

Article

Non-Destructive Classification of Concrete Moisture Levels Using Piezoelectric Contact Microphones and Impact-Based Acoustic Signals with a Hybrid Stacking Framework: A Controlled Experimental and Theoretical Study

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Abstract

The long-term durability of concrete structures is significantly affected by moisture. Excessive moisture may cause drying shrinkage, crack formation, and accelerated corrosion of embedded reinforcement; therefore, reliable and non-destructive moisture assessment is essential for structural durability evaluation. In this study, a controlled acoustic measurement method and a machine learning-based classification framework are presented for the non-destructive identification of moisture levels in concrete specimens. A magnet-assisted free-fall steel ball mechanism was used to generate standardized impacts instead of conventional manual hammer excitation. To reduce environmental vibration noise and capture internal material responses, acoustic signals were recorded using a piezoelectric contact microphone. Experiments were conducted on concrete specimens prepared at nine moisture levels under both large-sample (BIG) and small-sample (SMALL) conditions. Power Spectral Density (PSD) and Mel-Frequency Cepstral Coefficients (MFCC) were extracted from the recorded impact signals and used as input features. Individual machine learning classifiers were compared with a hybrid stacking ensemble model to evaluate discriminative performance and probabilistic reliability. The results showed that MFCC features provided higher classification performance than PSD features under both dataset conditions. For the BIG specimens, the MFCC-based model achieved an accuracy of 0.9872, whereas the PSD-based model achieved 0.9811. For the SMALL specimens, MFCC reached an accuracy of 0.9822, while PSD achieved 0.9750. The AUC-ROC values of the proposed model ranged from 0.9980 to 0.9996 in the multi-class classification of nine moisture levels. These findings demonstrate that controlled impact acoustics combined with MFCC-based representation and stacking-based ensemble learning provides a rapid, low-cost, and reliable NDT approach for concrete moisture classification.

Keywords: hybrid stacking model; Mel-Frequency Cepstral Coefficients; moisture content; percussion; Power Spectral Density



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1. Introduction

Concrete is among the most extensively utilized structural materials in the building sector, attributed to its superior compressive strength, fire resistance, and durability [1,2]. Notwithstanding these beneficial attributes, its prolonged mechanical performance and durability are significantly affected by environmental exposure, especially moisture levels. Fluctuations in internal moisture content significantly influence shrinkage behavior, crack development, and the corrosion rate of embedded reinforcement, rendering accurate moisture measurement essential for durability evaluation and structural health monitoring [3]. In addition to combination proportions, the strength and durability of concrete are influenced by environmental interactions during its service life [4]. Moisture ingress initiates physical and chemical processes that gradually modify the material's microstructure, resulting in deterioration mechanisms such as cracking and corrosion [5]. Thus, moisture content becomes a critical factor in the degradation of concrete buildings [6].

Research has shown that concrete performs best at ambient temperatures of 20–22 °C and relative humidity levels of 40–60% [7]. One of the main problems threatening the integrity of reinforced concrete structures is the corrosion of embedded steel, which is directly related to the moisture levels of the concrete [8]. The effects of moisture are generally divided into three categories: drying, shrinkage, and crack formation [9]. Furthermore, the porous structure of concrete allows chloride ions to penetrate into the concrete, negatively affecting the durability of both the concrete and the reinforcement within it [10].

Various methods have been developed to evaluate the moisture content of concrete, with non-destructive testing (NDT) techniques playing a significant role in this regard [11,12]. NDT technologies provide the benefit of identifying moisture without compromising the structure, therefore maintaining the integrity and functionality of the concrete [13]. These techniques provide a comprehensive study of extensive areas and the procurement of more intricate data in contrast to basic visual checks [14]. Recent studies have shown that advanced deep learning methods are increasingly used in acoustic signal-based SHM and NDT applications. TinyLSN demonstrated the effectiveness of lightweight networks for real-time acoustic emission-based pipeline leakage detection in IoT systems [15], while LDS-former showed that dual-stream Transformer models can capture both local transient responses and long-range temporal dependencies in crack evolution monitoring [16]. Graph-based approaches have also improved leakage localization and offshore pipeline monitoring by modeling spatial and topological relationships among acoustic measurement points [17,18]. In addition, energy evolution analyses in heterogeneous geomaterials and adaptive cross-channel dependency learning have highlighted the importance of localized energy dissipation and multi-feature interactions in complex signal interpretation [19,20]. Compared with these studies, the present work offers a simpler and low-cost NDT framework by combining standardized impact excitation, piezoelectric contact-based acoustic sensing, MFCC/PSD feature extraction, and hybrid stacking-based classification for concrete moisture assessment.

Notwithstanding recent progress in percussion-based moisture estimation using deep learning, current methodologies often depend on uncontrolled excitation conditions or singular model classifiers, hence constraining repeatability and statistical reliability. The lack of uniform impact energy and probabilistic calibration analysis diminishes confidence in practical deployment scenarios.

This study presents a controlled, non-destructive acoustic methodology for assessing moisture content in concrete specimens that overcomes these limitations. Moisture-driven physical and chemical alterations within the porous concrete matrix result in cracking, shrinkage, and reinforcement corrosion, thereby progressively undermining structural durability. The suggested method utilizes a magnet-assisted free-fall mechanism to produce

standardized impact energy, capturing internal acoustic responses using a piezoelectric contact microphone, in contrast to traditional destructive or low-precision techniques. This arrangement guarantees consistent excitation, constant sensor geometry, and minimized environmental noise interference, thus offering a steady and statistically accurate measuring environment.

The study incorporates spectral feature comparison and stacking-based ensemble learning inside a unified assessment framework, in addition to controlled excitation, to improve classification robustness and probabilistic calibration.

This work's primary contributions are summarized as follows:

- A cost-effective and swift measurement apparatus was developed to deliver consistent percussion stimulation by an electromagnetically activated mechanism with a fixed microphone-sample configuration, guaranteeing uniform excitation energy and minimized environmental fluctuations.
- A hybrid stacking-based ensemble architecture was created by amalgamating heterogeneous base learners with a Linear Discriminant Analysis (LDA) meta-learner to unify complementary decision-making processes. The effects of feature selection, feature fusion, and ensemble learning were methodically assessed using an ablation framework with reliability- and calibration-focused metrics, such as Specificity, Cohen's Kappa, Matthews Correlation Coefficient (MCC), LogLoss, and Brier Score, revealing statistically significant enhancements.

2. Materials and Methods

2.1. Feature Extraction Methods

2.1.1. Mel-Frequency Cepstral Coefficients

Mel-Frequency Cepstral Coefficients (MFCC), first proposed by Davis and Mermelstein [21,22], are widely used to extract informative features from speech signals [23]. MFCC converts the signal spectrum to the Mel (Koenig) scale in order to mimic the nonlinear frequency perception of the human auditory system [24]. This scale is linear for frequencies below approximately 1 kHz and logarithmic for frequencies above that [25]. According to psychoacoustic definitions, a 40 dB tone at 1 kHz is considered 1000 mel. The mel equivalent of a frequency f (Hz) by [24–26] can be calculated by the following equation:

$$f_{mel} = 2595 \log\left(1 + \frac{f}{700}\right), \quad (1)$$

The MFCC method is not limited to speaker or speech recognition applications; it is also used in various fields such as agriculture, medicine, concrete structure assessment, and even image processing [27,28].

Figure 1 shows a workflow where pre-emphasis (high-pass filter) is applied to emphasize high-frequency components and divide the signal into short segments with overlapping. Before analysis in the frequency domain for all segments, to reduce spectral leakage, a Hamming window is used [29].

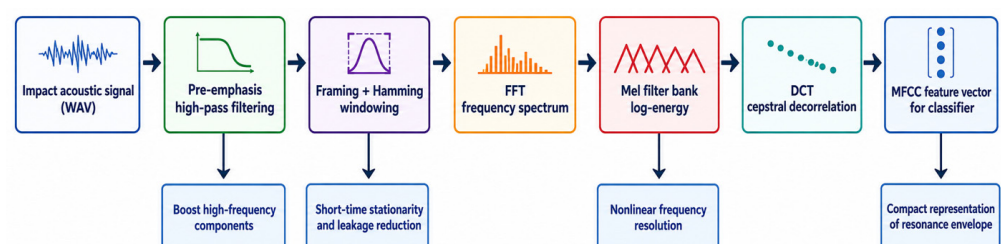


Figure 1. Improved MFCC feature extraction workflow for impact-based acoustic moisture classification.

The recorded impact signal is processed through pre-emphasis, framing, Hamming windowing, FFT, Mel filter-bank analysis, logarithmic compression, and DCT to obtain compact MFCC feature vectors.

To reveal the components of an audio signal in the frequency domain, Fast Fourier Transform (FFT) is applied. Mel filter banks, which model the logarithmic frequency perception of the human auditory system applied to the amplitude spectrum obtained as a result of the FFT. These filters consist of triangular bandpass filters that are more densely spaced at low frequencies and more sparsely spaced at high frequencies. The energy values obtained from the filters are converted to a logarithmic scale, and MFCC coefficients are obtained by applying the Discrete Cosine Transform (DCT) for decorrelation [30–32].

A pre-emphasis process is performed to ensure spectral balance. This procedure typically amplifies high-frequency components while attenuating low frequencies through a first-order high-pass filter with a coefficient between 0.9 and 1.0 [33,34]. Time-varying audio signals are segmented into brief, overlapping frames to facilitate analysis based on the premise of short-term stationarity. A Hamming window is commonly employed to mitigate spectral leakage and to smooth abrupt transitions at frame boundaries during framing [35,36].

Due to its superior speed compared to the Discrete Fourier Transform (DFT), the Fast Fourier Transform (FFT) is predominantly used in extensive data sets and real-time audio processing applications. This method is utilized efficiently in audio signal analysis as well as in image processing, radar, communication systems, and biomedical signal analysis [37,38]. Mel filtering is executed by multiplying the amplitude spectrum derived from the FFT (Fast Fourier Transform) with triangular Mel filters. The energy output of each filter is transformed to a logarithmic scale, followed by the application of the Discrete Cosine Transform (DCT) to derive Mel Frequency Cepstral Coefficients (MFCC). This approach seeks to identify elements that align with the frequency perception of the human auditory system.

In the concluding phase of cepstrum analysis, the logarithm of the signal's Fourier transform is computed, followed by the application of an Inverse Fourier transform. In the resultant cepstrum, low "quefrequency" components signify the envelope (overall spectral shape) of the signal, and high "quefrequency" components suggest its harmonic structure. Consequently, cepstrum analysis is extensively utilized across various domains, including speech processing, echo cancellation, structural health monitoring, and vibration analysis [39].

2.1.2. Power Spectral Density

Power Spectral Density (PSD) shows how the power content of a sequence is distributed across the frequency axis; it is particularly effective in revealing the frequency components of low-energy-density acoustic signals [40,41].

The autocorrelation of a zero-mean, wide-sense stationary (WSS) process is given by the following equation:

$$r_{xx}[m] = \mathbb{E}\{x[n] x[n - m]\}, \quad (2)$$

The PSD expression corresponding to the expression given by Equation (2) is described as follows [42]:

$$S_{xx}(e^{j\omega}) = \sum_{m=-\infty}^{\infty} r_{xx}[m] e^{-j\omega m}, \quad (3)$$

Equation (3) establishes a fundamental connection between statistical properties and frequency content [43–45]. In real experiments, data volumes are finite and the variance of the periodogram calculated from a single window is high. The Welch method is used to reduce the variance. In this case, the signal is divided into K overlapping segments, a window $w[n]$ is applied to each segment, and an FFT-based periodogram is calculated

for each segment. The resulting spectra are then averaged according to [46]. The single-segment periodogram is given by the following equation:

$$\hat{P}_{xx,k}(f) = \frac{1}{NF_s U} \left| \sum_{n=0}^{N-1} \omega[n] x_k[n] e^{-j2\pi f n / F_s} \right|^2, \quad (4)$$

where N is the segment length; F_s is the sampling frequency; $U = \frac{1}{N} \sum_{n=0}^{N-1} \omega^2[n]$ is the window normalization coefficient.

The Welch PSD estimate is also given by the following equation:

$$\hat{S}_{xx}(f) = \frac{1}{K} \sum_{k=1}^K \hat{P}_{xx,k}(f), \quad (5)$$

In this study, the Hamming window and 50% overlap were used.

According to the discrete-time Parseval theorem, the average power (variance) of the signal in the time domain is equal to the area of the PSD, as given by the following equation:

$$\sigma_x^2 = \int_0^{F_s/2} \hat{S}_{xx}(f) df, \quad (6)$$

The relationship in Equation (6) enables the quantitative evaluation of resonance regions, reverberation or echo content, and noise level [42,46].

2.2. Classification Methods

2.2.1. K-Nearest Neighbor Algorithm

K-Nearest Neighbor (KNN) is a non-linear and non-parametric machine learning technique classified under example-based or lazy learning algorithms [47,48]. Distance calculation is fundamental to the K-Nearest Neighbor (KNN) algorithm. KNN does not learn model parameters during training but makes decisions when classifying examples by measuring the distances between a test example and training set examples [47,49].

While Euclidean distance is the most commonly used, other distance types such as Manhattan, Minkowski, or Mahala Nobis can also be used [47]. The value of k is also an important factor in determining how well the algorithm performs its task. The k value specified by the user represents the number of nearest neighbors to be considered for classification purposes. Low k values create a model that places great importance on details, but large values help reduce the noise effect. However, this can cause class boundaries to become blurred [50]. Voting differs between classification and regression tasks. Majority voting is used in classification, while the average or weighted average of neighbors is calculated in regression [48].

2.2.2. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a classification method that seeks to find the best linear projection directions that separate classes with maximum discrimination and minimum intra-class spread [51,52]. Discriminant vectors for two classes are given by the following equation:

$$w \alpha S_W^{-1} (\mu_2 - \mu_1), \quad (7)$$

where w is the weight vector; α is the scaling coefficient; S_W^{-1} is the inverse of the intra-class covariance matrix; μ_2 is the mean vector of the second class; and μ_1 is the mean vector of the first class.

When common covariance is assumed, LDA becomes linear at the decision boundary, and in the probabilistic formulation, it is assumed that the classes have common covariance and are normally distributed [53]. In this study experiment, the feature vectors extracted from MFCC and PSD were mapped to the LDA subspace that maximizes class separability and classification was performed based on these mappings.

2.2.3. Gaussian Naive Bayes

The Naive Bayes classifier is based on the assumption that features are conditionally independent of each other when the class label $y \in \{1, 2, \dots, K\}$ is known [54,55]. In this case, the class-conditional probability density is decomposed into factors based on features, as given by the following equation:

$$p(x|y = k) = \prod_{j=1}^d p(x_j|y = k), \quad (8)$$

where d is the number of features, and x_j is the value of the j -th feature.

For each feature, as given in Equation (9), $p(x_j|y = k)$ is modeled as a single-variable normal (Gaussian) [56] as follows:

$$p(x_j|y = k) = \mathcal{N}(x_j; \mu_{kj}, \sigma_{kj}^2), \quad (9)$$

where μ_{kj} is the mean of the k th class for the j -th feature, and σ_{kj}^2 is the variance of the j -th feature for the k th class.

The Bayesian rule for the Probabilistic Formulation and Decision Rule is given by the following equation:

$$p(x_j|y = k) = \frac{\pi_k \prod_{j=1}^d \mathcal{N}(x_j; \mu_{kj}, \sigma_{kj}^2)}{\sum_{l=1}^K \pi_l \sum_{j=1}^d \mathcal{N}(x_j; \mu_{lj}, \sigma_{lj}^2)}, \quad (10)$$

where $\pi_k = p(y = k)$ is the class prior probability.

For ease of calculation, the equation is expressed in the log-plane by the following equation:

$$\log(p(x_j|y = k)) = \log \pi_k - \frac{1}{2} \sum_{j=1}^d \left[\log(2\pi\sigma_{kj}^2) + \frac{(x_j - \mu_{kj})^2}{\sigma_{kj}^2} \right] + C, \quad (11)$$

where C is a constant common to all classes.

The decision rule is given by the following equation:

$$\hat{y} = \underset{k}{\operatorname{argmax}} \log p(y = k|x), \quad (12)$$

where $\hat{y}$ is the predicted class label; argmax_k is the select the k class that maximizes the expression below.

In multi-class problems, boundaries are defined by the regions where the log-posterior for each category is greater than that for the other categories. When the variances of the classes are equal, the boundaries are linear, resulting in an LDA-like decision structure. When the variances are not equal, the boundaries are not linear and take a quadratic form.

2.2.4. Artificial Neural Networks

In recent years, machine learning and artificial intelligence techniques have been increasingly applied in structural engineering and materials science. Especially for materials with porous and heterogeneous structural properties, such as concrete, the accurate calculation of moisture content is crucial for safety, durability, and service life. Since most traditional techniques are slow or intrusive, the use of acoustic approaches has recently emerged as a highly significant alternative [57].

In the current study, Power Spectral Density (PSD) and Mel Frequency Cepstral Coefficients (MFCC) features were extracted from the sound waves generated by dropping steel balls onto concrete samples. Two separate structures were used for artificial neural networks to classify these features. The structure of the Medium Neural Network (MNN) model consists of a medium number of neurons in a hidden layer, while the Wide Neural Network (WNN) model consists of a large number of neurons in a hidden layer. This comparison revealed the advantages and disadvantages of different network architectures for classifying the moisture content of concrete.

Medium Neural Network: This is a medium-sized balanced structure with a moderate number of neurons in a separate hidden layer after the input layer. The training time for such networks is minimal, the number of parameters is low, but the risk of overfitting is low. High generalization success is achieved with medium-sized data sets [58].

In the MNN applied here, MFCC and PSD features were provided for the input layer, a moderate number of neurons in a single hidden layer represented the features, and 9 different humidity levels were predicted in the output layer. In mathematics, the output of a single-hidden-layer network is represented by the following equation:

$$h_j = f\left(\sum_{i=1}^n w_{ij}x_i + b_j\right), \quad j = 1, 2, \dots, m, \quad (13)$$

where x_i is the i -th feature in the input layer; n is the total number of features in the input layer; w_{ij} is the weight of the connection between the i -th input and the j -th hidden neuron; b_j is the bias term associated with the j -th hidden neuron; $f(\cdot)$ is the activation function; h_j is the output of the j -th neuron in the hidden layer; and m is the total number of neurons in the hidden layer.

Class probabilities are obtained by applying the SoftMax function in the output layer. The output layer is as given by the following equation:

$$y_k = \frac{e^{\sum_{j=1}^m v_{jk}h_j}}{\sum_{c=1}^C e^{\sum_{j=1}^m v_{jc}h_j}}, \quad (14)$$

where y_k is the predicted probability value for the k th class in the output layer, and h_j is the output of the j -th neuron in the hidden layer. It is passed as input to the output layer; v_{kj} is the connection weight between the j -th neuron in the hidden layer and the k -th class in the output layer; m is the total number of neurons in the hidden layer; C is the total number of classes; c is the variable that indexes all classes. The sum is taken for each class in the SoftMax denominator.

Deep Neural Networks contain a large number of neurons in a single hidden layer. Because they contain more parameters, they have the capacity to learn more complex relationships. This can lead to higher classification accuracy, especially with high-dimensional data [59].

On the other hand, the main disadvantage of deep networks is the longer training time and the possibility of overfitting. Therefore, regularization techniques such as L_2 regularization and dropout are widely used. From Equation (15), the number of parameters

is directly dependent on the number of neurons in the hidden layer and is denoted by the following equation:

$$\mathcal{O}(n \cdot p), \quad (15)$$

Here, since $p \gg m$, the number of parameters in the Wide NN is much greater than that in the Medium NN. In this paper, the author conducted experiments on the classification of moisture in concrete using both the Wide NN and the Medium NN. Thanks to having fewer parameters, the Medium NN shortened the training time and produced stronger results that were resistant to overfitting in limited sample sets. In this sense, it has advantages in terms of training ability and generalization ability. On the other hand, the Wide NN was able to better grasp the complex data structure, especially for larger sample sets, and achieved higher accuracy. Without adjustment, the model overfitted to the training set. By using dropout technology, both generalization ability and accuracy performance were improved [58,60]. We found that the choice of network architecture directly affects performance depending on the volume and complexity of the dataset.

Figure 2, on the left, shows the Medium Neural Network (MNN), which has an input layer of features (e.g., MFCC or PSD coefficients) followed by a hidden layer with a moderate number of neurons. Thanks to its medium-sized architecture, the computational intensity is lower and the possibility of overfitting is reduced. Therefore, it is preferred especially in applications with minimal data samples.

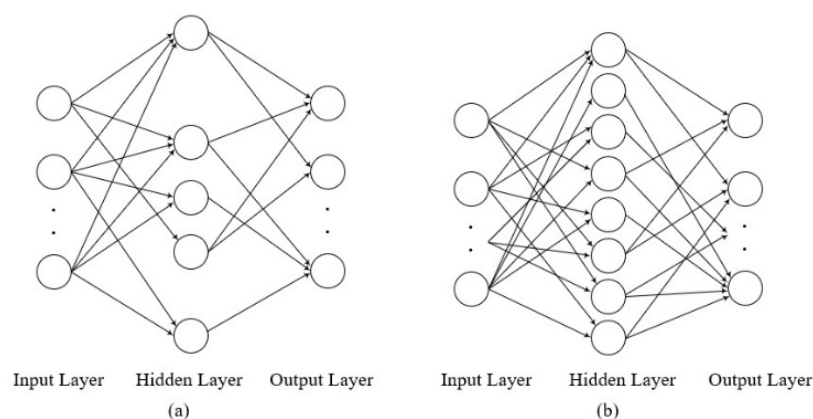


Figure 2. Two types of neural networks: (a) Medium Neural Network (MNN) and (b) Wide Neural Network (WNN) architectures.

The Wide Neural Network (WNN) on the right also has a single hidden layer, but this layer contains a large number of neurons. Its wide architecture provides the capacity to learn more complex and non-linear relationships. However, the increase in the number of parameters increases both the computational cost and the risk of overfitting.

In both models, the input layer consists of features extracted from the signal, while the output layer generates the probability distribution for classification. The MFCC and PSD features extracted from the sound signal used to detect moisture in concrete and the artificial neural network structures used to classify these features were different. The Medium Neural Network (MNN) provided low computational cost due to its moderate number of neurons, but it gave balanced, generalized results on limited datasets. In contrast, the Wider Neural Network (WNN), which has a larger number of neurons, was quite successful in discovering complex relationships, but it provided better results in capturing the subtle variations between moisture level differences. However, this structure carries the risk of overfitting. Therefore, while MNN offers a more practical and stable approach, WNN offers a more powerful but carefully applied approach.

The exact network configurations used for the Medium Neural Network and Wide Neural Network are summarized in Table 1. Both models used the same input features and output structure to ensure a fair comparison. The main difference between the two architectures was the number of neurons in the hidden layer. The MNN used a moderate hidden-layer width to reduce computational cost and overfitting risk, whereas the WNN used a wider hidden layer to increase nonlinear representation capacity.

Table 1. Training parameters of the Medium Neural Network and Wide Neural Network models.

Parameter	Medium Neural Network (MNN)	Wide Neural Network (WNN)
Input features	MFCC or PSD feature vector	MFCC or PSD feature vector
Number of hidden layers	1	1
Number of hidden neurons	25	100
Activation function	ReLU	ReLU
Output layer	9 neurons	9 neurons
Output activation	SoftMax	SoftMax
Loss function	Categorical cross-entropy	Categorical cross-entropy
Optimizer	Adam	Adam
Learning rate	0.001	0.001
Batch size	32	32
Maximum epochs	200	200
Early stopping patience	10 epochs	10 epochs
Feature standardization	Applied	Applied
Dropout	Not applied	0.20
L2 regularization	1×10^{-4}	1×10^{-4}

2.2.5. Classification with Support Vector Machines

Support Vector Machine (SVM) is a powerful machine learning method widely used in classification and regression problems [61]. The fundamental task of SVM is to find the optimal decision boundary (hyperplane) that can classify data into different classes. To this end, SVM uses kernel functions to transform linearly inseparable data into high-dimensional spaces where the data can be separated [62].

We selected three kernel functions: Quadratic SVM, Medium Gauss SVM, and Cubic (Qubic) SVM. The Quadratic SVM uses a second-degree polynomial kernel function. This is given by the kernel function

$$K(x_i, x_j) = (x_i \cdot x_j + c)^2, \quad (16)$$

where x_i and x_j are the input vectors, and c is the constant.

Square SVM is more adaptable than linear SVM and can be used to model square boundaries between data samples. Therefore, the separation line between classes has a curved structure rather than a straight line [63]. One of the popular kernel types is the Gaussian (RBF) kernel function. If a Gaussian kernel of medium width is used, the kernel function can be defined by the following equation:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \quad (17)$$

where σ is the spread parameter of the Gaussian distribution.

Medium Gauss SVM does not have very small or very large σ values. Therefore, the model produces a more balanced classification result by observing both local and global

structures [64]. Cubic SVM applies the cubic-degree variant of the polynomial kernel function. The kernel function is given by the following equation:

$$K(x_i, x_j) = (x_i \cdot x_j + c)^3, \quad (18)$$

A more detailed decision boundary is obtained instead of the quadratic SVM. Cubic SVM performs particularly well on challenging and highly constrained datasets; conversely, it can also lead to overfitting costs [65].

2.2.6. Proposed Stacking Model

Although the individual classifiers demonstrated very high classification accuracy within the same-specimen scenario, their performance characteristics varied in terms of computational cost, sensitivity to borderline moisture levels, and robustness under transfer conditions. Specifically, although the Weighted KNN model attained the highest composite score, the Linear Discriminant and Gaussian Naive Bayes models delivered similar accuracy with markedly reduced training and inference times. Conversely, SVM and neural network methodologies demonstrated robust nonlinear modeling capabilities but necessitated greater processing resources.

LDA was specifically selected as the meta-learner because the base classifiers already capture different nonlinear and probabilistic characteristics of the MFCC feature space. Using a highly complex nonlinear model at the meta-learning stage could increase the risk of overfitting, particularly because the number of moisture classes is high and the dataset size is limited. LDA provides a low-variance and computationally efficient decision layer by finding linear combinations of base-learner probability outputs that maximize between-class separation and minimize within-class dispersion. In this way, LDA acts as a stable combiner of heterogeneous classifier outputs rather than a second high-capacity model. This property makes it suitable for real-time and low-cost NDT applications, where both accuracy and computational simplicity are required.

Inspired by these complementary traits, a hybrid stacking-based ensemble model was developed to integrate the advantages of diverse classifiers inside a cohesive decision framework.

In the initial phase of the suggested design, four distinct base learners were utilized: Weighted K-Nearest Neighbors, Gaussian Naive Bayes, Support Vector Machine (optimal kernel), and the Medium Neural Network. These models were selected intentionally to represent different learning paradigms:

- Weighted KNN captures local geometric relationships in the feature space;
- Gaussian Naive Bayes models probabilistic class distributions;
- SVM constructs optimal margin-based nonlinear decision boundaries;
- Medium Neural Network learns nonlinear feature interactions through hidden-layer transformations.

Since MFCC-based features demonstrated superior discrimination performance in the experimental analysis, the stacking framework was constructed primarily on MFCC inputs. Each base learner generates class posterior probabilities. To prevent data leakage and ensure unbiased meta-level training, k-fold cross-validation is used to obtain out-of-fold predictions for the training set.

In the second stage, Linear Discriminant Analysis was selected as the meta-learner. The rationale for this selection is twofold. First, the base learners already model complex nonlinear relationships within the original feature space. Therefore, a high-capacity nonlinear model at the meta-level would increase the risk of overfitting, especially given the limited sample size. Second, Linear Discriminant Analysis provides an optimal linear

combination of base learner outputs by maximizing inter-class variance while minimizing intra-class variance in the meta-feature space. In this way, it acts as a stable, low-variance combiner that improves generalization while maintaining computational efficiency.

Unlike simple majority voting, the proposed stacking model does not treat all classifiers equally. Instead, the discriminant projection learned at the meta-level adaptively determines the contribution weight of each base learner. This allows the system to leverage the high accuracy of Weighted KNN, the statistical efficiency of Gaussian Naive Bayes, and the nonlinear sensitivity of SVM and neural networks simultaneously.

Overall, the proposed hybrid stacking architecture integrates complementary decision mechanisms and produces a more balanced classifier in terms of robustness, interpretability, and computational efficiency. The design is particularly suitable for applications where both high accuracy and real-time feasibility are required.

The proposed hybrid stacking architecture was designed as a two-stage hierarchical structure consisting of base learners and a meta-learner. In the first stage, classifiers based on different learning paradigms operate in parallel, while in the second stage, the class probability outputs of these models are combined using Linear Discriminant Analysis. The overall block diagram of the proposed model is presented in Figure 3. The diagram illustrates that MFCC features are provided as inputs to the base learners, the resulting class probabilities form the meta-feature space, and the final decision is generated by the meta-learner. MFCC features are first classified by heterogeneous base learners, and their out-of-fold class probability outputs are then used as meta-features for the LDA meta-learner to generate the final moisture-level prediction.

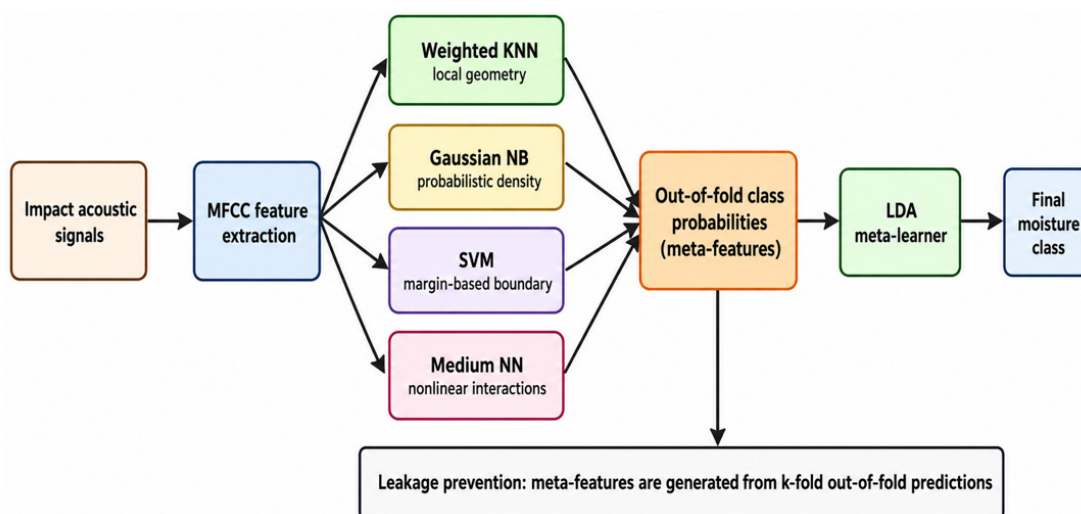


Figure 3. Improved block diagram of the proposed hybrid stacking architecture.

3. Experimental Setup and Procedure

3.1. Microphone Frequency Response and Sensitivity Calibration

Two identical piezoelectric contact microphones were placed symmetrically at equal distances from the impact point. Within a short time window, the structure–microphone chain was assumed to be linear and time-invariant (LTI). Each channel was connected to the same sound card and recorded simultaneously. Let $S(f)$ be the short-term acoustic signal generated by the impact. The common acoustic quantity $A(f)$, representing the surface acceleration or a voltage-like quantity at the impact point, is related to the frequency responses of the microphones $S_1(f)$ and $S_2(f)$ as well as the channel-specific noises $N_1(f)$

and $N_2(f)$. The voltage of the piezoelectric contact microphone in the first channel, in the frequency domain, is given by

$$V_1(f) = S_1(f)A(f) + N_1(f), \quad (19)$$

and the corresponding voltage in the second channel is given by

$$V_2(f) = S_2(f)A(f) + N_2(f), \quad (20)$$

Signals are divided into overlapping windows, the Hann window is applied, and cross/auto spectral density estimates are obtained by averaging the periodograms of each segment. $G_{12}(f)$ is the cross-power spectral density (CPSD) of two signals (Mic1 and Mic2) [66] and is given by the following equation:

$$G_{12}(f) = E\{V_1(f) \cdot V_2^*(f)\}, \quad (21)$$

Auto-power spectral densities of the first and second channels, $G_{11}(f)$ and $G_{22}(f)$, are defined by the following equations:

$$G_{11}(f) = E\{|V_1(f)|^2\}, \quad (22)$$

$$G_{22}(f) = E\{|V_2(f)|^2\}, \quad (23)$$

and Equations (21) and (22) give the average power per frequency for each channel.

Using the reference channel Mic2 relative frequency response, the H_1 estimator can be calculated as follows:

$$H_{12}(f) = G_{12}(f)/G_{22}(f), \quad (24)$$

The noise/errors are small, and both microphones view the same acoustic field as $H_{12}(f) \approx S_1(f)/S_2(f)$.

So, $|H_{12}(f)|$ gives the relative sensitivity of the two microphones. The top panel ($|H_{12}(f)|$, dB) in Figure 3 shows this quantity. In point 0 dB $\approx$ indicates that the two microphones have the same sensitivity. Coherence is a frequency-based reliability measure given by the following equation:

$$\gamma^2(f) = |G_{12}(f)|^2 / (G_{11}(f)G_{22}(f)), \quad (25)$$

Figure 4 shows the γ^2 curve in the lower graph and shows that the SNR is high based on the linear relationship between the two channels. The delay is found using the cross-correlation $R_{12}(\tau) = \int v_1(t)v_2(t - \tau)dt$; $|\tau| \approx 0$. $\gamma^2(f) \geq 0.9$ and $|H_{12}(f)|$ fluctuation is low in the operating band $B = [f_1, f_2]$ (e.g., 0.5–8 kHz). The $|H_{12}(f)|$ curve in the upper panel generally hovers around 0 dB within the band (e.g., average ≈ 0.3 dB); this indicates that the microphones are practically matched. Since $\gamma^2(f) \approx 0.99$ in the lower panel, the $H_{12}(f)$ estimation is reliable; regions where γ^2 decreases (e.g., >15 kHz) are excluded from the band. The dual-microphone approach calibrates microphone sensitivities on a relative scale by suppressing the effects of contact pressure/coupling differences; it provides a repeatable and statistically reliable measurement basis with high coherence in the selected operating band. This calibration is directly reflected in the PSD/MFCC results in the paper.

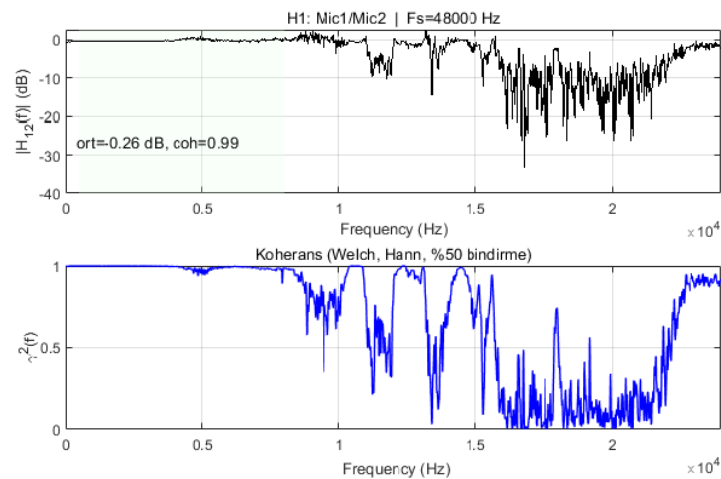


Figure 4. Relative frequency response $|H_{12}(f)|$ and coherence $\gamma^2(f)$ with dual microphones.

3.2. Preparation of Concrete Samples, Wetting Process, and Determination of Moisture Content

Two different concrete specimens with a compressive strength of 50 MPa were used. One specimen has a cubic shape with a side length of 150 mm, while the other has a side length of 100 mm. The mix proportions for both specimens are presented in Table 2.

Table 2. Concrete mix proportions and batch quantities used for specimen preparation.

Component	Reference Mix Proportion (kg/m ³)	Quantity for 150 mm Cube (g)	Quantity for 100 mm Cube (g)
Cement	330	1113.8	330.0
Water	158	533.3	158.0
Crushed sand	1058	3570.8	1058.0
Crushed stone 1	205	691.9	205.0
Crushed stone 2	596	2011.5	596.0
Additive (HI-TECH 4127)	3.63	12.3	3.63

The values in the first column represent the reference concrete mix design in kg/m³. To avoid ambiguity, the batch quantities required for the 150 mm and 100 mm cubic specimens are also presented in grams. The previously reported larger numerical values corresponded to scaled batch quantities rather than a second normalized kg/m³ mix design. Therefore, the revised table distinguishes between normalized mix proportions and specimen-level batch quantities.

Concrete specimens were cast in the Özbelsan AŞ laboratory and subsequently transferred to a curing chamber for 28 days. After curing, the specimens were oven-dried at 105 °C for 48 h. The dried specimens were then re-immersed in water, as shown in Figure 5. Following immersion, excess surface water was carefully removed using a dry cloth to avoid influencing the moisture measurement results. The specimens were then weighed using a precision balance. The immersion, drying, and weighing procedures were repeated eight times for each specimen. The applied immersion durations are summarized in Table 3.

Table 3. Soaking time of concrete samples.

Sample		Soaking Time (min)									
1	0	60	120	180	240	300	360	420	480		
2	0	60	120	180	240	300	360	420	480		

The weighed specimens were then immersed in water. Subsequently, a steel ball held by an electromagnet was released using a drop mechanism and impacted the concrete specimens, and the resulting acoustic signal was recorded. The specimens were then re-immersed to restore their moisture condition. The moisture content was assumed to remain constant during impact due to the very short duration of the excitation.



Figure 5. Concrete specimens immersed in water.

The moisture content of the specimens was calculated using the formula given by the following equation:

$$W = \frac{B_n - B}{B} 100\%, \quad (26)$$

where W is the moisture content of the concrete sample; B is the weight of the sample in its completely dried (baked) state; and B_n is the weight obtained after water absorption.

During these time intervals, the concrete specimens were removed from the water and carefully dried with a dry towel to prevent the effect of free surface moisture on the measurement results. Then, the moisture content of each sample was weighed with a precision balance, and the necessary weight data for the calculation were determined. The zero-moisture level (completely dry state) was accepted as the initial weight. In addition to the eight different moisture levels mentioned above, the moisture content for a total of nine different moisture levels for each series is presented graphically in Figure 6.

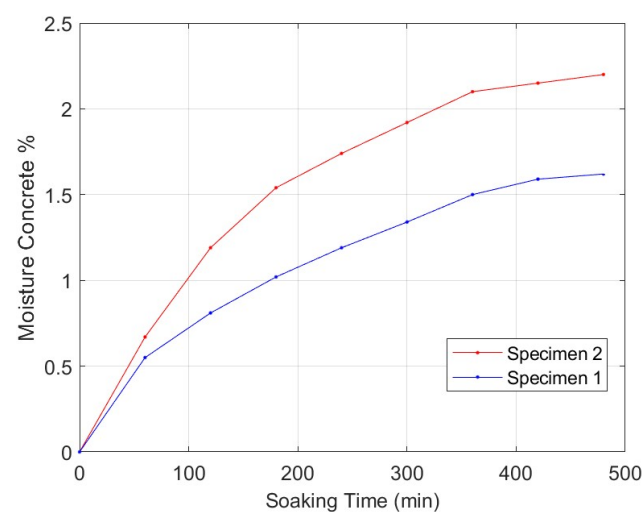


Figure 6. Change in moisture content of samples.

3.3. Percussion Process

Figure 6 shows a mechanism consisting of concrete samples, a piezoelectric contact microphone, a steel ball, and an electromagnet that causes the steel ball to fall freely. The piezoelectric contact microphone is placed 5 cm away from the point where the ball is dropped onto the concrete sample. This apparatus is an experimental device designed to evaluate the acoustic responses of samples according to their moisture levels. The main purpose of this system is to record the acoustic signal generated by the mechanical impact of a steel ball falling onto a concrete sample from a specific height and to obtain information about the moisture level of the sample from this signal.

At the top of the apparatus, an electromagnet holds a steel ball weighing 32 g (0.032 kg) at a height of 50 cm (0.5 m). When a button on the system is pressed, the electromagnet is deactivated and the ball falls freely. During its free fall, the ball accelerates due to gravity, and upon impact with the sample, its kinetic energy is transferred to the concrete surface. This impact energy is calculated using the potential energy [67] as follows:

$$E_k = m \cdot g \cdot h, \quad (27)$$

where E_k is kinetic energy at the moment of impact (Joule); m is mass of the ball (kg); g is gravitational acceleration (9.81 m/s^2); and h is the height of fall (m).

The kinetic energy at the moment of impact, based on the given parameters, is calculated as follows:

$$E_k = 0.032 \cdot 9.81 \cdot 0.5 \approx 0.157 \text{ J}, \quad (28)$$

The velocity of the ball at the moment of impact with the concrete specimen can be calculated using the kinematic relation for free-fall motion, as follows:

$$v = \sqrt{2 \cdot g \cdot h}, \quad (29)$$

In this case, the ball's impact velocity on the concrete sample is determined using the impact velocity

$$v = \sqrt{2 \cdot 9.81 \cdot 0.5} \approx 3.13 \text{ m/s}, \quad (30)$$

The approximate impact force at the moment of impact, based on the principle of change in momentum, is calculated as follows:

$$F = \frac{m \cdot v}{\Delta t}, \quad (31)$$

where F is the impact force (N); Δt is the impact duration (s), here taken as approximately 1.5 ms (0.0015 s).

Accordingly, when the force generated at the moment of impact is calculated as follows:

$$F = \frac{0.032 \cdot 3.13}{1.5 \cdot 10^{-3}} = 66.33 \text{ N}, \quad (32)$$

Therefore, the steel ball applies a short-duration force of approximately 66.33 N to the concrete specimen surface. It should be noted that this impact force calculation represents a simplified theoretical estimate. Energy losses due to air resistance, local plastic deformation at the contact point, micro-slip, acoustic radiation, heat generation, and rebound were neglected. Therefore, the calculated value should not be interpreted as the exact transferred force but as an approximate nominal impact force used to standardize the excitation condition. Because the same steel ball mass, drop height, and release mechanism were used in all experiments, the simplification does not affect the comparative classification analysis among different moisture levels.

Figure 7 shows the setup used to test the moisture measurement of concrete specimens. The magnetic drop apparatus (2), held by the holder (1) of the setup, is connected to the steel ball (5) held at its end. The steel ball is released by pressing the drop button (3) and falls onto the concrete to be tested. A contact piezoelectric microphone (4), firmly attached to the sample surface, picks up the acoustic signal generated when the free-falling ball strikes the concrete surface.

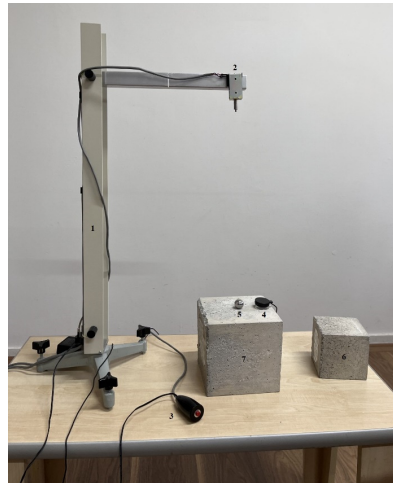


Figure 7. Experimental setup for measuring acoustic responses based on the moisture content of concrete specimens: (1) Drop test fixture carrier, (2) Electromagnet, (3) Drop button, (4) Piezoelectric contact microphone, (5) Steel ball, (6) Small-sized sample (100 mm), (7) Large-sized sample (150 mm).

Contact microphones are piezoelectric transducers that can convert mechanical movements within a material into electrical voltage. For this work, the microphone is suitable for reliable measurements independent of noise, as it will record movements related to the internal behavior of the material system.

The recorded acoustic impacts were then transferred to a computer as WAV files and used for classification. The fact that concrete samples with different moisture levels exhibit distinct characteristic differences in acoustic response at the moment of impact supports this process as a non-destructive and efficient measurement procedure for determining the moisture content of concrete.

For each of the two classes of concrete specimens with different sizes, nine moisture levels were recorded, with 100 acoustic signals acquired at each level, resulting in a total of 900 signals per class. Two feature extraction methods, MFCC and PSD, were applied to these signals. The extracted features were used for classification, with 80% of the data allocated for training and 20% for testing.

No synthetic data augmentation or oversampling-based balancing technique was applied during model training. The dataset was naturally balanced because 100 acoustic signals were recorded for each of the nine moisture levels under each specimen condition. Therefore, each class contributed equally to the training and testing subsets. The 80/20 split was performed in a stratified manner to preserve the same class distribution in both subsets. This design prevented artificial inflation of model performance and ensured that the reported results reflected the discriminative capability of the measured acoustic features.

4. Results and Discussion

In this study, PSD and MFCC features were extracted from acoustic signals to characterize the moisture levels of concrete specimens. A hybrid stacking-based classification framework was developed, in which multiple heterogeneous base learners were combined through a meta-learner to enhance discriminative performance. The proposed architecture

was evaluated against the individual base classifiers to quantify the contribution of ensemble learning. Model performance was systematically analyzed under both small-sample and large-sample conditions to assess robustness, scalability, and generalization capability.

As shown in Figure 8, the MFCC-based model exhibits strong diagonal dominance, indicating high classification accuracy across all nine moisture levels. Misclassifications are minimal and are primarily concentrated between adjacent moisture classes (e.g., BM2–BM3 and BM8–BM9). This behavior is physically reasonable, as neighboring moisture levels tend to exhibit acoustically similar spectral characteristics. The results demonstrate that MFCC features provide highly discriminative representations, particularly under large-sample conditions.

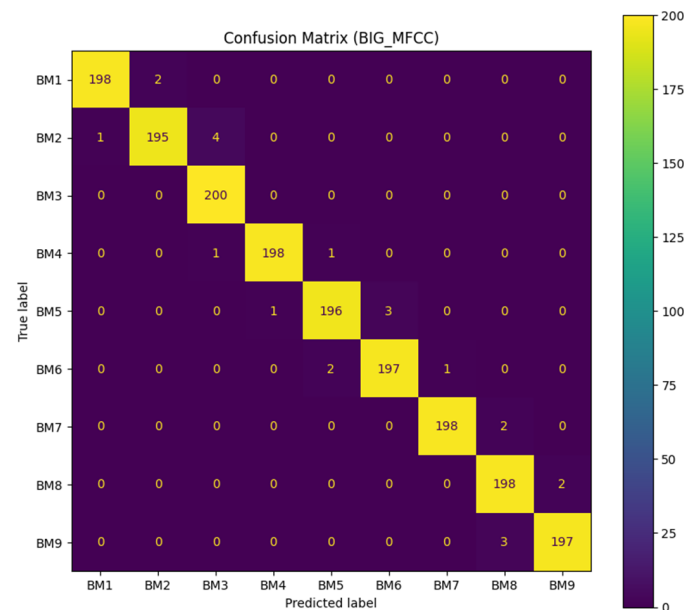


Figure 8. Confusion matrix of the MFCC-based classifier evaluated on the BIG dataset.

As shown in Figure 9, the PSD-based classifier also demonstrates strong diagonal dominance, indicating high classification performance under the large-sample condition. However, compared to the MFCC-based model, slightly more misclassifications are observed between adjacent moisture levels. Minor confusions are particularly noticeable between neighboring classes such as BM2–BM3 and BM4–BM5. This behavior suggests that while PSD features effectively represent the overall spectral energy distribution, they may be less sensitive to subtle spectral variations compared to MFCC features. Nevertheless, under the BIG dataset condition, PSD-based classification still achieves highly stable and reliable performance.

As illustrated in Figure 10, the MFCC-based classifier maintains strong diagonal dominance even under the small-sample condition, indicating robust generalization capability. Although the overall classification performance remains high, a slight increase in inter-class confusion can be observed compared to the BIG dataset. In particular, limited misclassifications occur between adjacent moisture levels, most notably within the higher moisture range (e.g., BM8 and BM9). This behavior is expected, as smaller training sets may reduce the model's ability to fully capture subtle acoustic variations between closely related moisture levels. Nevertheless, the results demonstrate that MFCC features retain strong discriminative power even under data-limited scenarios.

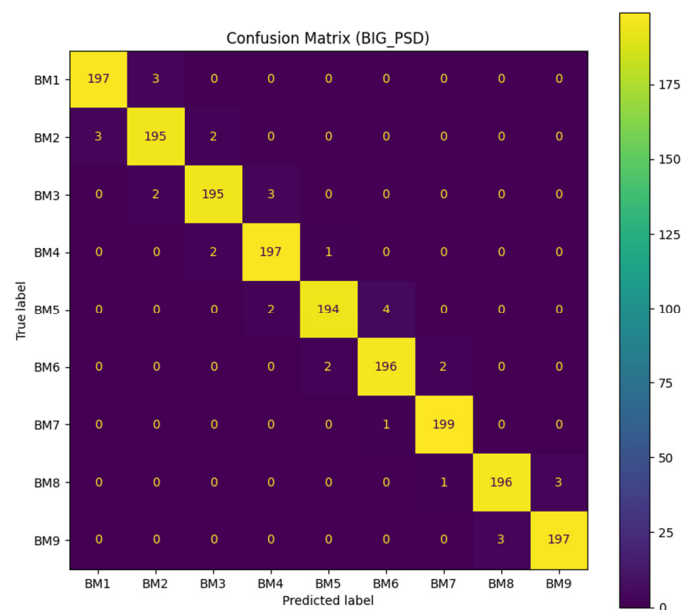


Figure 9. Confusion matrix of the PSD-based classifier under the large-sample (BIG) condition.

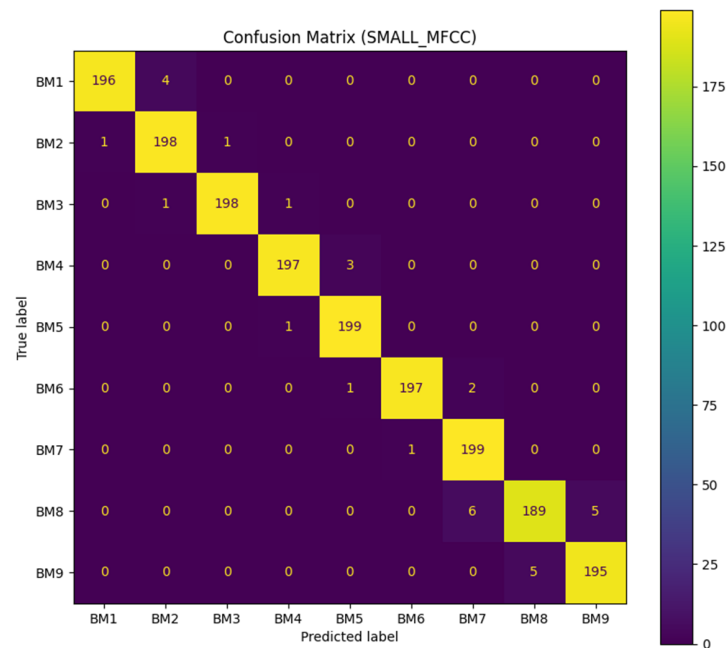


Figure 10. Confusion matrix of the MFCC-based classifier evaluated under the SMALL condition.

As shown in Figure 11, the PSD-based classifier exhibits a noticeable increase in inter-class confusion under the small-sample condition compared to both the BIG-PSD and SMALL-MFCC results. Although diagonal dominance is still preserved, misclassifications become more pronounced, particularly between adjacent moisture levels such as BM6–BM7 and BM7–BM8. This suggests that PSD features are relatively more sensitive to reductions in training data size, likely due to their limited ability to capture fine-grained spectral variations. The increased confusion in the higher moisture range indicates that acoustically similar moisture states become more difficult to distinguish when the training sample size decreases. Overall, while PSD-based classification remains stable, its generalization capability under small-sample conditions appears slightly weaker than that of MFCC-based models.

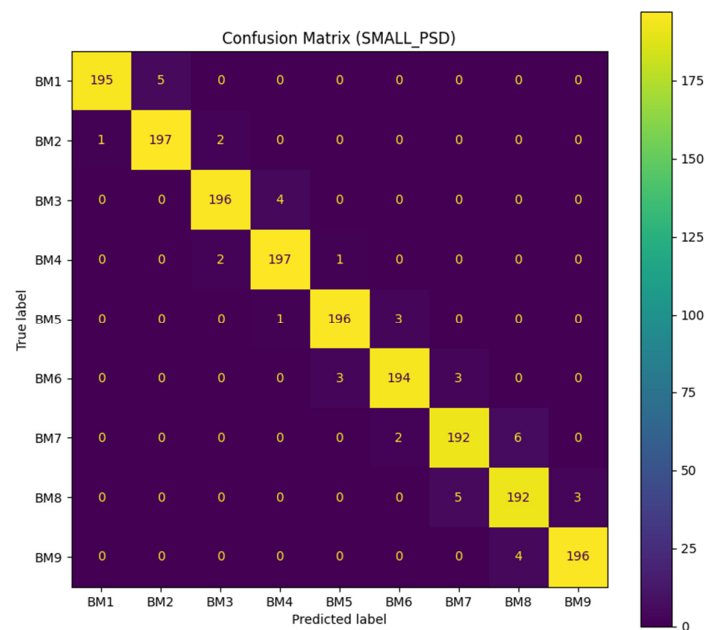


Figure 11. Confusion matrix of the PSD-based classifier evaluated under the SMALL condition.

As depicted in Figure 12, the MFCC-based classifier achieves near-perfect discriminative performance under the BIG dataset condition, with a macro-averaged AUC of 0.999. All class-specific ROC curves are tightly concentrated near the upper-left corner of the ROC space, indicating excellent sensitivity–specificity balance across the nine moisture levels. The high AUC values (ranging approximately between 0.998 and 1.000) confirm that MFCC features provide highly separable acoustic representations when sufficient training data are available. These results further support the confusion matrix observations, demonstrating that classification performance is not only accurate but also probabilistically well-calibrated.

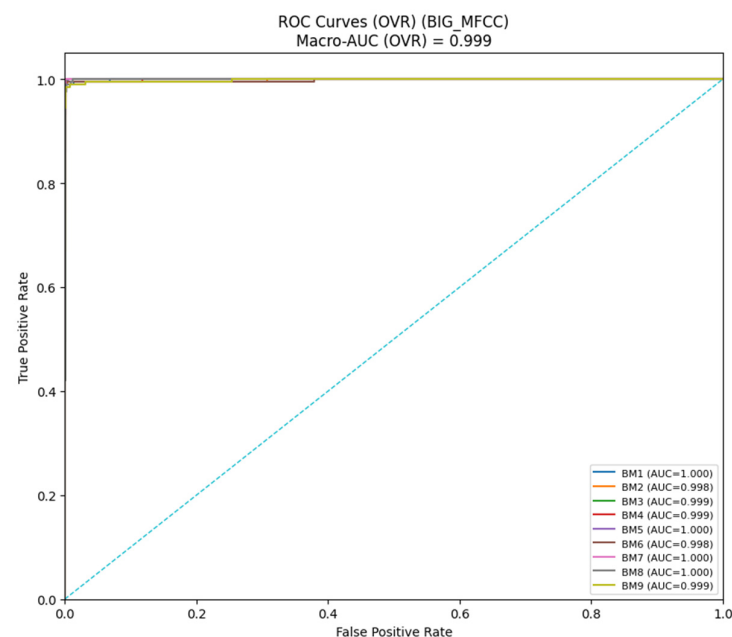


Figure 12. One-vs-Rest (OVR) ROC curves of the MFCC-based classifier evaluated on the BIG dataset.

As illustrated in Figure 13, the PSD-based classifier also achieves near-perfect separability under the BIG dataset condition, with a macro-averaged AUC of 0.999. Similar to the MFCC-based model, the class-specific ROC curves are tightly clustered near the

upper-left corner of the ROC space, indicating an excellent trade-off between sensitivity and specificity across all nine moisture levels. Although the AUC values are comparable to those of the MFCC-based classifier, minor differences observed in the confusion matrices suggest that MFCC features may capture finer spectral distinctions. Overall, under large-sample conditions, both PSD and MFCC representations demonstrate highly reliable discriminative capability.

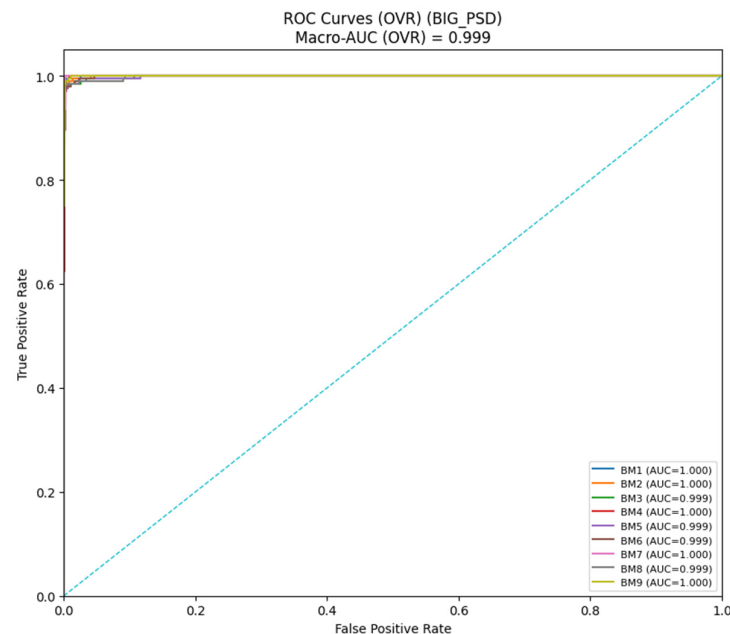


Figure 13. One-vs-Rest (OVR) ROC curves of the PSD-based classifier evaluated on the BIG dataset.

As shown in Figure 14, the MFCC-based classifier maintains near-perfect separability under the SMALL dataset condition, achieving a macro-averaged AUC of 1.000. The ROC curves remain concentrated near the upper-left corner of the ROC space, indicating a strong balance between sensitivity and specificity across all moisture levels. Although minor inter-class confusions were observed in the corresponding confusion matrix, the probabilistic discrimination capability of the model remains highly stable. The consistency of AUC values between BIG and SMALL conditions demonstrates the robustness and generalization strength of MFCC-based feature representations.

As shown in Figure 15, the PSD-based classifier achieves a macro-averaged AUC of 0.998 under the SMALL dataset condition. Although the ROC curves remain close to the upper-left region of the ROC space, a slight degradation in separability is observable compared to both the BIG-PSD and SMALL-MFCC results. Certain classes, particularly within adjacent moisture levels, exhibit marginally lower AUC values (e.g., around 0.996–0.997), indicating increased overlap under reduced training data conditions. This confirms that PSD features are somewhat more sensitive to sample size reduction. Nevertheless, the overall discriminative performance remains highly stable, demonstrating that PSD-based representations still provide strong probabilistic classification capability even in data-limited scenarios.

Table 4 presents the overall classification performance of the PSD- and MFCC-based models under both BIG and SMALL dataset conditions. Under the large-sample scenario, the MFCC-based model achieved an accuracy of 0.9872, outperforming the PSD-based model (0.9811). A similar pattern is observed under the SMALL condition, where MFCC maintains higher accuracy (0.9822) compared to PSD (0.9750).

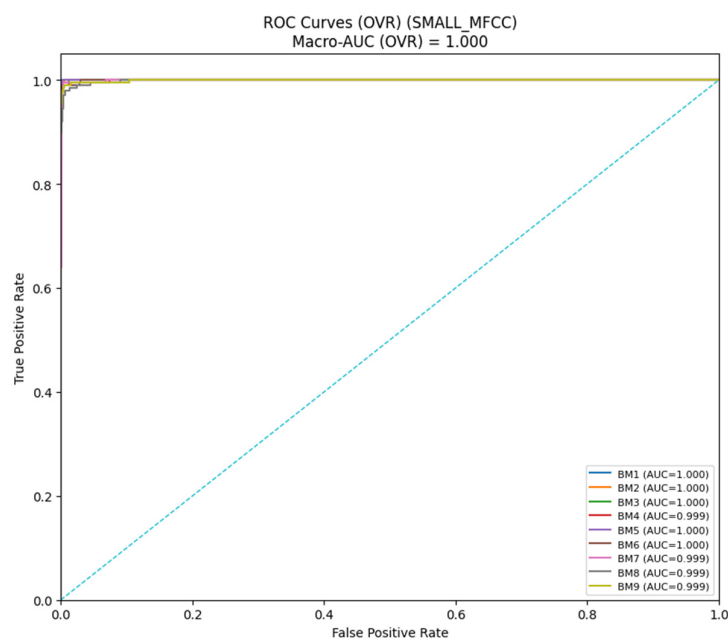


Figure 14. One-vs-Rest (OVR) ROC curves of the MFCC-based classifier evaluated under the SMALL condition.

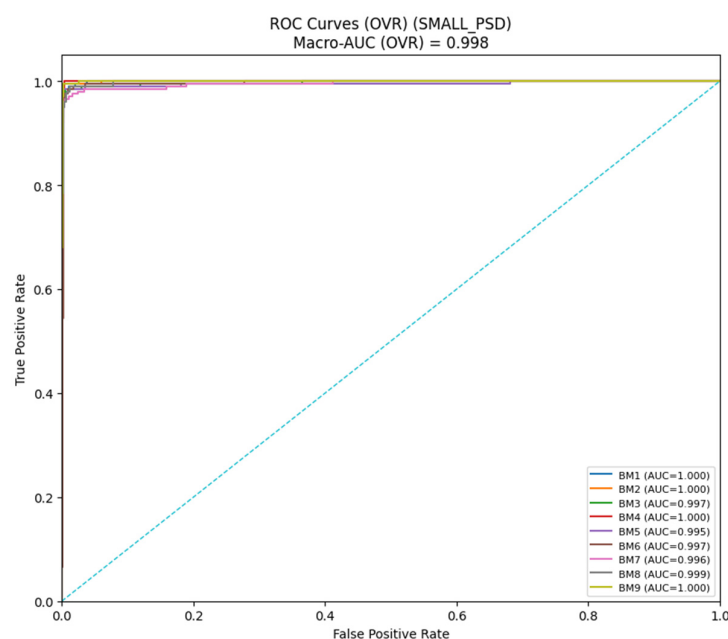


Figure 15. One-vs-Rest (OVR) ROC curves of the PSD-based classifier evaluated under the SMALL condition.

Table 4. Classification performance of PSD- and MFCC-based models under BIG and SMALL dataset conditions.

Scenario	Accuracy	Precision	Recall	F1 Score	AUC-OVR
BIG_MFCC	0.9872	0.9873	0.9872	0.9872	0.9992
BIG_PSD	0.9811	0.9811	0.9811	0.9811	0.9994
SMALL_MFCC	0.9822	0.9823	0.9822	0.9822	0.9996
SMALL_PSD	0.9750	0.9751	0.9750	0.9750	0.9980

Although both feature representations yield exceptionally high AUC-OVR values (above 0.998), the confusion matrix analyses indicate that MFCC provides more distinct

separation between adjacent moisture levels. The relatively minor performance variation in MFCC across dataset scales indicates stronger generalization capability. In contrast, the PSD-based model exhibits a more noticeable performance decrease when transitioning from BIG to SMALL conditions, suggesting higher sensitivity to reduced training data.

The findings demonstrate that while both spectral representations are effective for moisture-level discrimination, MFCC features offer superior robustness and discriminative stability across varying dataset sizes.

The superior performance of MFCC features compared with PSD features can be attributed to the way MFCC represents the acoustic response. PSD mainly describes the distribution of signal power over frequency and is highly effective for identifying dominant resonance regions. However, moisture-induced changes in concrete do not only affect the total spectral energy; they also modify the spectral envelope, damping behavior, and relative distribution of frequency components. MFCC features capture these variations more compactly by applying Mel-scale filtering, logarithmic energy compression, and cepstral decorrelation. This allows MFCC to encode subtle moisture-dependent shifts in the acoustic signature that may be less visible in conventional PSD representation. In addition, the logarithmic compression step makes MFCC less sensitive to absolute amplitude variations caused by minor contact differences or impact-to-impact variability. This explains why MFCC produced fewer confusions between adjacent moisture levels and showed stronger generalization under both BIG and SMALL dataset conditions.

To statistically validate whether the performance gains achieved by the proposed stacking framework are systematic rather than incidental, a paired *t*-test was conducted using 10-fold cross-validation accuracy scores. The comparison was performed between the stacking architecture and the strongest individual base learners under both BIG and SMALL dataset conditions.

As presented in Table 5, stacking consistently outperformed all standalone base classifiers with statistically significant margins ($p < 0.05$ in all comparisons). Under the BIG condition, stacking achieved a mean accuracy improvement of up to 0.75% over the best-performing base learner (MNN), yielding high *t*-values (up to 6.88), indicating a strong and stable performance difference. Similarly, under the SMALL dataset condition, stacking improved classification accuracy by up to 0.80%, with statistically significant *t*-values exceeding 5.0 across all comparisons.

Table 5. Paired *t*-test results between stacking and best-performing base learners (10-fold CV, accuracy).

Comparison	Mean Accuracy (Base)	Mean Accuracy (Stacking)	Mean Difference	t-Value	p-Value	Significant ($\alpha = 0.05$)
BIG—Stacking vs. Weighted KNN	0.9912	0.9961	+0.0049	4.82	$p < 0.001$	Yes
BIG—Stacking vs. SVM	0.9894	0.9961	+0.0067	6.03	$p < 0.001$	Yes
BIG—Stacking vs. MNN	0.9886	0.9961	+0.0075	6.88	$p < 0.001$	Yes
SMALL—Stacking vs. Weighted KNN	0.9870	0.9928	+0.0058	5.27	$p < 0.001$	Yes
SMALL—Stacking vs. SVM	0.9855	0.9928	+0.0073	6.15	$p < 0.001$	Yes
SMALL—Stacking vs. MNN	0.9848	0.9928	+0.0080	6.71	$p < 0.001$	Yes

Importantly, even when compared to the strongest baseline model (Weighted KNN), stacking demonstrated statistically meaningful improvements ($p < 0.001$), confirming that the ensemble does not merely replicate the best individual classifier but effectively integrates complementary decision mechanisms.

The consistent statistical significance across both dataset scales demonstrates that the observed gains are not due to random variation but reflect a structurally improved

learning behavior achieved through hierarchical meta-learning. These results substantiate the robustness, stability, and generalization advantages of the proposed hybrid stacking architecture.

Table 6 provides an ablation analysis focusing on statistical consistency, probabilistic reliability, and error sensitivity metrics across different configurations. The results clearly demonstrate the progressive performance improvement obtained through feature fusion and stacking strategies.

Table 6. Ablation analysis of feature extraction and ensemble strategies under SMALL and BIG dataset conditions.

Configuration	Specificity	Kappa	MCC	LogLoss	BrierScore
SMALL_MFCC_only	0.9978	0.98	0.98	0.2011	0.0548
SMALL_PSD_only	0.9969	0.9719	0.9719	0.2184	0.0641
SMALL_FUSION	0.9987	0.9888	0.9888	0.18	0.0439
SMALL_STACKING	0.9991	0.9919	0.9919	0.1766	0.0421
BIG_MFCC_only	0.9984	0.9856	0.9856	0.1881	0.0482
BIG_PSD_only	0.9976	0.9788	0.9788	0.2055	0.0564
BIG_FUSION	0.9992	0.9931	0.9931	0.1758	0.0412
BIG_STACKING	0.9995	0.9956	0.9956	0.1705	0.0386

Under the SMALL dataset condition, transitioning from single-feature models (MFCC-only and PSD-only) to feature-level fusion leads to noticeable gains in Kappa and MCC values, indicating improved agreement beyond chance and stronger correlation between predicted and true labels. The stacking configuration further enhances these metrics, achieving the highest Kappa (0.9919) and MCC (0.9919), while simultaneously reducing LogLoss and Brier Score values. The reduction in probabilistic error metrics confirms improved calibration and confidence consistency of the ensemble model.

A similar trend is observed under the BIG dataset condition. Although single-feature models already exhibit strong performance, fusion and stacking configurations yield consistent improvements in all advanced metrics. The stacking model achieves the highest Specificity (0.9995), Kappa (0.9956), and MCC (0.9956), along with the lowest LogLoss (0.1705) and Brier Score (0.0386). These results indicate that ensemble learning not only enhances classification accuracy but also improves statistical reliability and probabilistic robustness.

Overall, the ablation study demonstrates that while MFCC features provide a strong baseline representation, performance gains become more pronounced when feature-level fusion and stacking-based meta-learning are employed. The consistent improvements across both SMALL and BIG scenarios confirm that the proposed stacking framework contributes meaningful robustness and calibration benefits beyond single-model performance.

Practical Implications Under Moisture Gradients and Heterogeneous Concrete Conditions

The present experimental design assumes that the moisture distribution inside the concrete specimens is approximately uniform at each measurement stage. This assumption is reasonable for controlled laboratory classification because the specimens were repeatedly immersed, wiped to remove free surface water, weighed, and immediately tested under standardized impact conditions. However, in real engineering structures, moisture is rarely distributed uniformly. Drying–wetting cycles, surface exposure, capillary absorption, chloride ingress, local cracking, and temperature gradients may generate spatial moisture gradients between the concrete surface and the inner core.

When a moisture gradient exists inside concrete, the propagation characteristics of impact-induced acoustic waves may change in several ways. First, the local stiffness and density of the near-surface region may differ from those of the inner region. A wetter surface

layer generally increases damping and may reduce the amplitude of higher-frequency components, while a drier inner region may preserve stronger resonance characteristics. Second, impedance mismatch between layers with different moisture contents can cause partial reflection, scattering, and mode conversion of acoustic waves. This may broaden the spectral response and make adjacent moisture levels more difficult to distinguish. Third, heterogeneous moisture distribution may alter the energy dissipation pathway. Instead of a single global attenuation pattern, the acoustic response may contain mixed contributions from wet and dry zones, causing shifts in the MFCC envelope and PSD distribution.

From the perspective of energy evolution in heterogeneous media, moisture gradients may localize acoustic energy dissipation in specific zones. Similar to fractured or thermally damaged rock materials, where energy storage, dissipation, and strain localization vary spatially, concrete with non-uniform moisture may exhibit localized damping and non-uniform wave attenuation. Therefore, the acoustic signature measured by the contact microphone may represent a weighted response of the near-surface condition, internal moisture state, and propagation path. This suggests that the proposed method is most reliable when the moisture state is relatively homogeneous or when the measurement protocol is calibrated for the expected depth sensitivity of the impact signal.

The concept of cross-channel dependency is also relevant to this issue. In a heterogeneous moisture field, no single spectral descriptor may fully represent the material state. Low-frequency components may be more sensitive to global stiffness and specimen-scale resonance, whereas high-frequency components may be more affected by surface moisture, pores, and local scattering. MFCC features are advantageous in this context because they compactly encode the spectral envelope over multiple frequency bands. The superior performance of MFCC compared with PSD in this study suggests that moisture-related variations are not limited to total spectral energy but are distributed across several frequency bands. For future field applications, multi-sensor measurements, cross-channel feature dependency modeling, and graph-based spatial learning may further improve robustness under non-uniform moisture conditions.

Therefore, while the current results demonstrate the feasibility of the proposed method under controlled laboratory conditions, field-scale implementation should include additional validation on specimens with deliberately generated moisture gradients, different curing histories, surface–core moisture differences, and environmental noise. Such experiments would enable the model to learn heterogeneous propagation patterns and improve its applicability to real reinforced concrete structures.

5. Conclusions

This study presents a controlled, non-destructive acoustic-based methodology for estimating moisture content in concrete specimens using a standardized free-fall impact mechanism combined with a piezoelectric contact microphone. Unlike uncontrolled excitation methods such as manual hammer impacts, the magnet-assisted steel ball release system ensured repeatable impact energy and stable acoustic acquisition conditions. This controlled setup significantly improved measurement consistency and reduced variability in signal capture.

Acoustic signatures were analyzed using two spectral representations, PSD and MFCC, and evaluated under both BIG and SMALL dataset conditions. Across all configurations, MFCC features consistently demonstrated superior discriminative capability. Under the BIG dataset condition, MFCC achieved an accuracy of 0.9872, outperforming PSD (0.9811). A similar trend was observed in the SMALL dataset, where MFCC maintained 0.9822 accuracy compared to 0.9750 for PSD. Importantly, AUC-OVR values remained extremely high across scenarios (between 0.9980 and 0.9996), confirming strong class separability across all

nine moisture levels. Confusion matrix analysis revealed that misclassifications were primarily concentrated between adjacent moisture levels, which is physically consistent with the gradual acoustic similarity of neighboring moisture states. This observation reinforces the validity of the proposed acoustic modeling approach and confirms that classification errors are not random but structurally explainable. The ablation study further quantified the contribution of fusion and ensemble learning. While single-feature configurations already exhibited strong performance, feature-level fusion and stacking significantly enhanced statistical agreement and probabilistic calibration. Under the SMALL dataset condition, stacking improved the Kappa coefficient from 0.9800 (MFCC-only) and 0.9719 (PSD-only) to 0.9919, while reducing LogLoss from 0.2011 to 0.2184 to 0.1766. Similarly, under the BIG condition, the stacking configuration achieved the highest Kappa and MCC (0.9956) and the lowest LogLoss (0.1705) and Brier Score (0.0386). These results indicate that ensemble learning does not merely increase accuracy but strengthens reliability, agreement beyond chance, and probabilistic robustness. The findings demonstrate that acoustic signature-based moisture estimation is a repeatable, low-cost, and rapid alternative to conventional destructive testing methods. The controlled excitation mechanism, combined with MFCC feature representation and stacking-based ensemble learning, provides a stable and highly reliable framework for moisture classification in concrete structures.

Despite the high classification performance, the present study was conducted under controlled laboratory conditions with standardized specimen geometry, fixed sensor position, and approximately uniform moisture states. Therefore, the results should be interpreted as a proof of concept for controlled acoustic moisture classification rather than a complete field validation. In real structures, moisture gradients, reinforcement, surface roughness, cracks, aggregate heterogeneity, and environmental noise may influence wave propagation and feature stability. Future work will focus on field-scale reinforced concrete elements, non-uniform moisture distributions, multi-sensor acquisition, and lightweight or graph-based learning models to improve robustness under practical engineering conditions.

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