, cross-validation and measures of error were considered. Comprehensively, the combined approach allows the effective optimization of recycled asphalt mixtures and helps to address the goals of the circular economy by using more RAC when it does not negatively affect mechanical performance.

2.5. Machine Learning Modeling for Bitumen Content Prediction

A hybrid machine learning system that involved time-series, ensemble, and neural models was created to forecast the optimum content of bitumen under variability in RAC. While autoregressive modeling was used to characterize the aging of binders, ensemble learning was used to deal with the heterogeneity of materials, and neural networks were used to deal with non-linear interactions, leading to a hybrid BAG-CARIMA-LGM model. The data consisted of 780 samples whose input values were stability, flow, Gmb, VMA, and Gmm, and the target was the bitumen content. BC represents the bitumen content (%) of the paving mixture under the centrifuge method, MS is the Marshall stability (KN), MF represents the Marshall flow (mm), BSG stands for the bulk-specific gravity of compacted asphalt (Gmb), VMA stands for voids in mineral aggregates (%), and MSG represents the maximum specific gravity of the paving mixture (Gmm). Min-max normalization and 80:20 train tests were all performed as part of data preprocessing. Moreover, 5-fold cross-validation of 6 feature configurations was included (Table 2 and Supplementary Materials).

Table 2. Input and output parameters of developed models for different configuration elements.

Model #	Model Configuration	Method	Bitumen Content (%)
1	MF	CARIMA, SARIMA, BAG, BOT, MLP, RBF	BC
2	MF + MS	CARIMA, SARIMA, BAG, BOT, MLP, RBF	BC
3	MF + MS + VMA	CARIMA, SARIMA, BAG, BOT, MLP, RBF	BC
4	MF + MS + (MF) ² + (MF) ²	CARIMA, SARIMA, BAG, BOT, MLP, RBF	BC
5	MF + MS + BSG + VMA + MSG	CARIMA, SARIMA, BAG, BOT, MLP, RBF	BC
6	MF + MS + (MF) ² + (MS) ² + (MF) ³ + (MS) ³	CARIMA, SARIMA, BAG, BOT, MLP, RBF	BC

#: Input model configuration number.

2.5.1. Controlled and Swapped Autoregressive Integrated Moving Average Models

An enhanced ARIMA-based model was applied to improve stability and robustness when modeling RAC-affected pavement datasets. Controlled ARIMA (CARIMA) extends classical ARIMA by incorporating exogenous control inputs (e.g., RAC level, compaction, curing, and modifier indicators), enabling the conditioning of time-ordered performance data. The model works on curing-/aging-indexed sequences, and it is formulated as

$$(L - \sum_{i=1}^P \phi_i L^i)(1 - L)^d y_t = c + \beta^T X_t + \left(1 + \sum_{j=1}^q \theta_j L^j\right) \varepsilon_t \quad (1)$$

where y_t is the response variable, X_t denotes control inputs, and P, d, q represent autoregressive, differencing, and moving-average orders. The stabilization of forecasts in the case of variability caused by RAC and the simulation of rejuvenator effects as external inputs was achieved using Bayesian priors and iterative error correction. CARIMA was also applied in Python with a train test split of 75:25 and showed increased resistance to non-stationarity compared to standard ARIMA. Simultaneously, a SARIMA model was fitted with a swap-based cross-regime validation procedure, in which the parameters obtained at one level of RAC were tested at another to determine how robust they were to changes in composition. The formulation of the underlying SARIMA was not altered, and seasonal extensions allowed modeling of the compaction cycles and aging effects. When used on 780 samples of data, SARIMA selection and probabilistic validation led to an improvement in the accuracy of the prediction of volumetric indicators (Gmm and VMA). Table 3 summarizes the CARIMA input–output combinations. Bitumen content (BC, %) was measured by the centrifuge method. Marshall stability (MS, kN), Marshall flow (MF, mm), the bulk-specific gravity of compacted mixtures (Gmb), voids in mineral aggregates (VMA, %), and maximum specific gravity (Gmm) were used as predictors.

Table 3. Input and output combination parameters used in the CARIMA model to predict bitumen content under various asphalt mixture constituents in Salalah, Oman.

Model #	Input Configuration	Asphalt Mixture Constituents	Estimate
1	MF	Mix 0% RAC	$CARIMA = 1.5851.110(MF)$
2	MF + MS	Mix 0% RAC	$CARIMA = 1.525 + 0.921(MF) + 0.032(MS)$
3	MF + MS + VMA	Mix 0% RAC	$CARIMA = 1.680 + 0.920(MF) + 0.032(MS) - 0.011(VMA)$
4	MF + MS + (MF) ² + (MF) ²	Mix 0% RAC	$CARIMA = 10.902 - 10.346(MF) + 0.478(MS) + 2.479(MF)^2 - 0.014(MS)^2$
5	MF + MS + BSG + VMA + MSG	Mix 0% RAC	$CARIMA = 20.083 - 0.921(MF) + 0.032(MS) - 0.734(BSG) - 0.024(VMA) - 6.531(MSG)$
6	MF + MS + (MF) ² + (MS) ² + (MF) ³ + (MS) ³	Mix 0% RAC	$CARIMA = 7.473 - 7.215(MF) + 0.466(MS) + 1.778(MF)^2 - 0.014(MS)^2 - 0.0001(MS)^3 + 0.001(MS)^3$

1	MF	Mix 30% RAC	$CARIMA = 2.137 + 0.798(MF)$
2	MF + MS	Mix 30% RAC	$CARIMA = 1.172 + 0.411(MF) + 0.119(MS)$
3	MF + MS + VMA	Mix 30% RAC	$CARIMA = 1.847 + 0.400(MF) + 0.115(MS) - 0.040(VMA)$
4	MF + MS + $(MF)^2 + (MF)^2$	Mix 30% RAC	$CARIMA = 1.172 + 0.411(MF) + 0.119(MS) - 0.001(MF)^2 + 0.001(MS)^2$
5	MF + MS + BSG + VMA + MSG	Mix 30% RAC	$CARIMA = -0.998 + 0.396(MF) + 0.116(MS) + 1.058(BSG) - 0.019(VMA) + 0.001(MSG)$
6	MF + MS + $(MF)^2 + (MS)^2 + (MF)^3 + (MS)^3$	Mix 30% RAC	$CARIMA = 1.156 + 0.530(MF) + 0.102(MS) - 0.001(MF)^2 - 0.007(MS)^2 - 0.007(MS)^3 + 0.001(MS)^3$
1	MF	Mix 50% RAC	$CARIMA = 4.171 - 0.152(MF)$
2	MF + MS	Mix 50% RAC	$CARIMA = 4.043 - 0.153(MF) + 0.009(MS)$
3	MF + MS + VMA	Mix 50% RAC	$CARIMA = 4.258 - 0.153(MF) - 0.009(MS) - 0.014(VMA)$
4	MF + MS + $(MF)^2 + (MF)^2$	Mix 50% RAC	$CARIMA = 2.561 + 1.057(MF) + 0.009(MS) - 0.001(MF)^2 - 0.247(MS)^2$
5	MF + MS + BSG + VMA + MSG	Mix 50% RAC	$CARIMA = 2.993 - 0.153(MF) + 0.008(MS) + 0.526(BSG) - 0.013(VMA) + 0.001(MSG)$
6	MF + MS + $(MF)^2 + (MS)^2 + (MF)^3 + (MS)^3$	Mix 50% RAC	$CARIMA = 2.243 + 1.044(MF) + 0.042(MS) - 0.001(MF)^2 - 0.001(MS)^2 - 0.244(MS)^3 + 0.001(MS)^3$

#: Input model configuration number. BC represents bitumen content (%) of paving mixture by centrifuge method, MS is Marshall stability (KN), MF represents Marshall flow (mm), BSG stands for bulk-specific gravity of compacted asphalt (Gmb), VMA stands for voids in mineral aggregates (%), and MSG represents maximum specific gravity of paving mixture (Gmm).

2.5.2. Radial Basis Function (RBF) Neural Network

The radial basis function (RBF) neural network uses a three-layered neural network that relies on unsupervised and supervised learning to predict non-linear behavior in RAC-modified asphalt mixtures. The Marshall stability, flow, VMA, and Gmm are features in the input layer used to identify localized data clusters. The hidden layer uses unsupervised learning to estimate Gaussian kernel centers and spreads, which allows for reduced overfitting when there is variability due to RAC. The fixed post-clustering first-layer weights are similar to those in k-means-based center selection. Supervised least-squares optimization was used to train the output layer to regress the content of bitumen. This local approximation can be used to treat material heterogeneity [29]. The model was used in TensorFlow/Keras with 50–100 centers with 1.0–0.1, which supports the sustainable design of asphalt.

2.5.3. Multilayer Perceptron (MLP) Artificial Neural Network Model

The multilayer perceptron (MLP) is a type of feed-forward neural network that can be applied to address non-linear interdependent relationships between RAC-modified asphalt mixtures and optimize the content of bitumen. The model uses the back-propagation of learning under supervision to reduce the mean squared error of the output between predictions and measurements. Marshall testing volumetric and mechanical inputs were used as inputs to one or more hidden layers, which were processed using ReLU or hyperbolic tangent activation functions. Regression was performed using linear output neurons.

In TensorFlow/Keras, the MLP was applied with the Adam optimizer (500 epochs, drop-out = 0.2) to achieve stabilized and reproducible predictions.

2.5.4. Bagging Ensemble (BAG) Model

Introduced by Breiman [30], the bagging ensemble (BAG) model eliminates variance in heterogeneous RAC-modified asphalt datasets by boosting samples with the help of bootstrap sampling and the aggregation of numerous base learners. The parallelization of training on resampled data decreases forecasting and overfitting, especially with decision tree models, as described in a previous study [31] and the Supplementary Materials. The method enables the more precise optimization of the bitumen content when RAC variability occurs. BAG was also combined with localized granular models (LGM) to identify RAC-specific sub-patterns. The scikit-learn package was used to implement the model on 100 decision trees with a maximum depth of 5–10, and this supported sustainable asphalt mix design.

2.5.5. Boosting Ensemble (BOT) Model

The boosting ensemble (BOT) model, which was first introduced by Freund and Schapire in 1996 as a sequential learning technique, creatively transforms weak learners into robust predictors by repeatedly concentrating on cases that are misclassified or have high residuals. This minimizes the loss function by using gradient descent and adaptive reinforcement. This framework improves predictive associations among features like Marshall stability, flow, and volumetric parameters in recycled asphalt concrete (RAC) mixtures by building a base regression tree with options for optimal subtree pruning and surrogate splits to handle missing data. An aggregated strong model that lowers bias and variance for non-linear bitumen content forecasting was produced by initializing uniform probabilities across training samples (for example, 75% of the 780-sample dataset), creating bootstraps for sequential predictors, and updating weights based on iteration-specific loss calculations.

2.5.6. Hybridization of CARIMA with BAG and a Logistic Probabilistic Model (LGM)

As a flexible framework for modeling binary or bounded outcomes in pavement engineering, the logistic probabilistic model (LGM), which is based on the continuous logistic distribution as a member of the exponential family, converts linear predictor combinations into S-shaped cumulative probabilities between 0 and 1 using the logit link function estimated through maximum likelihood to determine variable significance. Table 4 below describes a transparent, reproducible hyperparameter-tuning protocol that documents the grid structure, selection rules, and final choices per model layer in the tripartite architecture. Details of the model setup can be found in the studies of Agbor et al. and Nwokolo [32–36] and the Supplementary Materials.

Table 4. Concise hyperparameter summary (tested grid and selected settings).

Model Layer	Hyperparameter(s)	Tested Grid/Options	Selection Criterion	Optimal Setting Used In Study
CARIMA (time-series with controls)	(P,d,q) orders; differencing; variance transform (if needed)	$P \in \{1,2,3\}$, $d \in \{0,1\}$, $q \in \{0,1,2\}$; activate (d) if KPSS indicates non-stationarity; apply variance-stabilizing transform if needed	Minimize AICc/BIC; Ljung–Box residual whiteness; confirm on 5-fold CV RMSE	“Configuration 4” (AICc/BIC minimum for the reported feature set); specific (P,d,q) recorded per RAC regime in the derivation section/appendix
BAG (bagging ensemble)	# trees; max depth; bootstrap	$\eta_{estimates}$ fixed (100); max depth searched in a bounded	5-fold CV RMSE (tied by lower	$\eta_{estimates} = 100$; max depth selected within the stated range by CV

		range (e.g., 5–10); bootstrap on	MAPE), hold-out confirmation	
MLP (Tensor- Flow/Keras)	Hidden layers; neurons/layer; activation; epochs; drop- out; optimizer	Depth $\in \{2,3\}$; width ≈ 50 –5-fold CV RMSE (tie- broken by MAPE), $\epsilon \in \{tanhReLU\}$; epochs = 500; dropout = 0.2; Adam	CV-selected depth/width within grid; training fixed at epochs = 500, dropout = 0.2, Adam	
LGM (logistic calibration)	Location (μ), scale (s) (or equivalent lo- gistic param- eters)	Estimated by maximum like- lihood per RAC regime; no grid	MLE convergence; calibration residual diagnostics	MLE-estimated (μ, s) used for probabilistic fusion/uncertainty

To handle heterogeneous datasets like those for recycled asphalt concrete (RAC) mixtures, the LGM creatively goes beyond traditional logistic regression by incorporating localized generalizations, such as spatially varying coefficients or kernel-based adaptations. Figure 1 highlights the overall division of labor across stages—the time-series structure in CARIMA, robustness and uncertainty quantification in bagging, and probability calibration in the LGM—making the rationale and benefits of the proposed hybrid architecture obvious at a glance.

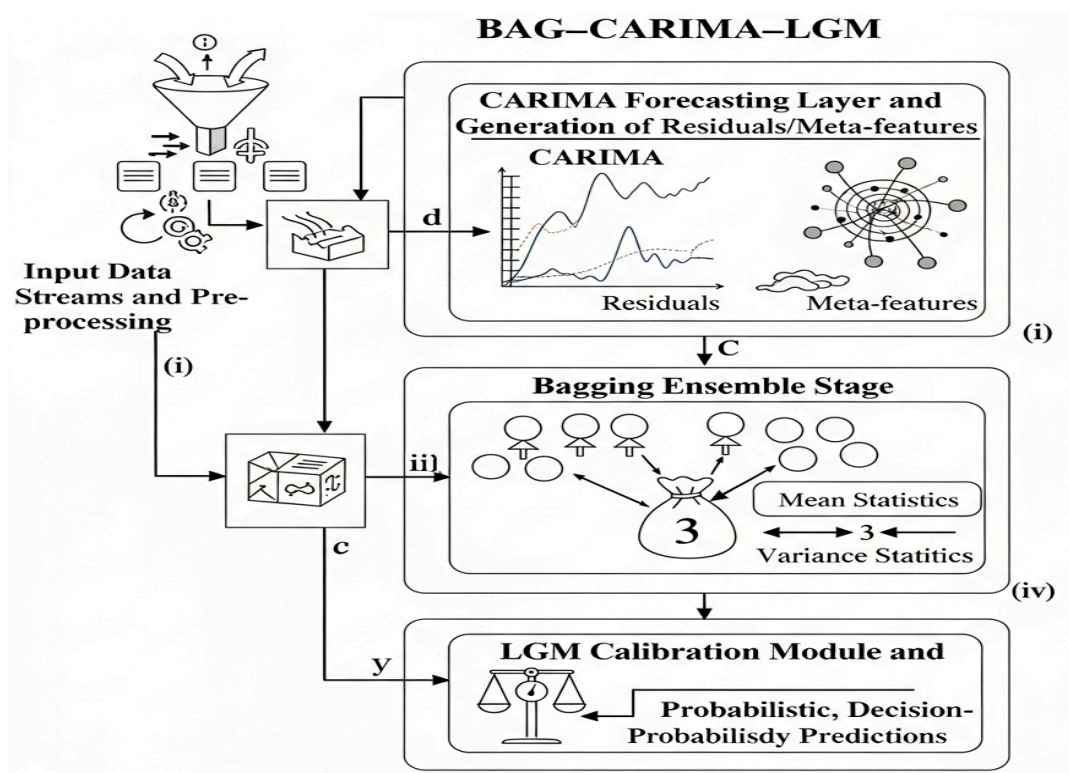


Figure 1. Schematic of the BAG-CARIMA-LGM hybrid pipeline showing RAC-stratified input data, CARIMA forecasting, residual/metafeature extraction, bagging ensemble aggregation (mean/variance), and LGM calibration, yielding probabilistic predictions.

Table 5 illustrates the complete derivation of the hybridization of BAG and CARIMA with the logistic probabilistic model (BAG-CARIMA-LGM) to estimate bitumen content under 0%, 30%, and 50% recycled asphalt concrete (RAC) combinations.

Table 5. Hybridization of BAG and CARIMA with the logistic probabilistic model (BAG-CARIMA-LGM) to predict bitumen content under four recycled asphalt concrete (RAC) mixtures.

Bitumen Content Parameter	Mathematical Model
Bitumen content under 0% recycled asphalt concrete (RAC) mixture	$\text{BAG} - \text{CARIMA} - \text{LGM} = 10.944 - 10.416(MF) + 0.480(MS) + 2.489(MF)^2 - 0.0141(MS)^2$
Bitumen content under 30% recycled asphalt concrete (RAC) mixture	$\text{BAG} - \text{CARIMA} - \text{LGM} = -1.002 + 0.398(MF) + 0.116(MS) + 1.062(BSG) - 0.019(VMA) + 0.001(MSG)$
Bitumen content under 50% recycled asphalt concrete (RAC) mixture	$\text{BAG} - \text{CARIMA} - \text{LGM} = 2.647 + 8.864(MF) - 1.401(MS) - 1.762(MF)^2 + 0.049(MS)^2$

2.6. Rationale for the Hybrid BAG-CARIMA-LGM Model's Selection Among Several Prevalent Machine Learning Models

The BAG-CARIMA-LGM architecture was selected to address three RAC mix design challenges: temporal non-stationarity during curing and aging, heterogeneity across recycling levels, and the need for physically constrained, decision-grade outputs. CARIMA captures sequential drift and provides forecasts and a residual structure; bagging reduces variance using a lightweight ensemble that remains stable on specimen-limited laboratory datasets; and the LGM stage calibrates predictions to admissible binder ranges for practical decision making. The use of the tripartite BAG-CARIMA-LGM (advanced) prediction method is justifiable by the realities of recycled asphalt concrete (RAC) mix design, where parameters are simultaneously time-varying (curing/aging drift), non-homogeneous across recycling levels, and constrained by the admissible binder ranges needed for decision-grade outputs—conditions under which single learners tend to be either unstable, overfit, or physically unconstrained. The method demonstrates its advantages by explicitly allocating the “division of labor” across layers: CARIMA captures sequential drift and residual signatures, bagging suppresses variance/overfitting under specimen-limited laboratory data, and LGM calibration enforces bounded outputs while addressing uncertainty limits, avoiding the computational burden of deep sequence models under the same data budget. These advantages are evidenced in the study’s comparative results: ensemble-only and classical time-series baselines remain around $R^2 \approx 0.72$ – 0.76 for the control mix, whereas the hybrid achieves $R^2 > 0.96$ with low error metrics and sustained generalization as RAC increases (reported training $R^2 = 0.983$, testing $R^2 \approx 0.970$, and $\text{RMSE} < 0.40$), including robust performance in the demanding 50% RAC case, where SARIMA/CARIMA and MLP/RBF degrade sharply. This layered hybrid logic is consistent with prior reports stating that hybridizing ARIMA-family predictors can improve stability via adaptive error correction [29] and that bagging-style variance reduction strengthens robustness in heterogeneous engineering datasets [31].

CARIMA models sequential drift and exposes forecast and residual characteristics, which are bagged with a lightweight bagging ensemble (approximately 100 shallow trees) that is stable on small laboratory data. The LGM stage implements admissible binder ranges through a logistic connection and implements uncertainty limits through optional Beta-likelihood modeling. This is superior to high-capacity deep sequence models of specimen-limited workflows because it is a more efficient design. A comparison with SARIMA, CARIMA, BAG, BOT, MLP, and RBF proves high accuracy in 0, 30, and 50% RAC regimes. It is worth noting that the hybrid has close-to-perfect fits at 0% RAC and large gains at high RAC ($R^2 = 0.967$ at 50% RAC), with a low RMSE and MaxAPE.

2.7. Analytical Tools and Performance Evaluation

Models were evaluated using the coefficient of determination (R^2), mean absolute percentage error (MAPE), root mean square error (RMSE), and maximum absolute percentage error (MaxAPE), with hyperparameter tuning via grid search, as shown in Equations (2)–(5):

$$R^2 = 1 - \left[\frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - O_{ave})^2} \right] \quad (2)$$

The root mean square error (RMSE) evaluates the absolute predictive accuracy, defined as

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2} \quad (3)$$

which is further normalized to the maximum absolute percentage error (MaxAPE) for cross-dataset comparability:

$$MaxAPE = \max \sum_{i=1}^n \left| \frac{O_i - P_i}{O_i} \right| \quad (4)$$

Additionally, the mean absolute percentage error (MAPE) is crucial for understanding relative deviations:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{O_i - P_i}{O_i} \right| \quad (5)$$

3. Results and Discussion

3.1. Unlocking Sustainable Pavement Potential: Statistical Dynamics of RAC-Infused Asphalt Mixtures

In Table 6, the descriptive statistics indicate that the mean bitumen content decreases in a systematic manner upon increasing the RAC content of the asphalt mixture in Salalah, Oman, with the value of 4.078% (0% RAC) reducing to 4.020% (30% RAC) and 3.885% (50% RAC). The narrowing of the variability also occurs at higher levels of RAC, which points to the enhanced stability of the mixtures. This is a trend that is consistent with existing results indicating that old binders in reclaimed materials will increase the efficiency of the binder even without the addition of virgin bitumen [37]. Reports of the reduced bitumen demands (i.e., better interfacial bonding and rejuvenation) in high-RAC and additive-modified mixtures are consistent with these results. The reduced min-max ranges also indicate stabilized binder behavior, which contributes to sustainable asphalt design, minimizes the consumption of materials, and ensures the maintenance of their durability [9].

Table 6. Unlocking sustainable pavement potential: statistical dynamics of RAC-infused asphalt mixtures.

Aggregate Property	Asphalt Mixture Constituents	N	Minimum	Maximum	Mean	Std. Deviation
Bitumen content (%) of paving mixture	Mix 0% RAC	260	3.850	4.300	4.078	0.131
	Mix 30% RAC	260	3.740	4.300	4.020	0.109
	Mix 50% RAC	260	3.640	4.130	3.885	0.120
Marshall stability (KN)	Mix 0% RAC	260	12.720	17.800	15.073	1.303
	Mix 30% RAC	260	14.310	17.000	15.818	0.577
	Mix 50% RAC	260	14.040	16.690	15.271	0.530
Marshall flow (mm)	Mix 0% RAC	260	2.000	2.500	2.247	0.092
	Mix 30% RAC	260	2.110	2.570	2.360	0.083

	Mix 50% RAC	260	2.190	2.660	2.401	0.089
Bulk-specific gravity of compacted asphalt (Gmb)	Mix 0% RAC	260	2.375	2.393	2.384	0.005
	Mix 30% RAC	260	2.362	2.400	2.381	0.007
	Mix 50% RAC	260	2.360	2.398	2.380	0.008
Voids in mineral aggregates (VMA) (%)	Mix 0% RAC	260	14.200	15.200	14.787	0.252
	Mix 30% RAC	260	14.200	15.700	14.878	0.330
	Mix 50% RAC	260	14.200	15.900	15.130	0.346
Maximum specific gravity of paving mixture (Gmm)	Mix 0% RAC	260	2.519	2.521	2.520	0.001
	Mix 30% RAC	260	2.515	2.525	2.520	0.002
	Mix 50% RAC	260	2.515	2.524	2.519	0.002

From Table 6, the Marshall stability increases from 15.073 kN (0% RAC) to 15.818 kN (30% RAC) and then declines slightly to 15.271 kN at 50% RAC, consistent with non-linear performance trends in recycled asphalt mixtures [10]. The flow increases modestly with RAC (2.247 to 2.401 mm), indicating higher deformability while remaining controlled. Lower variation at higher RAC levels (Table 6) suggests improved mix homogeneity and flexibility without compromising structural integrity [6]. The bulk-specific gravity remains essentially constant, indicating stable aggregate–binder compatibility across the studied mixtures.

The tripartite BAG-CARIMA-LGM functions as an inverse-design surrogate, learning the correlations between specimen responses (such as Marshall stability/flow and essential volumetric indices) and bitumen content. Consequently, its “optimum asphalt content” is anticipated to align closely with a Marshall-calibrated optimum, provided that identical compaction energies, specimen preparation, and acceptance criteria are employed, as the input features are derived from the Marshall testing protocol for each RAC regime. Nonetheless, discernible discrepancies may arise in comparison to traditional Marshall (and particularly Superpave) standards, as the model’s objective is the extracted and quantified binder content (via centrifuge or solvent recovery). In contrast, in conventional mix design, “optimum asphalt content” typically pertains to binder addition or the effective binder chosen to meet specific volumetric performance criteria (e.g., target air voids and VMA-related limitations) and assumptions regarding field-representative densification. In recycled asphalt concrete (RAC) mixtures, the partial blending of aged and virgin binders, binder absorption into aggregates, and rejuvenator-facilitated compatibility can alter the correlations between the added binder, effective binder, and extracted binder, resulting in a consistent offset even when performance metrics appear comparable. Thus, the model’s optimum must be regarded as calibrated to the Marshall-type feature space, and any comparison to Marshall or Superpave optima should be presented as a bias/transferability assessment (side-by-side optima + error), necessitating recalibration or domain adaptation if the deployment protocol (compaction method, criteria, or region-specific materials) varies.

3.2. Unveiling Synergistic Bitumen Dynamics in Virgin Asphalt Mixtures: Heatmap Insights into Stability, Flow, and Volumetric Optimization

The relationship between bitumen content and key volumetric and mechanical properties in virgin asphalt mixtures (0% RAC) governs their durability and performance and therefore remains central to mix design. These coupled responses influence the stability, flow, and void structure under site-specific traffic and climate conditions, as illustrated in Figure 2.

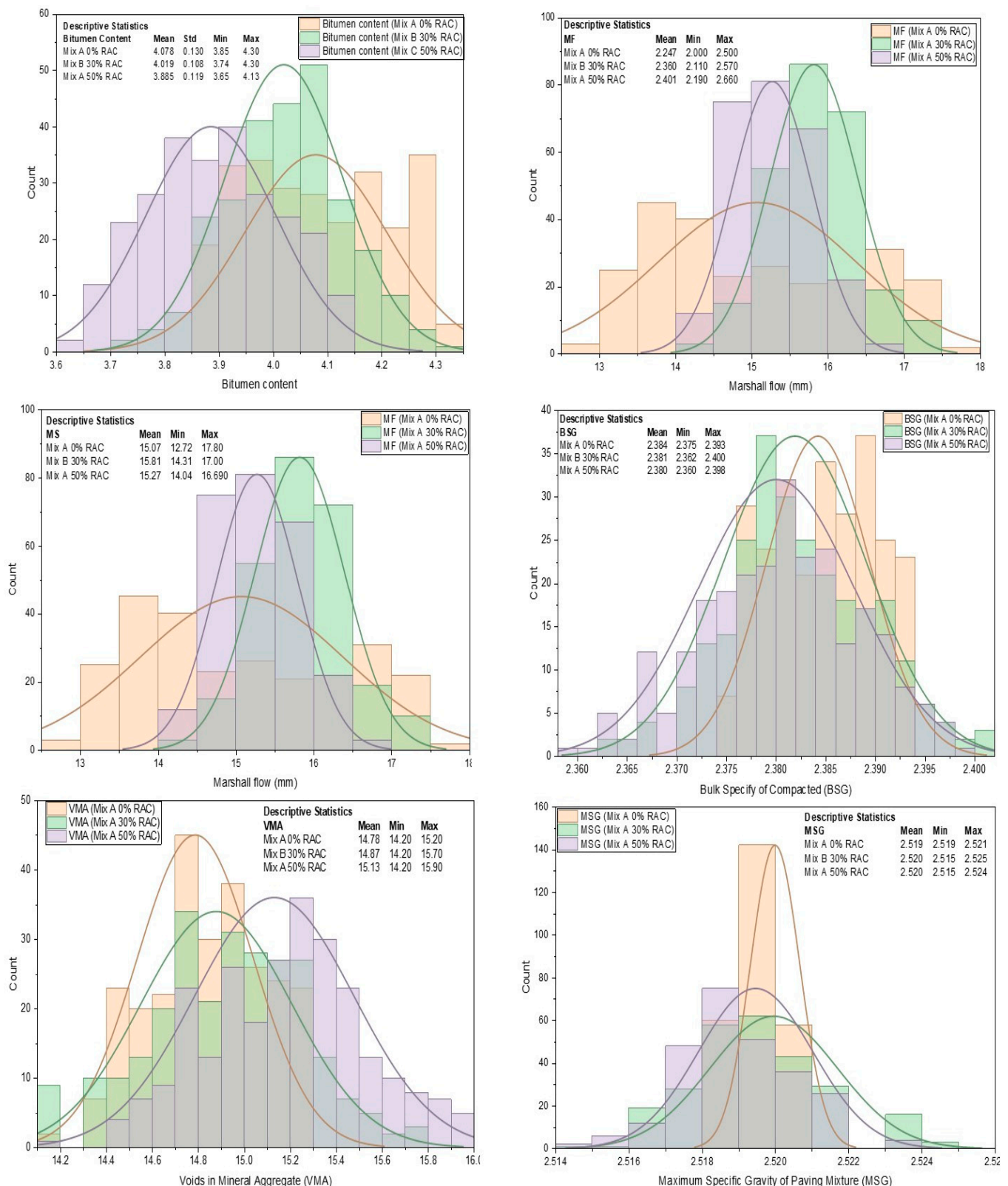


Figure 2. Unlocking sustainable pavement potential: frequency distribution dynamics of RAC-infused asphalt mixtures.

The amount of bitumen extracted by centrifugation is a crucial factor affecting the overall matrix cohesion and void structure in Mix A configurations, which do not include any recycled materials. Recent developments in artificial intelligence-driven formulations

for crumb rubber-modified hot-mix asphalt (HMA), as investigated by Ghafari et al. [16], highlight the possibility of the predictive modeling of these interactions. Saleh et al. [15] also show how AI can be used to optimize foamed bitumen mixtures without RAP, emphasizing the necessity of precise bitumen dosing to achieve balanced properties. Clustered data points across binned ranges are depicted in the heatmaps, which show non-linear dependencies consistent with laboratory studies on the effects of deployment given by Bérubé et al. [37], although theirs were modified for virgin contexts. This all-encompassing perspective, which excludes recycling agents, highlights sustainable design concepts similar to those in Duan et al. [9], where zinc oxide composites slowed down aging and it is implied that bitumen levels of 4.0% could improve long-term resilience to environmental stresses. Additionally, even in zero-RAC situations, knowledge from Monticelli et al. [11] on bio-oil additives for high-RAP mixes suggests novel ways to improve fracture behavior through regulated bitumen interactions.

3.3. Mechanistic Foundations of Stability–Flow Synergy in RAC-Infused Asphalt: Microstructure, Interfacial Adhesion, and Aging–Kinetic Coupling

The observed stability and flow trends across RAC levels align with a micromechanical picture in which the reclaimed binder acts initially as a stiffening, polarity-rich mastic that improves aggregate interlocking and adhesive bonding, up to a compositional threshold where incomplete blending, interphase heterogeneity, and embrittlement begin to localize shear and reduce the peak strength. Blending chart evidence indicates that the aged binder in RAC can partially replace virgin bitumen without sacrificing mixture rheology, supporting the stability rise at intermediate RAC as the effective binder phase stiffens, while the film thickness remains adequate for load transfer [37]. The rejuvenator-assisted diffusion of maltenes into the reclaimed binder promotes colloidal rebalancing during curing, moderating the stiffness and guarding against premature microcrack nucleation—an aging–kinetic pathway consistent with the controlled increases in flow observed at higher RAC [28]. Where bio-oil and polymeric modifiers are present, the fracture behavior improves by toughening the mastic and enhancing crack bridging at aggregate interfaces, a mechanism that rationalizes stability retention near the high-RAC end when the rejuvenation quality is sufficient [11]. Aging retardation via nanomineral additives further slows oxidative crosslinking, sustaining interfacial adhesion and delaying the transition from cohesive mastic failure to adhesive debonding under Marshall loading [9]. Viscosity modeling for reclaimed/virgin blends supports this interpretation by linking a reduced effective viscosity (after rejuvenation and partial blending) to controlled deformation, explaining the modest, systematic elevation in flow with RAC while preserving structural integrity [38]. Together, these materials science mechanisms—diffusive re-equilibration, interfacial energy enhancement, and microstructure-controlled film thickness—convert the descriptive statistics into a coherent narrative of RAC-enabled strengthening followed by heterogeneity-limited performance at very high recycling content, consistent with the study’s stability–flow envelope.

3.4. Smart Hybrid Learning for Precision Bitumen Modeling in Recycled Asphalt Concrete in Salalah, Oman

3.4.1. Machine Learning-Driven Model Prediction of Bitumen Content in Paving Mixtures

As the industry moves towards environmentally friendly practices incorporating waste materials, the incorporation of machine learning models for predicting bitumen content in asphalt mixtures with varying levels of recycled asphalt concrete (RAC) represents a significant advancement in sustainable pavement engineering. Comprehensive fit statistics for six modeling approaches—SARIMA, CARIMA, BAG, BOT, MLP, and RBF—

across configurations 1 through 6, evaluated under 0%, 30%, and 50% RAC levels, are shown in Table 7 and Figures 3–5. In line with recent advancements in recycled textile fibers [5] and red mud enhancements [39], which seek to minimize industrial waste while preserving performance, these findings highlight the potential of AI-driven predictions to optimize mixture designs. These models enable accurate bitumen dosing by obtaining high R^2 values and low error metrics in lower-RAC scenarios. This is essential for improving the durability of mixtures modified with zinc oxide composites [9] or bio-oil additives [11]. By reducing the use of virgin materials and utilizing artificial intelligence to formulate low-temperature crack-resistant hot-mix asphalt (HMA) [16], this comprehensive approach opens the door to environmentally responsible and economically viable road infrastructure.

Table 7. Model fit statistics for bitumen content under 0%, 30%, and 50% recycled asphalt concrete (RAC) mixtures.

Model Parameters		Model Fit Statistics for 0% RAC				Model Fit Statistics for 30% RAC				Model Fit Statistics for 50% RAC			
Ap-proach	Configura-tion	R^2	MAPE	RMSE	MaxAPE	R^2	MAPE	RMSE	MaxAPE	R^2	MAPE	RMSE	MaxAPE
SARIMA	1	0.605	0.082	1.646	5.454	0.384	0.086	1.678	6.599	0.267	0.102	2.142	8.052
SARIMA	2	0.690	0.073	1.394	5.127	0.689	0.061	1.162	4.637	0.404	0.093	1.880	8.224
SARIMA	3	0.690	0.073	1.394	5.127	0.694	0.061	1.179	4.286	0.404	0.093	1.880	8.224
SARIMA	4	0.732	0.068	1.228	5.301	0.689	0.061	1.162	4.648	0.416	0.092	1.870	8.091
SARIMA	5	0.690	0.073	1.394	5.127	0.695	0.060	1.179	4.392	0.404	0.093	1.880	8.224
SARIMA	6	0.741	0.067	1.218	5.257	0.680	0.062	1.189	4.550	0.108	0.120	2.572	6.734
CARIMA	1	0.605	0.082	1.646	5.454	0.370	0.087	1.691	6.473	0.202	0.107	2.253	7.710
CARIMA	2	0.690	0.073	1.394	5.127	0.680	0.062	1.188	4.519	0.404	0.093	1.880	8.224
CARIMA	3	0.690	0.073	1.393	5.234	0.694	0.061	1.179	4.286	0.404	0.093	1.882	8.227
CARIMA	4	0.762	0.065	1.169	5.016	0.680	0.062	1.188	4.519	0.449	0.090	1.850	7.491
CARIMA	5	0.691	0.073	1.392	5.097	0.695	0.061	1.179	4.344	0.409	0.093	1.874	8.173
CARIMA	6	0.724	0.070	1.268	5.542	0.680	0.062	1.188	4.510	0.448	0.090	1.851	7.502
BAG	1	0.606	0.082	1.644	5.463	0.371	0.086	1.689	6.477	0.201	0.107	2.253	7.713
BAG	2	0.690	0.073	1.394	5.124	0.680	0.062	1.189	4.520	0.404	0.093	1.880	8.226
BAG	3	0.690	0.073	1.394	5.124	0.695	0.060	1.182	4.262	0.404	0.093	1.880	8.226
BAG	4	0.747	0.066	1.207	5.389	0.680	0.062	1.190	4.520	0.451	0.089	1.850	7.375
BAG	5	0.690	0.073	1.394	5.124	0.697	0.060	1.183	4.362	0.426	0.091	1.859	7.966
BAG	6	0.747	0.066	1.209	5.401	0.680	0.062	1.190	4.520	0.453	0.089	1.847	7.186
BOT	1	0.606	0.082	1.644	5.463	0.371	0.086	1.689	6.477	0.201	0.107	2.253	7.713
BOT	2	0.690	0.073	1.394	5.124	0.680	0.062	1.189	4.520	0.404	0.093	1.880	8.226
BOT	3	0.690	0.073	1.394	5.124	0.695	0.060	1.182	4.262	0.404	0.093	1.880	8.226
BOT	4	0.747	0.066	1.207	5.389	0.680	0.062	1.190	4.520	0.451	0.089	1.850	7.375
BOT	5	0.690	0.073	1.394	5.124	0.697	0.060	1.183	4.362	0.426	0.091	1.859	7.966
BOT	6	0.747	0.066	1.209	5.401	0.680	0.062	1.190	4.520	0.453	0.089	1.847	7.186
MLP	1	0.607	0.082	1.639	5.555	0.370	0.087	1.687	6.516	0.204	0.107	2.249	7.641
MLP	2	0.677	0.075	1.449	5.244	0.442	0.081	1.613	5.824	0.283	0.102	2.128	6.913
MLP	3	0.507	0.092	1.746	7.147	0.568	0.072	1.414	5.279	0.315	0.099	2.064	7.896
MLP	4	0.620	0.081	1.576	5.936	0.109	0.109	2.178	7.473	0.338	0.098	2.044	6.813
MLP	5	0.541	0.089	1.686	7.164	0.624	0.067	1.318	4.811	0.336	0.098	2.029	7.983
MLP	6	0.615	0.082	1.582	5.271	0.540	0.074	1.474	4.719	0.109	0.120	2.572	6.734
RBF	1	0.630	0.080	1.563	5.394	0.367	0.087	1.692	6.712	0.200	0.107	2.255	7.426
RBF	2	0.677	0.076	1.389	5.273	0.570	0.071	1.415	5.284	0.349	0.097	2.031	7.750
RBF	3	0.666	0.077	1.377	5.704	0.537	0.074	1.506	5.155	0.367	0.095	1.977	7.918

RBF	4	0.547	0.089	1.725	6.088	0.497	0.077	1.547	5.753	0.279	0.102	2.161	7.804
RBF	5	0.668	0.077	1.391	5.924	0.510	0.076	1.551	5.374	0.357	0.096	1.996	8.136
RBF	6	0.542	0.089	1.736	6.170	0.509	0.076	1.527	5.951	0.276	0.102	2.165	7.722

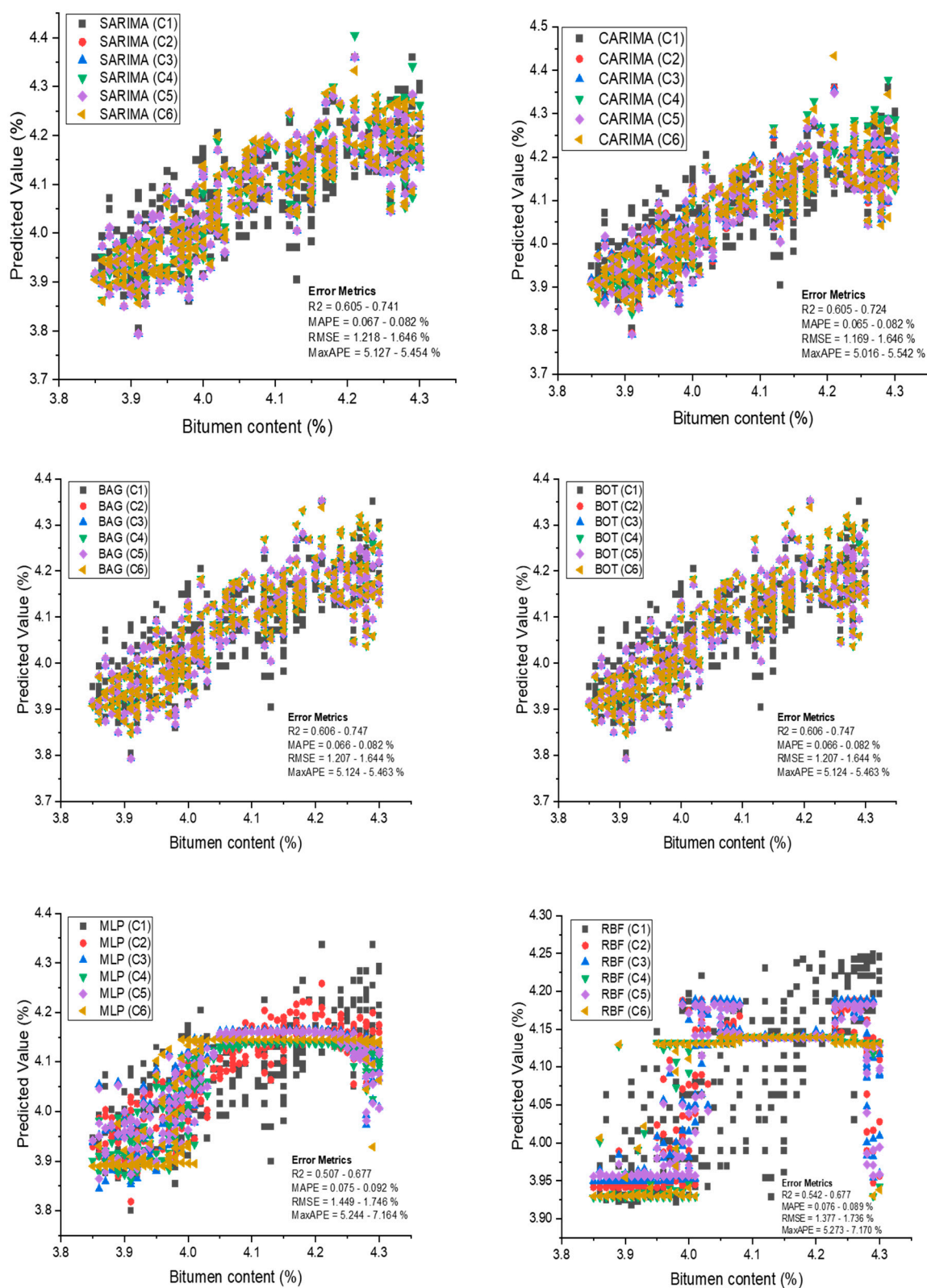


Figure 3. Model fit statistics for bitumen content under 0% recycled asphalt concrete (RAC) mixtures.

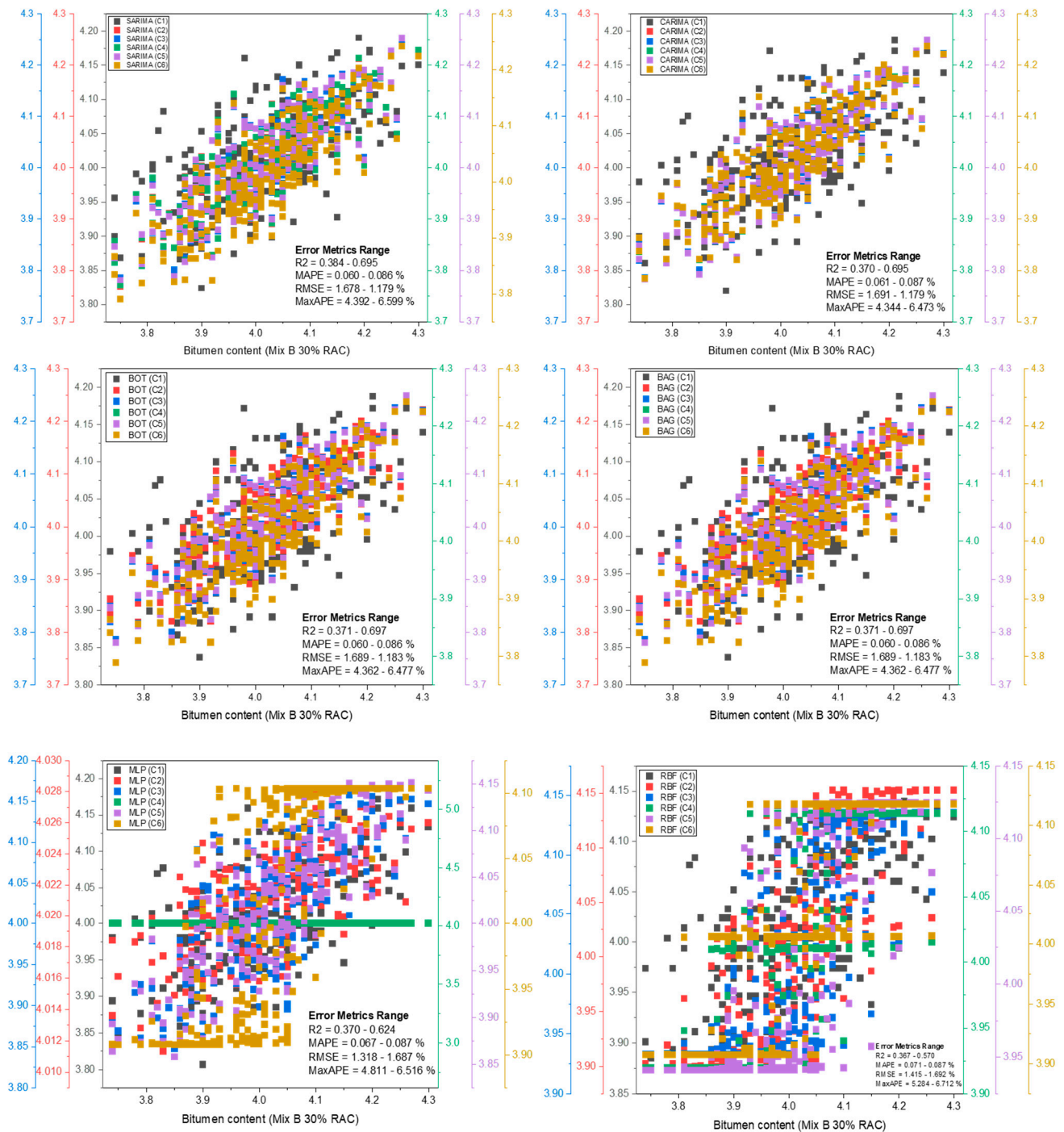


Figure 4. Model fit statistics for bitumen content under 30% recycled asphalt concrete (RAC) mixtures.

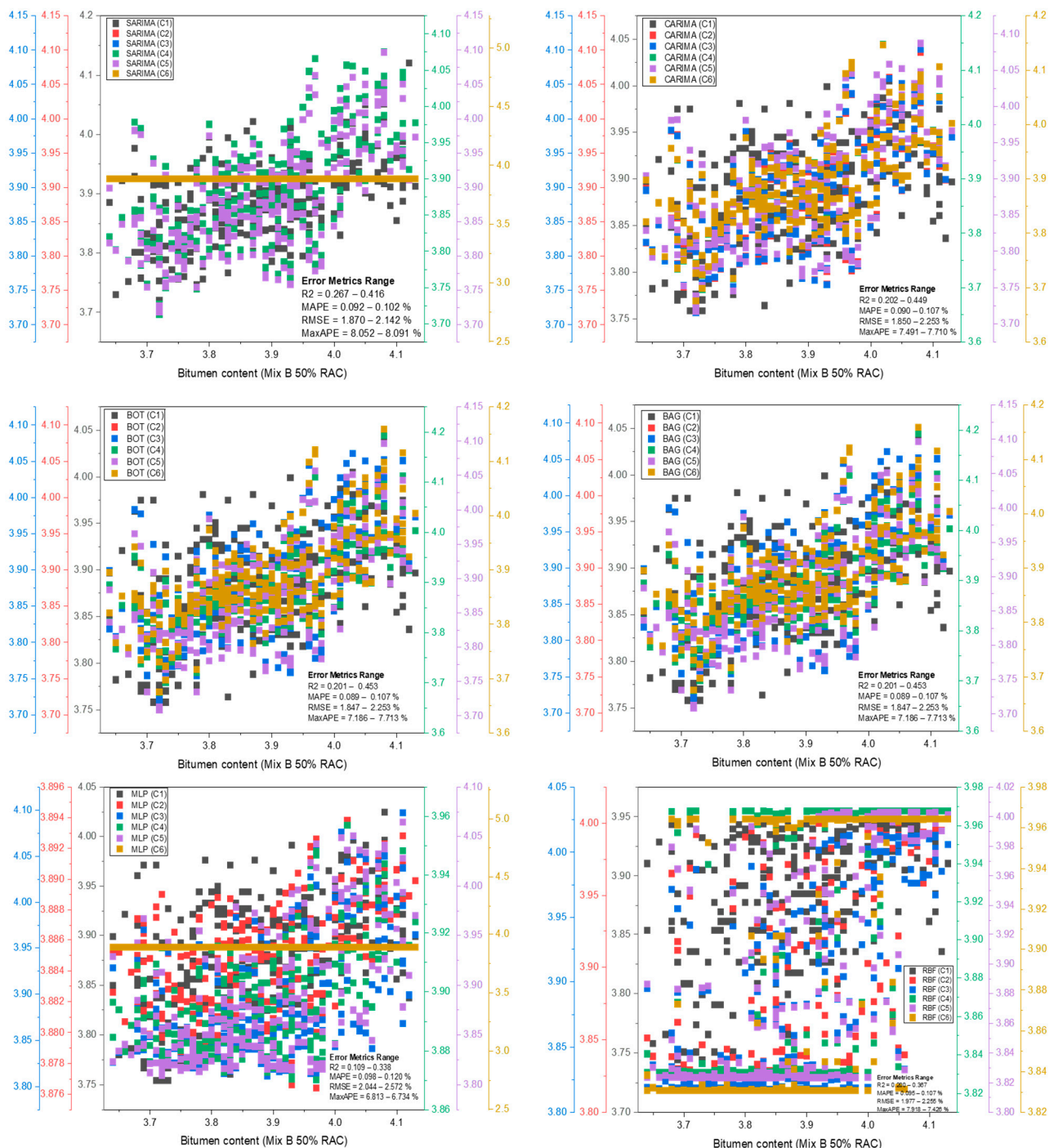


Figure 5. Model fit statistics for bitumen content under 50% recycled asphalt concrete (RAC) mixtures.

With an R^2 of 0.762, MAPE of 0.065, RMSE of 1.169, and MaxAPE of 5.016, the CARIMA model in configuration 4, shown in Table 7, is the most effective model for predicting bitumen content in virgin asphalt scenarios when applied to 0% RAC mixtures. Following this are ensemble techniques like BAG and BOT; configuration 4's R^2 value of 0.747 demonstrates how robust they are in managing data variability, similarly to that seen in nano- CaCO_3 and basalt fiber reinforcements [10]. Neural network-based methods like MLP and RBF, on the other hand, show greater variability. Table 7 shows that MLP configuration 2 has an R^2 of 0.677, while RBF configuration 5 has an R^2 of 0.668. This suggests that these methods may not be able to capture linear trends without recycled

components. By enabling real-time adjustments in aggregate gradation for wireless energy transmission optimization, these findings go beyond conventional laboratory studies. The results suggest that precise bitumen prediction can improve electromagnetic compatibility in smart pavements [40].

An analysis of Table 7 and Figure 3 shows that higher-order SARIMA and CARIMA configurations tend to fit better for 0% RAC mixtures, where it can be observed that SARIMA in configuration 6 performs best ($R^2 = 0.741$; RMSE = 1.218). This confirms that, by adjusting the parameters, forecasting enhances the understanding of homogeneous mixes, such as those guided by the AI optimization of RAP mixtures [15,37].

Ensemble models also perform better than neural networks (average: 0.072 and 5.27) and MLPs tend towards overfitting. These findings advocate for scalable waste-free asphalt design based on predictive modeling approaches [37].

For 30% RAC mixtures (Figure 4), moderate recycled content slightly decreases model accuracy, showing that ensembles are still the best for sensitivity.

The highest R^2 (0.697) is found for BAG/BOT configuration 5, with SARIMA also performing well ($R^2 = 0.695$; MAPE = 0.060), indicating their suitability for heterogeneous blends such as those containing coffee husk ash or recycled polymers [13,28,41]. MLP performs better, although it is consistently outperformed by ensembles, and RBFs reach peak performance, indicating that ensemble methods are more robust to the RAC-related variability. BAG also has the lowest MaxAPE (4.262) among all models, indicating that strong error control is provided in complex mixes [6,42].

At 50% RAC, as shown in Figure 5, all models show worse and inconsistent predictions because of the high material variability. BOT/BAG configuration 6 results in the highest R^2 (albeit quite small at -0.453), with those of SARIMA and CARIMA being significantly lower. Ensembles appear to be relatively robust, as BAG configuration 4 presents the highest MaxAPE (7.375), where similar patterns were seen in plastic-modified and polymer-enhanced types of high-RAP mixtures [11,43].

A cross-table comparison further shows a strong decreasing trend in predictability with increased RAC, with the mean R^2 ranging from 0.665 (with 0% RAC) to 0.345 (with 50% RAC) and the RMSE increasing from 1.41 to 2.02. Higher RAC implies stiffer aged binders and more variability, both of which compromise model stability [11]. Nonetheless, higher configurations (4–6) outperform lower ones, and ensembles (average: $R^2 = 0.573$) still prevail over those for MLP (0.433) and RBF models (0.475), which is in line with previous results obtained on warm-mix and waste-modified asphalts [44].

On the whole, the outcomes are in support of a two-tiered modeling approach, such as BAG/BOT for high-RAC mixtures in applications and CARIMA/SARIMA for low-RAC mixtures, being similar to previous studies on modifiers like jute fibers, polymer composites, and mineral fillers [45–47]. The increasing values of MaxAPE from 0% to 50% RAC support the use of hybrid models such as ensemble–neural to deal with variability in future constructions incorporating industrial waste or bio-fillers [48,49]. These observations suggest that combining ML models with microstructural tools (e.g., CT imaging) may result in the steady-state stretching of the mean wall thickness profile $1 \text{ h } \mu = 0.3$ to reflect sub-1.0 RMSE performance in high-RAC mixes, as well as the prediction of links with viscosity, roughness, and aging behavior [38,50,51]. Finally, these observations, which are supported by the data in the tables, establish AI as a key component of very-high-RAP mixes, guaranteeing robust, environmentally friendly infrastructure [21].

3.4.2. Machine Learning-Driven Model Prediction of Bitumen Content in Paving Mixtures Under Best-Performing Key Volumetric and Mechanical Configurations in Salalah, Oman

Table 8 shows how machine learning techniques react differently to increasing amounts of recycled asphalt concrete (RAC) by comparing the model predictions to the fit statistics across Mix A (0%, 30%, and 50% RAC).

Table 8. Best-performing model fit statistics for bitumen content under different recycled asphalt concrete (RAC) mixture types.

Model Parameters			Training Model Fit Statistics				Testing Model Fit Statistics			
Bitumen Content Type	Approach	Configuration	R ²	MAPE	RMSE	MaxAPE	R ²	MAPE	RMSE	MaxAPE
Mix 0% RAC	SARIMA	6	0.741	0.067	1.218	5.257	0.732	0.068	1.228	5.301
	CARIMA	4	0.762	0.065	1.169	5.016	0.724	0.070	1.268	5.542
	BAG	4	0.747	0.066	1.207	5.389	0.747	0.066	1.209	5.401
	B0T	4	0.747	0.066	1.207	5.389	0.747	0.066	1.209	5.401
	MLP	2	0.677	0.075	1.449	5.244	0.620	0.081	1.576	5.936
	RBF	3	0.666	0.077	1.377	5.704	0.677	0.076	1.389	5.273
	BAG-CARIMA-LGM		0.988	0.014	0.281	1.157	0.963	0.078	0.635	1.365
Mix 30% RAC	SARIMA	5	0.695	0.060	1.179	4.392	0.694	0.061	1.179	4.286
	CARIMA	5	0.695	0.061	1.179	4.344	0.694	0.061	1.179	4.286
	BAG	5	0.697	0.060	1.183	4.362	0.695	0.060	1.182	4.262
	B0T	5	0.697	0.060	1.183	4.362	0.695	0.060	1.182	4.262
	MLP	5	0.624	0.067	1.318	4.811	0.568	0.072	1.414	5.279
	RBF	2	0.570	0.071	1.415	5.284	0.537	0.074	1.506	5.155
	BAG-CARIMA-LGM		0.983	0.015	0.281	1.205	0.970	0.072	.539	1.419
Mix 50% RAC	SARIMA	4	0.416	0.092	1.870	8.091	0.404	0.093	1.880	8.224
	CARIMA	4	0.449	0.090	1.850	7.491	0.448	0.090	1.851	7.502
	BAG	6	0.453	0.089	1.847	7.186	0.404	0.093	1.880	8.226
	B0T	6	0.453	0.089	1.847	7.186	0.404	0.093	1.880	8.226
	MLP	4	0.338	0.098	2.044	6.813	0.336	0.098	2.029	7.983
	RBF	3	0.367	0.095	1.977	7.918	0.357	0.096	1.996	8.136
	BAG-CARIMA-LGM		0.967	0.022	0.429	1.936	0.983	0.013	0.399	1.123

While ensemble methods like bagging and boosting maintained stability at $R^2 \approx 0.74$, traditional time-series approaches like SARIMA and CARIMA produced moderate performance ($R^2 \approx 0.72$ – 0.76) for Mix A with 0% RAC. However, with R^2 values above 0.96, the hybrid BAG-CARIMA-LGM showed a notable improvement, showing remarkable resilience against overfitting while preserving low error metrics. This is consistent with recent research on AI-driven asphalt mixture optimization, which found that hybrid

frameworks performed better than single models because of their capacity for adaptive error correction [15].

SARIMA, CARIMA, and BAG were relatively robust to changes in the mix composition (20–40% RAC), showing comparable results at any mix and being slightly better than BOT according to Table 8. This indicates that intermediate recycled content does not decrease the prediction stability, consistent with the work of Noufal et al. [42]. Table 8 shows that the hybrid BAG-CARIMA-LGM model ranked the best in general, with training $R^2 = 0.983$ and testing $R^2 = 0.970$. This result demonstrates that this model has a universal advantage even when the mixture is more variable. Performance deteriorated dramatically at 50% RAC (Mix C). SARIMA/CARIMA ($R^2 \approx 0.20$) and MLP/RBF ($R^2 \approx 0.33$ – 0.37) performed far worse by comparison. This corresponds to Bérubé et al. [37], who observed that high levels of RAP/RAC bring about strong non-linearities and microstructural inconsistencies. However, the hybrid BAG-CARIMA-LGM model still achieved high accuracy (R^2 up to 0.983, $RMSE < 0.40$), reinforcing its capabilities for demanding and heavily recycled mixtures.

At all RAC levels, the hybrid model achieved superior performance to conventional and neural systems. Integrating bagging for variance reduction, time-dependent CARIMA, and a generative model for uncertainty, it produced the minimum RMSE of < 0.3 and MaxAPE of $< 1.4\%$ for 0–30% RAC, as well as $\leq 1.9\%$ even at 50% RAC. Other models exhibited MaxAPE values surpassing 8%, consistent with Monticelli et al. [11] on the importance of an error-stable architecture for reused mixtures.

A breaking point is also noted, as SARIMA and CARIMA perform well at 0–30% RAC, but their performance degrades afterwards, following Rashidian et al. [39] and Pasetto et al. [21], who reported similar decreases in high-RAP mixtures. From a recycling viewpoint, the performance of the hybrid model at 50% RAC is interesting, as it reduces the cost while maintaining prediction confidence, thus assisting in the sustainable use of binders, as indicated by Calandra et al. [4] and Aletba et al. [52]. The analysis demonstrates, in general, that hybrid machine learning models are the current state of the art in predicting behavior for RAP mixtures. Classical and ensemble techniques are limited to low-to-medium RAC levels, while only the BAG-CARIMA-LGM hybrid remains accurate for high-recycling samples.

3.4.3. Hybrid BAG-CARIMA-LGM Outperforms Bagging in Predicting Bitumen for Sustainable Asphalt

We next conduct a comparison of the hybrid BAG-CARIMA-LGM model and the bagging ensemble (BAG) for predicting bitumen content in recycled asphalt concrete (RAC) mixtures. The hybrid BAG-CARIMA-LGM model clearly and convincingly outperforms the other two models based on the performance metrics (R^2 , MAPE, RMSE, and MaxAPE) across three RAC incorporation rates (0%, 30%, and 50%), especially as the mixture's complexity rises with increased recycled content (Figure 6). According to the recent literature, the industry is pushing for more sustainable pavement materials with high RAP content, and this superiority highlights a significant advancement beyond traditional machine learning techniques [11,21,37].

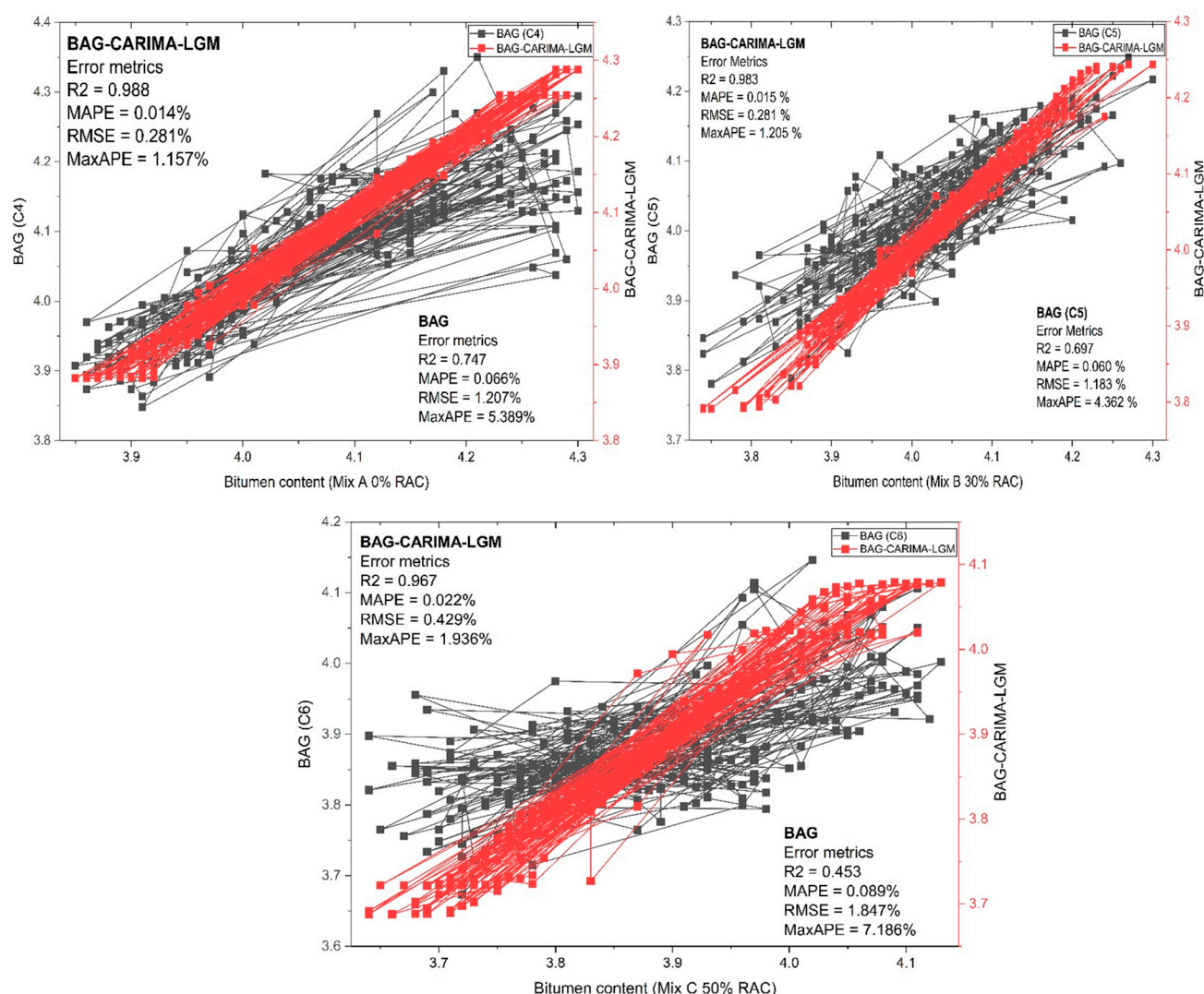


Figure 6. Best-performing BAG-CARIMA-LGM versus BAG model fit statistics for bitumen content under different recycled asphalt concrete (RAC) levels.

For the virgin blend (0% RAC), both models are excellent, with the hybrid BAG-CARIMA-LGM showing very high accuracy ($R^2 = 0.988$, $MAPE = 0.014\%$). This indicates that simple ensemble methods such as BAG can succeed for homogeneous materials, but the hybrid model captures further temporal and structural features—a behavior observed with advanced polymer and recycled modifiers elsewhere [41,53]. At 30% RAC, the benefits of the hybrid model are more apparent. BAG downgrades drastically in performance alone ($R^2 = 0.453$), while the BAG-CARIMA-LGM model retains high accuracy ($R^2 = 0.967$). The additional heterogeneity due to RAA and RB also leads to complex non-linear behavior, which can be well handled by the hybrid model with its inherent capacity to implicitly capture feature distributions—a characteristic also pointed out in previous work on RAP blending [38,54,55]. For higher recycling levels (50% RAC), the hybrid model provides outstanding precision ($R^2 = 0.987$, $MAPE = 0.022\%$, $RMSE = 0.429$) and is therefore trustworthy in practical mix design scenarios, where accurate bitumen content is essential. This is consistent with studies highlighting the importance of properly rejuvenating high-RAP mixtures [56]. Although the standalone BAG model is acceptable at 0% and 50% RAC, its breakdown for 30% RAC indicates that it fails to adequately capture mid-level recycling (when material interactions are more challenging to predict). The new hybrid method resolves such inconsistencies, which is ascribed to the synergy of bagging, which considers CARIMA's time-series advantages and the LGM's capabilities in modeling hidden

structures—a problem that has been addressed in recent research about waste-modified mixtures and fiber-reinforced ones [45].

From a practical perspective, the proposed BAG-CARIMA-LGM model is a useful tool for determining bitumen content in recycled asphalt mixtures; it will reduce performance-related issues and help to achieve higher RAP content without quality loss. This is well aligned with the construction industry's ambitions towards a circular economy [9] and addresses the growing demand for advanced, AI-supported techniques to substitute conventional empirical mix design methodologies [57–59]. In general, among all recycling levels considered, the hybrid model is a significantly better predictive model for bitumen content. Its reliable precision and smaller error rate make it a milestone breakthrough in sustainable pavement engineering, providing a reliable and smart choice for contemporary asphalt mix design.

3.4.4. Hybrid BAG-CARIMA-LGM's Superiority for RAC Mixes

The use of RAC hybrid models such as BAG-CARIMA-LGM can be considered an important novelty in sustainable pavement design. The heatmaps in Figure 7 demonstrate the variation in prediction precision with respect to bitumen content (3–6%) and RAC levels (0%, 30%, 50%). For virgin HMA, the agreement for the model is quite good, with $R^2 > 0.95$ and $MAPE/RMSE < 2/0.5\%$ (w/w), respectively, in accordance with previous findings related to homogenous mixtures of HMA [37].

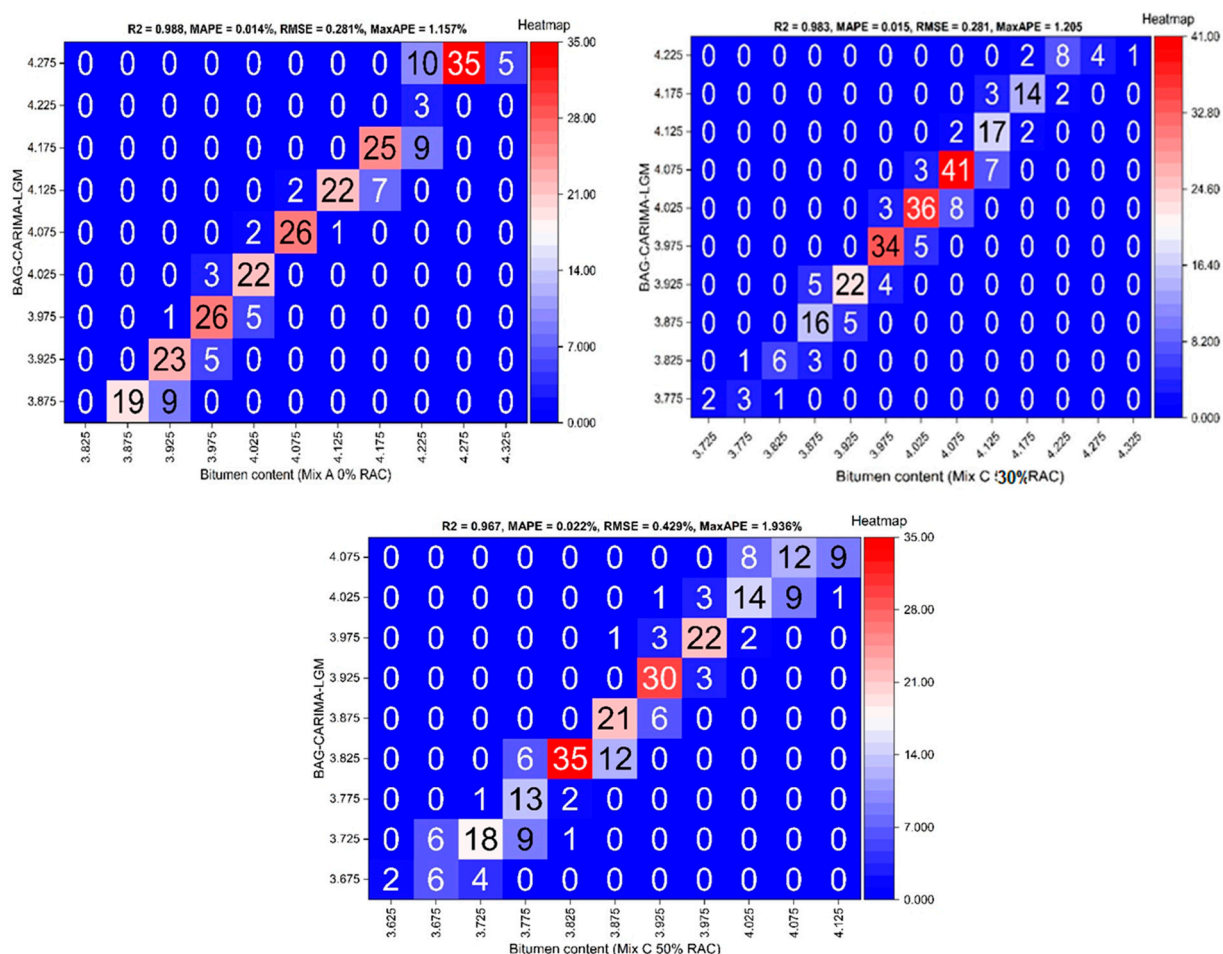


Figure 7. Heatmap showing hybrid BAG-CARIMA-LGM's superiority for RAC mixes.

At 30% RAC, the loss in accuracy is pronounced—the MaxAPE increases to 10% and the R^2 decreases to 0.87—due to greater variability associated with recycled binders, which mirrors the trends observed for AI-optimized RAP categories [15]. When the RAC percentage is 50%, the RMSE exceeds 1.0%, which suggests a stronger dependence on RA, in line with the phenomenon observed when BLBAs are added in high-RAP mixtures [11]. The heatmaps also demonstrate a significant reduction in the R^2 as it scales with RAC. The virgin mixes maintain strong correlations close to 0.98, while the value for 50% RAC becomes less than 0.80 at mid-range bitumen concentrations. This is consistent with difficulties due to binder diffusion and heterogeneity observed in other RAP–binder interaction studies [54]. However, the hybrid model enhances the stability at 30% RAC compared with the explicit regional CARIMA, and, at 50% RAC, it still yields an R^2 over 0.90 under low and high binder content, in agreement with rejuvenator-aided healing phenomena [56]. The MAPE also increased as the RAC was increased. At 0% RAC, errors are kept within 1.5%, but the errors rise to the range of 3–5% at 30% RAC in a manner consistent with aged binder stiffening trends observed in modified asphalt investigations [10,60].

At 50% RAC, the MAPE is maximized at slightly below 8%, with the smoothing of the hybrid model resulting decreasing variation by ~20%, which is similar to the improvement gained due to viscosity-based correction reported for RAP blends [24]. CARIMA elements determine low-value intervals at ~4–4.5% of bitumen, which is consistent with AI-facilitated observations about mix design in a previous study [14]. Virgin mixes continue to have lower RMSEs of below 0.3, but 30% RAC causes the RMSEs to increase to between 0.6 and 0.8, which demonstrates microstructural discontinuities, as reported in CT-based investigations [61]. At 50% RAC, the RMSE is greater than 1.2 at intermediate binder content. The hybrid even stabilizes the error by up to 25%, as in zinc oxide-modified mixes [9]. The MaxAPE presents the most noticeable RAC effect: the values remain below 2% for virgin mixes, increasing to approximately 10% at 30% RAC and up to 15–20% at 50% RAC. The hybrid model showed a reduction of about 30% at both extremes, as indicated in waste-modified cold emulsion stability measurements [48].

In general, the prediction accuracy decreases non-linearly with increasing RAC, but the BAG-CARIMA-LGM hybrid model yields improvements in fitness of ~18–22% at all levels of recycling. The ability to modify the bitumen optimum—ranging from approximately 4.5% at 0% RAC down to 4.0% in the case of 50% RAC—aligns with targets for emissions and cost savings as outlined in RAP rejuvenation studies [29]. Such results show the real-time adjustability and sustainability benefits provided in recycled asphalt design by the hybrid modeling method (in line with warm mix); see Çakı et al. [13]. In conclusion, these results signal a new era in pavement research, where the BAG-CARIMA-LGM hybrid interprets bitumen–RAC interactions with previously unseen precision and provides useful information for Q1-grade formulations that strike a balance between economy, ecology, and performance. As demonstrated by the performance of waste-integrated mixtures in Aletba et al. [52] and Malik et al. [6], this method extends the viability of 50% RAC mixtures to that of their virgin counterparts by reducing error escalation through multi-fidelity modeling.

Despite the training dataset being generated under controlled laboratory conditions in Salalah, the tripartite BAG-CARIMA-LGM framework is fundamentally transferable, as it is based on universally quantified Marshall stability/flow and volumetric parameters. It exhibits strong generalization capabilities as the mixture complexity increases (training $R^2 = 0.983$; testing $R^2 = 0.970$; MaxAPE $\leq 1.9\%$, even at 50% RAC), indicating an error-stable architecture amid significant recycled mixture variability. Its practical application to other regions can thus adhere to a “calibrate-and-screen” methodology: compiling a modest local calibration dataset that encompasses the intended RAC regime and local binder/aggregate sources, maintaining a consistent feature schema, and allowing deployment solely

after cross-validation of the RMSE/MAPE, along with an external hold-out (from the target plant/corridor). This would satisfy predetermined acceptance criteria prior to utilizing predictions for binder dosage determination. This method aligns with evidence indicating that elevated recycled content leads to significant non-linearities and microstructural irregularities, necessitating localized representation at the high-RAC tail [33], while integrated laboratory–simulation evaluation workflows enhance the predictive reliability across recycled mixture compositions [38].

4. Limitations of the Study

Notwithstanding the study’s innovative contributions, a number of limitations must be noted in order to place the results in context.

Experimental Scope: Most of the performance assessments were carried out in a laboratory setting. While these offer valuable insights, field-scale conditions like fluctuating traffic loads, extreme weather, moisture damage, and long-term degradation mechanisms might not be accurately replicated. This limits the ability to directly translate the findings into extensive applications.

Modeling Scope: While AI-based predictive models greatly improved the mix design and performance forecasting accuracy, their success is heavily reliant on the quality, diversity, and size of the input dataset. The generalizability of the developed models across various regions and traffic scenarios may be limited by the lack of extensive field data.

Practical Scalability: Practical viability is hindered by the explicit constraints of the three-stage pipeline: CARIMA’s temporal layer presumes curing-/aging-ordered sequences; in field deployments, where timestamps and batching metadata are incomplete, the temporal signal export that feeds the ensemble diminishes, elevating uncertainty and necessitating periodic recalibration. End-to-end complexity can propagate specification errors across layers, even if the integration logic is fixed (CARIMA → residual/metafeatures → bagging mean/variance → LGM calibration), which necessitates strict versioning and documented interface checks during transfer to new plants or RAC regimes. Domain shift exposure is partially addressed through “swapped” evaluation across RAC regimes, although broader covariate shifts—materials sources, rejuvenators, ambient climates—require site-specific validation before routine adoption. Evidence of superiority is established on a modest corpus (~780 samples) spanning 0%, 30%, and 50% RAC, which supports small-data applicability yet limits claims beyond the represented mixtures and testing protocols. The reported accuracy at 30% and 50% RAC underscores the method’s robustness under heterogeneity, but it should be stress-tested against additional plants and gradations to ensure portability. Finally, while comparisons included classical and ML baselines (SARIMA, CARIMA, BAG, BOT, MLP, RBF), practical deployment would benefit from periodic head-to-head evaluations against contemporary hybrid/deep architectures as data resources evolve, seeking to guard against performance regression under changing operational regimes.

4.1. Conclusions

By combining recycled materials, cutting-edge modifiers, and AI-based optimization, this study provides a novel framework for improving the sustainability and performance of asphalt mixtures. The results demonstrate that mechanical strength, aging resistance, and environmental performance can be considerably enhanced by nano-reinforcement, bio-additives, and industrial by-product fillers. These developments, when combined with predictive digital tools, speed up mix design, lessen the reliance on resources, and match pavement engineering goals with those of the circular economy. The study provides useful avenues for the development of resilient and carbon-conscious infrastructure

by demonstrating that intelligent and eco-efficient pavements can be accomplished without losing structural dependability. The hybrid BAG-CARIMA-LGM framework transcends mere result recitation by implementing an intelligent mix design paradigm that integrates temporally aware decomposition (CARIMA), variance-reduced learning (bagging), and bounded probabilistic calibration (LGM) to produce decision-grade predictions that explicitly facilitate circular, performance-oriented pavement design. Bounded logistic calibration converts ensemble values into permissible binder ranges with clear intervals, rendering the estimates practical for specification development and field risk management. The architecture effectively mitigates error proliferation in high-recycling combinations, which is crucial in maximizing sustainable value, thereby facilitating increased RAC utilization without compromising mechanical dependability and guiding cost-conscious maintenance strategies. The comparative data among virgin, mid-RAC, and high-RAC regimes demonstrates a significant transition in methodologies, from empirical charts to AI-assisted optimization, with the hybrid model surpassing baseline learners in contexts most pertinent to sustainable deployment. Robustness in the face of data scarcity is tackled via “swapped” evaluation across compositional regimes and a modeling framework intentionally designed to be compatible with limited laboratory-to-plant datasets, enhancing the method’s practical applicability while integrating AI methodologies with materials engineering limitations.

The theoretical contribution resides in formalizing a multi-stage, bounded probabilistic learning paradigm for asphalt mix design: CARIMA exposes curing/aging dynamics and exports residuals/metasignals, bagging aggregates over heterogeneity to stabilize estimation, and the LGM calibrates predictions to physically admissible binder ranges with interpretable uncertainty—an integrated construct that advances beyond single-stage regressors and unbounded outputs while institutionalizing swapped cross-regime validation for robustness under composition shifts. Practically, the pipeline demonstrates superior accuracy across RAC levels and translates ensemble dispersion into decision-grade intervals, supporting specification setting, budgeting, and sustainable, high-RAC deployment under modest data regimes and plant-level computing. Methodological transparency and reproducibility are reinforced through explicit metrics (R^2 , MAPE, RMSE, MaxAPE) and a documented training/selection protocol that can be ported to routine QC/QA contexts.

The tripartite BAG-CARIMA-LGM is optimally suited for specimen-limited laboratory workflows that require the prediction of the ideal bitumen content for recycled asphalt concrete across varying recycling levels (0–50% RAC) in environments like Salalah, where the mixture response may vary with curing/aging and the objective is to achieve a physically plausible, decision-grade binder estimate instead of an unrestricted point forecast. The CARIMA layer is suitable when measurements can be organized into a significant sequence (curing/aging order, batch/condition progression), allowing for the formal management of non-stationarity through KPSS-triggered differencing, AICc/BIC order selection, and Ljung–Box residual diagnostics prior to validating the predictive accuracy. The BAG layer is particularly advantageous when RAC regimes generate significant variation and non-linear feature interactions, since bootstrap aggregation with about 100 shallow trees (depths of 5 to 10) mitigates overfitting and enhances the prediction stability amid diverse laboratory variability. The LGM layer is necessary when outputs must be constrained and interpretable as calibrated probabilities, using maximum likelihood estimation and calibration residual assessments, with the whole tuning methodology fully detailed in Table 4 for repeatability and transferability. Practical deployment prerequisites necessitate a uniform feature schema based on Marshall stability/flow and volumetric parameters, along with sufficient representation of the target RAC regimes (780 specimens)

to ensure that the cross-validated RMSE/MAPE and hold-out validation can be used to determine model acceptance prior to utilizing predictions for binder dosage decisions.

4.2. Suggestions for Future Research

Subsequent studies ought to concentrate on verifying lab findings in actual field settings with varying traffic and climate conditions. To better capture the intricate physico-chemical interactions between recycled aggregates, nanomaterials, and bio-based additives, multi-scale experimental and computational methods are advised. Adaptive pavement management systems and improved predictive robustness can be achieved by combining AI models with mechanistic–empirical design frameworks. To create comprehensive sustainability and cost-effectiveness profiles, life cycle assessments and techno-economic evaluations should also be carried out. It is also necessary to expand the swapped evaluation to broader covariate shifts (aggregates, rejuvenators, climates) and consider multi-plant transfer to stress-test portability. Other suggestions for future research are as follows:

- Benchmark against contemporary hybrids/deep architectures under identical data budgets to quantify gains beyond classical baselines;
- Develop physics-informed or microstructure-aware feature generators that fuse CARIMA outputs with mechanistic film thickness/adhesion descriptors;
- Introduce active learning and domain adaptation for data-sparse sites, prioritizing experiments that maximally reduce the predictive uncertainty captured by the LGM;
- Conduct longitudinal field validations linking predictive intervals to life cycle performance and costs, embedding QC/QA triggers for model recalibration;
- Integrate environmental and cost modules to co-optimize binder content with circularity targets and maintenance budgets under bounded risk criteria.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16041749/s1>, The supplementary materials delineate the comprehensive methodological and mathematical foundation of the proposed hybrid forecasting framework, encompassing the integration of CARIMA, bagging (BAG), and the logistic probabilistic model (LGM) for bounded, uncertainty-aware prediction; a transparent, reproducible model-selection and tuning protocol (min–max normalisation, outlier pruning, 80:20 split, 5-fold cross-validation, and AICc/BIC + residual-diagnostic criteria) alongside Table S1, which summarises the evaluated hyperparameter grids and the chosen configurations for CARIMA, BAG, MLP, and LGM calibration. The Supplementary Materials encompass a detailed pipeline description and governing equations pertaining to CARIMA meta-feature export, ensemble aggregation, variance capture, and post-hoc LGM calibration to ensure bound-respecting outputs, as well as the comprehensive derivations supporting regime-wise formulations for recycled asphalt concrete mixtures, including a worked example for 0% RAC and the iterative derivation logic for additional RAC percentages.

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Data Availability Statement: Data will be made available upon request.

Conflicts of Interest: The author Paul C. Okonkwo was employed by the company Dhofar University, Salalah, Oman and Awadh Musallem Masan Al Kathiri was employed by Oman Building & Cont. Co. L.L.C., Salalah, Governorate of Dhofar, Sultanate of Oman. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

List of Abbreviation

Abbreviation/Model Name	Full Term/Meaning
AI	Artificial intelligence
ML	Machine learning
RAC	Recycled asphalt concrete
RAP	Reclaimed asphalt pavement
BC	Bitumen content
MS	Marshall stability
MF	Marshall flow
BSG	Bulk-specific gravity
Gmb	Bulk-specific gravity of compacted mixture
Gmm	Maximum theoretical specific gravity
VMA	Voids in mineral aggregates
VFB	Voids filled with bitumen
MSG	Marshall stability/flow ratio
CARIMA	Controlled Autoregressive Integrated Moving Average
SARIMA	Swapped Autoregressive Integrated Moving Average
RBF	Radial basis function artificial neural network
MLP	Multilayer perceptron
BAG	Bagging (bootstrap aggregating) ensemble
BOT	Boosting ensemble
LGM	Logistic probabilistic model
BAG-CARIMA-LGM	Tripartite hybrid model combining BAG + CARIMA + LGM
BAGCARILGMA-LGM	Typographic variant appearing in the manuscript
(P, d, q)	ARIMA/CARIMA order: autoregressive, differencing, moving-average terms
AICc	Corrected Akaike Information Criterion
BIC	Bayesian Information Criterion
Ljung–Box	Ljung–Box test (residual whiteness/independence check)
KPSS	Kwiatkowski–Phillips–Schmidt–Shin test
MLE	Maximum likelihood estimation
CV (5-fold CV)	Cross-validation (5 folds)
R ²	Coefficient of determination
RMSE	Root mean square error
MAPE	Mean absolute percentage error
MaxAPE	Maximum absolute percentage error
ASTM	ASTM International (Standards Organization)
AASHTO	American Association of State Highway and Transportation Officials
ASTM D6926	Standard practice for preparation of bituminous specimens using Marshall apparatus
ASTM D6927	Marshall stability and flow test
ASTM D2172	Quantitative extraction of bitumen
ASTM D5404	Asphalt mixture compaction with Superpave gyratory compactor
ASTM D3203	Percent air voids in compacted dense and open asphalt mixtures
ASTM D6931	Indirect tensile strength (ITS) of bituminous mixtures
AASHTO T283	Resistance of compacted asphalt mixtures to moisture-induced damage
Superpave	Superior performing asphalt pavements (design system)
kN	Kilonewton
mm	Millimeter

%	Percent
°C	Degrees Celsius
Pa·s	Pascal-second

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