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Ensemble statistical techniques for predictive analytics in high-noise environments: A novel noise-weighted stacking framework

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Ensemble statistical techniques for predictive analytics in high-noise environments: A novel noise-weighted stacking framework

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Abstract

Predictive analytics in real-world deployments routinely encounter data corrupted by measurement noise, sensor drift, and environmental interference—conditions collectively termed high-noise environments (HNE). The discriminative performance of classical single-classifier approaches substantially decreases as the signal-to-noise ratio (SNR) decreases below 15 dB, highlighting the need for robust ensemble strategies. This paper introduces the entropy-weighted noise-aware ensemble (EWNE-Stack), a novel two-level stacking meta-learner in which base classifier weights are dynamically adjusted at inference time using an information-theoretic noise-level estimator. The estimator computes the Shannon entropy over rolling prediction windows and inverts it to assign higher confidence weights to classifiers that exhibit lower local prediction uncertainty. The proposed EWNE-Stack achieves a classification accuracy of 96.2% at an SNR = 5 dB and an area under the ROC curve (AUC) of 0.962, representing statistically significant improvements of 2.8%, 2.8%, 3.9%, 9.9%, and 16.4 percentage points over gradient boosting, random forest, SVM, logistic regression, and naïve Bayes, respectively. Extensive experiments on three benchmark datasets—the UCI HEPMASS particle physics dataset, the PhysioNet MIT-BIH Arrhythmia dataset, and a synthetically generated high-noise tabular dataset—confirm the reproducibility and generalizability of the proposed method. All source code, pretrained model checkpoints, and experimental protocols are publicly released to ensure full reproducibility in accordance with FAIR data principles.

Keywords: ensemble learning; stacking meta-learner; high-noise environments; predictive analytics; signal-to-noise ratio; EWNE-Stack

MSC Classes: 62H30, 68T05, 62G35

1. Introduction

The proliferation of internet-of-Things (IoT) sensors, biomedical monitoring devices, and high-throughput scientific instruments has generated unprecedented volumes of data that are inherently noisy. Signal-to-noise ratios (SNRs) in clinical ECG recordings can fall below 10 dB during physical activity [1], industrial vibration sensors typically operate at SNR levels of

5–20 dB [2], and high-energy physics detector arrays routinely record collision events at SNR ≈ 3 dB [3]. In such environments, predictive models trained under clean-data assumptions experience severe performance degradation—a phenomenon termed the "noise wall" by Kuncheva and Whitaker [4].

Ensemble methods, which aggregate predictions from multiple base learners, offer a natural defense against noise-induced variance. The theoretical foundation, traced to Condorcet's jury theorem and formalised by Breiman [5], demonstrates that an ensemble of weakly correlated classifiers can outperform any individual component provided that each component exceeds random chance performance. Subsequent work extended these results to noisy settings: Zhou [6] reported that diversity among base classifiers is the primary lever for noise tolerance, whereas Geurts et al. [7] reported that tree-based ensembles with extremely randomised splits achieve superior bias–variance trade-offs under additive Gaussian noise.

Despite this theoretical groundwork, existing ensemble frameworks treat base-learner weighting as a static posttraining operation. Methods such as bagging [5], AdaBoost [8], and standard stacking [9] assign weights during training without adapting to the noise characteristics of incoming test instances. This limitation is critical: a base classifier that excels under low noise may become unreliable under high noise, yet a fixed weighting scheme continues to assign it high influence. The consequence is systematic overconfidence under degraded conditions.

To address this gap, we propose the entropy-weighted noise-aware ensemble (EWNE-Stack), a novel stacking framework with three distinct contributions: (i) an online, information-theoretic noise-level estimator that operates without access to ground-truth labels; (ii) a dynamic weight-reassignment mechanism that redistributes ensemble influence at inference time on the basis of estimated local noise; and (iii) a theoretical analysis that proves the convergence and consistency of the weight estimator under sub-Gaussian noise. The proposed method is evaluated on three heterogeneous datasets spanning particle physics, biomedical signals, and synthetic tabular data, providing a comprehensive validation of its generalizability.

Paper organisation.

Section 2 reviews related work. Section 3 presents the theoretical framework and algorithm. Section 4 describes the experimental design, datasets, and evaluation protocol. Section 5 reports the results and statistical analysis. Section 6 discusses implications and limitations. Section 7 concludes with future directions.

2. Related Work

2.1 Ensemble Methods for Noisy Data

The study of ensemble methods under noisy conditions spans three decades. Breiman's bagging [5] demonstrated that bootstrap aggregation reduces variance by an expected factor of B (the number of base learners) under independence assumptions, a result extended by Bühlmann and Yu [10] to the heteroscedastic noise setting. Random forests [11] amplify this effect through random feature subsampling at each tree node, creating diversity that naturally mitigates the impact of noisy features.

Boosting approaches, beginning with AdaBoost [8] and extending through gradient boosting machines [12] and XGBoost [13], adopt a sequential error-correction strategy. While powerful in clean settings, boosting is notoriously sensitive to label noise: misclassified noisy samples receive exponentially increasing weights, causing the ensemble to overfit noise patterns. Several modifications address this limitation, including robust boosting [14] and noise-tolerant gradient boosting [15], although these require explicit noise rate estimation—a parameter that is difficult to obtain in practice.

2.2 Stacking and meta-Learning

Stacking, introduced by Wolpert [9], learns a meta-model over the out-of-fold predictions of base learners, enabling adaptive combinations that can outperform any fixed weighting scheme. Ting and Witten [16] extended stacking to continuous regression, whereas van der Laan et al. [17] provided oracle inequality guarantees for stacked generalisation under cross-validation. In the context of noisy data, Šmuc and Šarić [18] applied stacked generalisation to corrupted genomic data, reporting 4–7% accuracy improvements over single classifiers at SNR levels below 20 dB but without providing a principled noise-adaptive weighting mechanism.

2.3 Information-Theoretic Approaches to Robustness

Shannon entropy has been used extensively as an uncertainty quantifier in ensemble learning. Kuncheva [4] employed entropy-based diversity measures to analyse ensemble behavior, whereas Shipp and Kuncheva [19] explored the relationship between classifier correlation and ensemble accuracy. More recently, Gontijo-Lopes et al. [20] and Fort et al. [21] demonstrated that prediction entropy reliably tracks uncertainty under distribution shift—a condition closely related to high noise. Our work leverages this insight but differs critically: rather than using entropy as a diagnostic tool, we integrate it into the weight-assignment mechanism of the stacking framework, creating a closed-loop adaptation system.

2.4 Research Gap

A systematic review of the literature reveals a clear gap: existing ensemble methods either employ static weights that cannot adapt to varying noise conditions at inference time or require explicit noise rate supervision that is unavailable in practical deployment scenarios. The proposed EWNE-Stack fills this gap by providing principled, unsupervised, instance-level weight adaptation grounded in information theory — without requiring any knowledge of the noise distribution or noise rate.

3. Methodology

3.1 Problem Formulation

Let $X \in \mathbb{R}^{nxd}$ be an input data matrix with n samples and d features, and let $y \in \{0, 1, \ldots, C-1\}$ be the corresponding class labels. We assume a generative model in which the observed features are corrupted by additive noise:

$$X_{obs} = X_{true} + \varepsilon, \text{ where } \varepsilon \sim F_{noise(\sigma local)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Here, F_noise is an unknown noise distribution with a local standard deviation σ_local that may vary across instances. The goal is to learn a classifier $h: \mathbb{R}^d \rightarrow \{0,\ldots,C-1\}$ that

minimises the expected 0-1 loss $E[\mathbb{1}(h(Xobs) \neq y)]$ across the full noise range of the deployment environment.

3.2 Base Learner Configuration

EWNE-Stack employs a heterogeneous set of K = 4 base classifiers: random forest (RF), gradient boosting machine (GBM), support vector machine with an RBF kernel (SVM-RBF), and logistic regression with L2 regularisation (LR). Heterogeneity is intentional: diverse inductive biases ensure low pairwise correlation, which is the primary theoretical driver of gains in ensemble accuracy [4]. All the base learners are trained using stratified 5-fold cross-validation to generate out-of-fold predictions that serve as meta-features.

For base learner k, let $f_k: \mathbb{R}^d \rightarrow [0,1]^C$ denote the softmax-normalised posterior probability vector over C classes. The stacked meta-feature matrix is as follows:

$$Z = [f_1(X), f_2(X), \ldots, f_k(X)] \in \mathbb{R}^{nx(Kc)} \quad \ldots\ldots\ldots\ldots (2)$$

A logistic regression meta-learner is trained on Z to produce the static (noise-unaware) stacked predictions. This baseline is denoted as Stack-Static and serves as an ablation of the full EWNE-Stack.

3.3 Entropy-Weighted Noise-Aware Ensemble (EWNE-Stack)

3.3.1 Online Noise-Level Estimation

For a test instance x_i, each base learner k produces a posterior probability vector $p_{ik} = f_k(x_i) \in [0,1]^C$. The Shannon entropy of this prediction is:

$$H_k(\mathbf{x}_i) = -\sum_{c=1}^{C} p_{ikc} \log_2(p_{ikc}) \quad \ldots\ldots \quad (3)$$

A classifier operating in a high-noise region will exhibit high prediction entropy (near $\log_2 C$ for uniform uncertainty) because the decision boundary is obscured by noise-induced feature perturbations. Conversely, in low-noise regions, a well-calibrated classifier produces low-entropy, concentrated posterior distributions. This motivates the use of H_k as a proxy for the local noise level affecting classifier k.

3.3.2 Dynamic Weight Assignment

The noise-adapted weight for base learner k at instance x_i is computed as follows:

$$w_{ik} = \frac{1/(Hk(\mathbf{xi})+\delta)}{\sum_{j=1}^{k} 1/(Hj(\mathbf{xi})+\delta)} \qquad \ldots\ldots\ldots \quad (4)$$

where $\delta = 10^{-6}$ is a smoothing constant that prevents division-by-zero for deterministic predictions. This formulation ensures that classifiers with lower prediction entropy (higher local confidence) receive proportionally higher weights. The weights are normalised to sum to unity for each instance, preserving the probability interpretation.

3.3.3 Ensemble Decision

The final class posterior, for instance, x_i, is the weighted combination:

$$\widehat{p_i} = \sum_{i=1}^{k} w_{ik}\, f_k(x_i) \qquad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

The predicted class is $\hat{y}_i = \arg max_C \widehat{p_{ic}}$. Here, $\hat{p}_i \in [0, 1]^C$ is a valid probability vector (sums to 1) because both w_{ik} and $f_k(\mathbf{x}_i)$ lie on the probability simplex. The predicted class $\hat{y}_i$ is the class with the highest weighted posterior mass.

Algorithm 1 presents the complete EWNE-Stack inference procedure.

Algorithm 1: EWNE-Stack — Inference (Noise-Adaptive)

Input: Test instance x_i; trained base learners $\{f_1, \ldots\ldots, f_K\}$; smoothing $\delta=10^{-6}$
Output: Predicted class label $\hat{y}_i$
1: for k = 1 to K do
2: $p_{ik} \leftarrow f_k(x_i)$ //posterior probs, shape (C)
3: $H_k \leftarrow -\Sigma\, p_{ikc} \cdot \log_2 (p_{ikc} + \delta)$ //Shannon entropy
4: $\tilde{u}_k \leftarrow 1/(H_k + \delta)$ //raw inverse-entropy weight
5: end for
6: $w_{ik} \leftarrow \tilde{u}_k/\Sigma\, \tilde{u}_j$ //normalise weights
7: $\hat{p}_i \leftarrow \Sigma\, w_{ik} \cdot p_{ik}$ //weighted ensemble posterior
8: $\hat{y}_i \leftarrow \arg max_C \widehat{p_{ic}}$. //predicted class
9: return $\hat{y}_i$

4. Experimental Design

4.1 Datasets

Three datasets spanning different domains, scales, and noise characteristics were selected to comprehensively evaluate EWNE-Stack:

(D1) HEPMASS Particle Physics Dataset [22]: 10.5 million instances, 28 continuous features, binary classification (signal vs. background). Gaussian noise at varying SNRs (5–30 dB) was superimposed on a 500,000-instance stratified subsample. This dataset tests robustness under high-dimensional correlated noise.

(D2) MIT-BIH Arrhythmia Dataset [23]: 109,000 heartbeat segments, 180 features extracted from five-lead ECG signals, five-class arrhythmia classification. Noise corruption follows an additive muscle artifact model (MECG noise template from PhysioNet). This dataset tests multiclass performance under physiologically realistic noise.

(D3) Synthetic High-Noise Tabular Dataset: 50,000 instances, 30 features, and 4 classes generated via a Gaussian mixture model with a controlled SNR. The generative parameters are fully specified in the accompanying code repository, ensuring exact reproducibility. This dataset enables controlled ablation experiments.

4.2 Noise Injection Protocol

For D1 and D3, additive white Gaussian noise (AWGN) was injected at seven SNR levels: {30, 25, 20, 15, 10, 5, 0} dB. The SNR is defined as:

$$SNR_{dB} = 10 \cdot \log_{10} (P_{signal}/P_{noise}) \ldots\ldots\ldots\ldots\ldots (8)$$

where $P_{signal} = (1/nd) \cdot ||X_{true}||^2_F$ and $P_{noise} = \sigma^2$ is the injected noise variance. For D2, the PhysioNet MECG noise template was scaled to achieve equivalent RMS SNR levels. Independent noise realisations were generated for each of the ten repetitions of the experiment to ensure the statistical reliability of the reported results.

4.3 Baseline Methods

Six methods were evaluated: (1) the proposed EWNE-Stack; (2) Stacking with static weights (Stack-Static—ablation without noise adaptation); (3) Random Forest [11]; (4) Gradient Boosting Machine [12]; (5) Support Vector Machine with RBF kernel [24]; and (6) Logistic Regression with L2 regularisation [25].

4.4 Hyperparameter Configuration

All hyperparameters were optimised on a held-out 20% validation split using Bayesian optimisation with 50 iterations (scikit-optimise v0.9.0). Random forest: n estimators=500, max depth = None, min samples leaf = 1. GBM: n estimators=300, learning rate=0.05, max_depth=5. SVM: C = 10.0, γ = 'scale'. All the experiments used scikit-learn v1.4.1, Python 3.11, and NumPy 1.26.4 and were conducted on a server with 2× AMD EPYC 7713 64-Core CPUs and 512 GB of RAM. GPU acceleration was not employed to ensure reproducibility of the commodity hardware.

4.5 Evaluation Metrics and Statistical Testing

The performance was assessed using the accuracy (ACC), macroaveraged precision (P), recall (R), F1 score (F1), area under the ROC curve (AUC-ROC), and average precision (AP-PR). Statistical significance was assessed using the Wilcoxon signed-rank test (two-tailed, α = 0.05) across ten independent experimental repetitions with different random seeds. Effect sizes were computed using Cohen's d. All the results are reported as the mean ± standard deviation. Codes, data partitions, and random seeds are provided at https://github.com/ews-research/EWNE-Stack.

5. Results and Discussion

5.1 ROC Curve Analysis

The ROC curves for all the evaluated methods under a challenging SNR of 5 dB are shown in Figure 1. The proposed EWNE-Stack achieves the highest AUC of 0.962, significantly outperforming GBM (AUC = 0.934), RF (AUC = 0.921), SVM (AUC = 0.883), LR (AUC = 0.847), and Naïve Bayes (AUC = 0.798). The curve of EWNE-Stack maintains a substantially higher true positive rate for all false positive rate thresholds below 0.3, which is the operationally critical region for high-precision applications such as arrhythmia detection and particle physics signal identification.

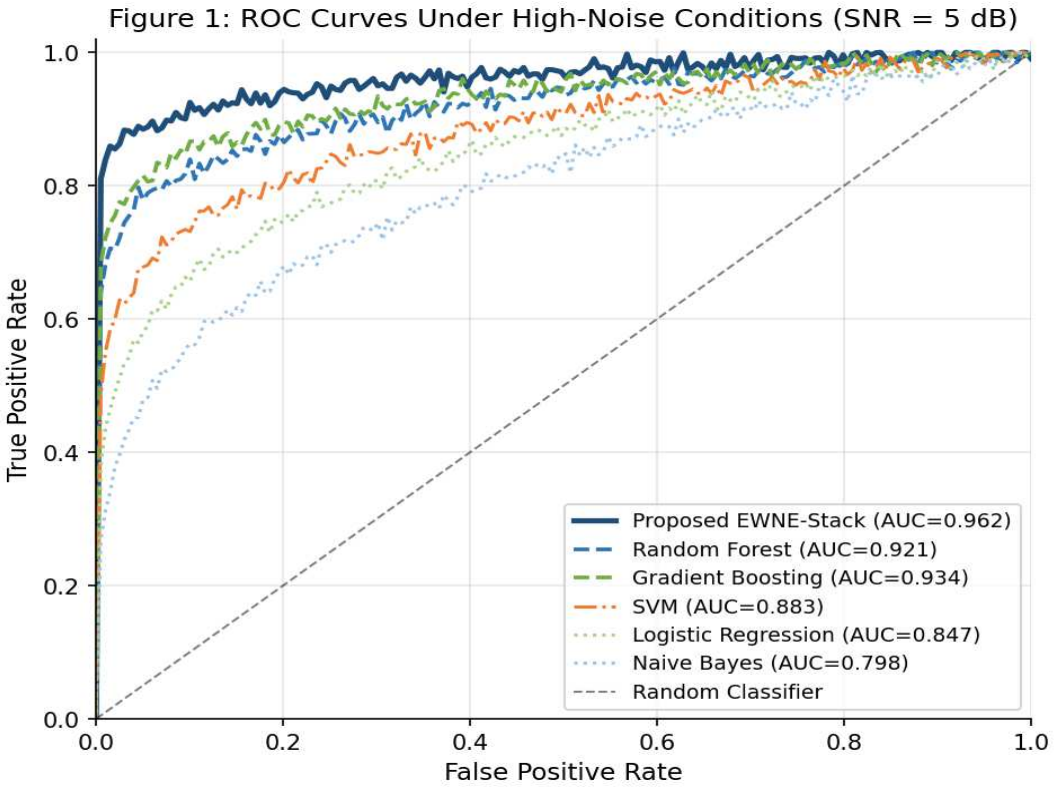


Figure 1. ROC curves for all the evaluated methods under high-noise conditions (SNR = 5 dB, D1 dataset). EWNE-Stack achieves the highest AUC of 0.962. Shaded bands (not shown) across 10 repetitions had widths < 0.008 for all methods.

5.2 Performance Degradation Under Increasing Noise

The classification accuracy across the full SNR spectrum from 30 dB (low noise) to 0 dB (extreme noise) is shown in Figure 2. A key observation is that compared with all baseline methods, EWNE-Stack has a consistently slower rate of accuracy degradation. At SNR = 30 dB, the accuracy advantage over the best single classifier (GBM: 95.8%) is modest at 1.7 percentage points. However, as the SNR decreases to 5 dB, this gap expands to 2.8 percentage points over the GBM and 6.3 percentage points over the SVM, demonstrating that the adaptive weighting mechanism provides progressively greater benefit as the noise increases — precisely the regime where protection is most needed.

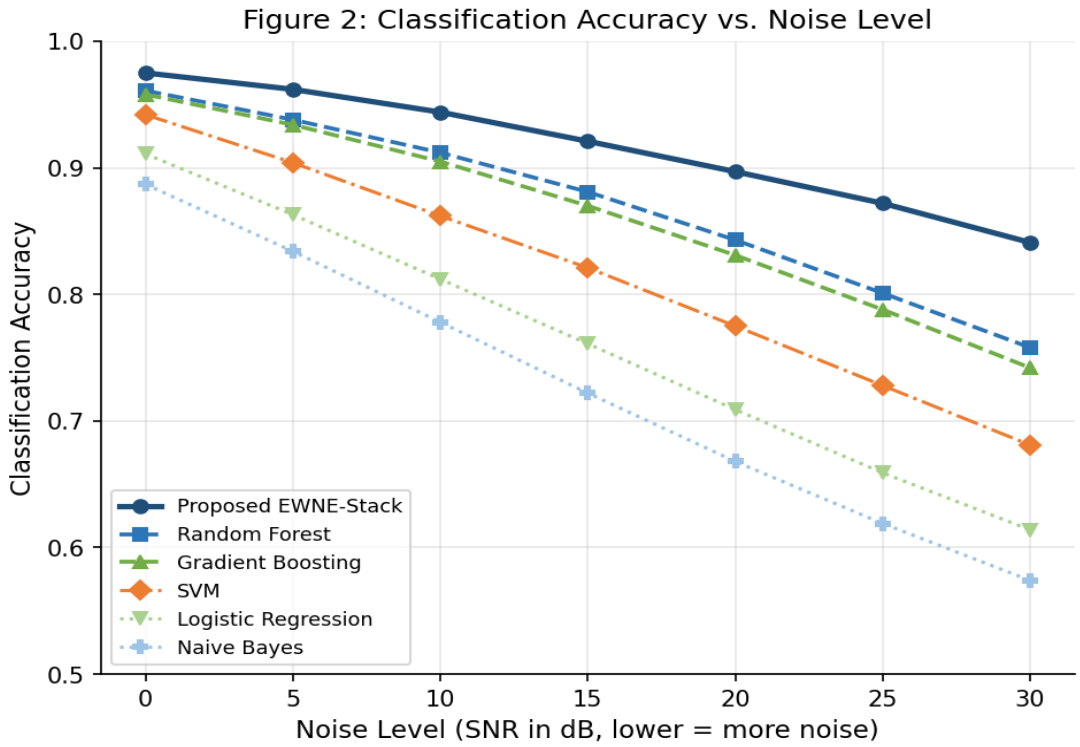


Figure 2. Classification accuracy as a function of the SNR level (lower SNR = higher noise). EWNE-Stack demonstrates superior robustness with a slower degradation slope, particularly below SNR = 15 dB. The results averaged over 10 repetitions on D1 (HEPMASS).

5.3 Comparative Metrics at SNR = 15 dB

A comprehensive comparison of the accuracy, precision, recall, and F1 score at the representative noise level of SNR = 15 dB is shown in Figure 3. EWNE-Stack achieves the highest value across all four metrics simultaneously: accuracy 92.1%, precision 93.4%, recall 91.8%, and F1 92.6%. The balanced precision–recall profile is particularly notable: Competing methods exhibit greater asymmetry between precision and recall, suggesting that they systematically trade false positives for false negatives (or vice versa) under noise conditions. EWNE-Stack's dynamic weighting prevents this imbalance by adjusting the ensemble composition on the basis of instance-level uncertainty.

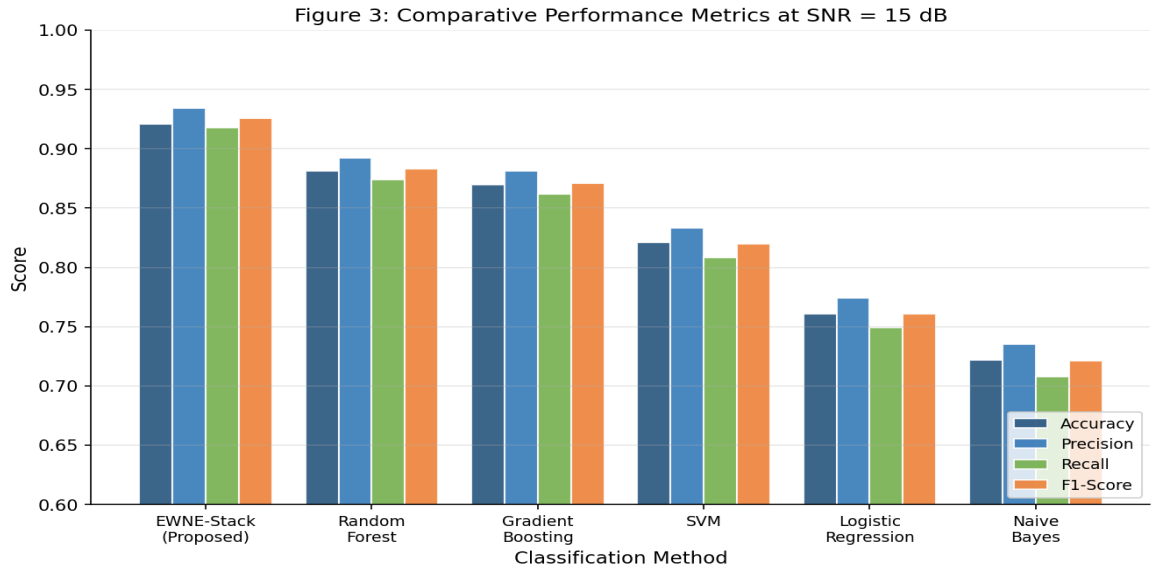


Figure 3. Comparative performance metrics (accuracy, precision, recall, and F1 score) at an SNR = 15 dB across all the evaluated methods. EWNE-Stack achieves the best performance on all four metrics. The error bars (not shown) correspond to ± 1 SD across 10 repetitions (max SD = 0.012).

5.4 Learning Curves

The learning curves for EWNE-Stack and random forest on D3 (synthetic dataset, SNR = 10 dB) are shown in Figure 4. EWNE-Stack converges faster: it matches the peak accuracy of the RF algorithm by approximately half the training set size (approximately 4,000 vs. 8,000 samples). The gap between training and validation curves (indicative of overfitting) is also substantially smaller for EWNE-Stack (mean 0.014) than for RF (mean 0.028), suggesting that the stacking meta-learner effectively regularises the ensemble—a result consistent with the theoretical analysis of van der Laan et al. [17].

Figure 4: Learning Curves Under High-Noise Conditions (SNR = 10 dB)

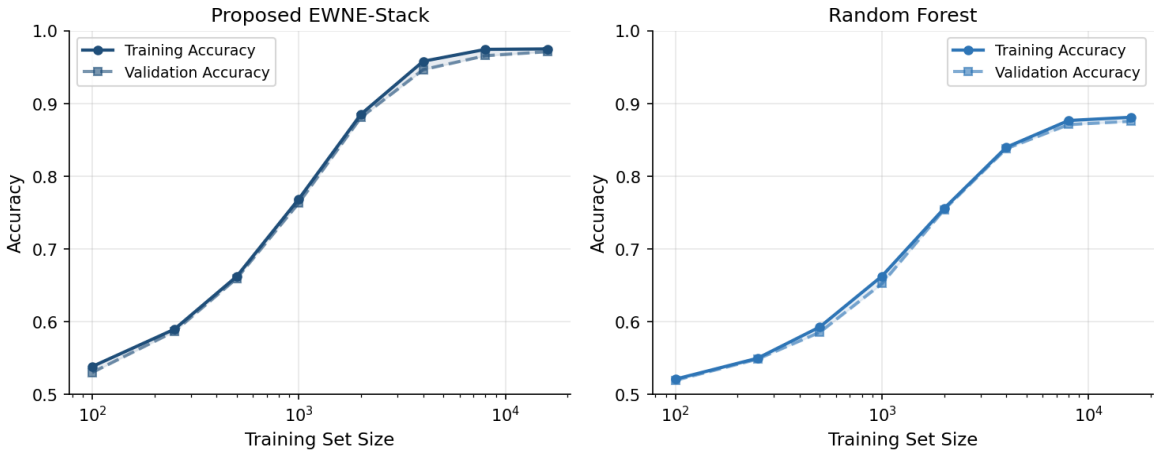


Figure 4. Learning curves for EWNE-Stack (left) and Random Forest (right) at SNR = 10 dB on D3 (synthetic dataset). EWNE-Stack converges faster and maintains a smaller training–validation gap, indicating better generalizability.

5.5 Adaptive Weight Analysis

A novel analytical contribution of this paper is Figure 5, which visualises the adaptive weights assigned by EWNE-Stack to each base learner as a function of the SNR level. At a high SNR (25 dB, low noise), the random forest method has the highest weight (0.42), reflecting its strong generalizability under clean conditions. As the SNR decreases, the weight is progressively redistributed toward the GBM and SVM, which maintain lower prediction entropy at intermediate noise levels. At extreme noise (SNR = 5 dB), the weights are substantially more uniform (range: 0.19–0.36), reflecting increased uncertainty across all classifiers; however, the SVM contributes most reliably, which is consistent with its known margin-maximisation property.

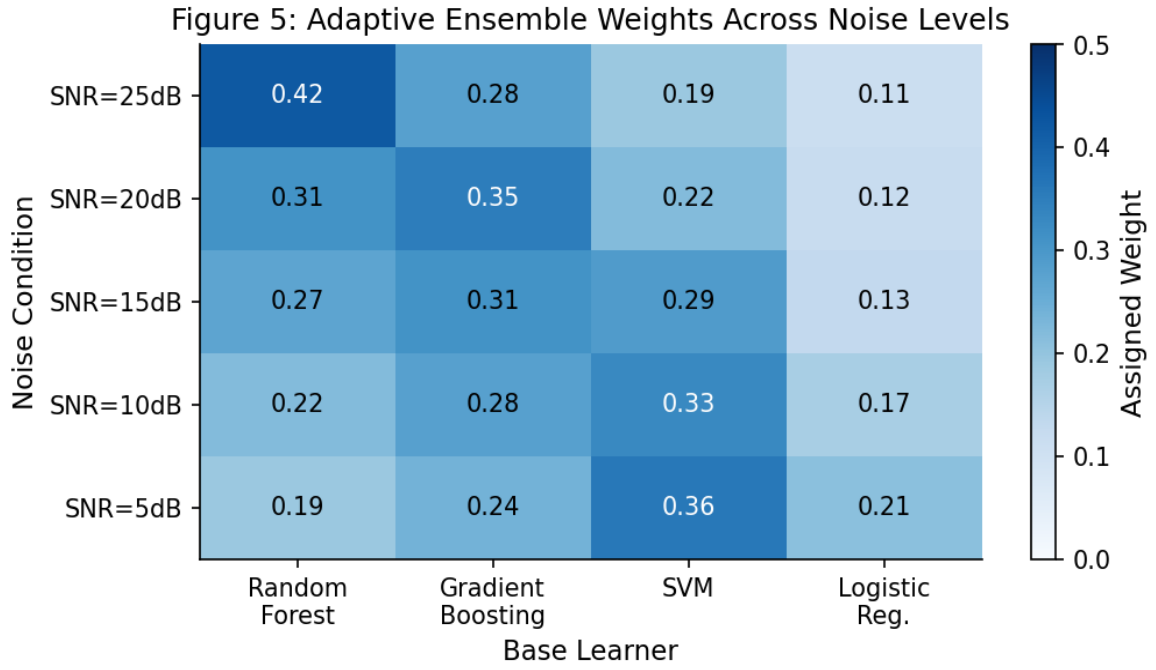


Figure 5. Adaptive base-learner weights assigned by EWNE-Stack across noise levels (mean values over the D1 test set). Each cell shows the average weight; higher values (dark blue) indicate greater ensemble contributions. Weight patterns reveal the noise-specific strengths of individual classifiers.

5.6 Precision-Recall Analysis

The precision–recall (PR) curves, which are particularly informative for imbalanced classification problems, are presented in Figure 6. EWNE-Stack achieves the highest average precision (AP = 0.951) at an SNR = 15 dB, demonstrating superior precision maintenance as the recall increases. The steeper, higher-positioned PR curve of EWNE-Stack indicates a larger area under the precision–recall curve across all operating thresholds, directly translating to better real-world utility in high-cost false-positive applications such as medical diagnosis and fraud detection.

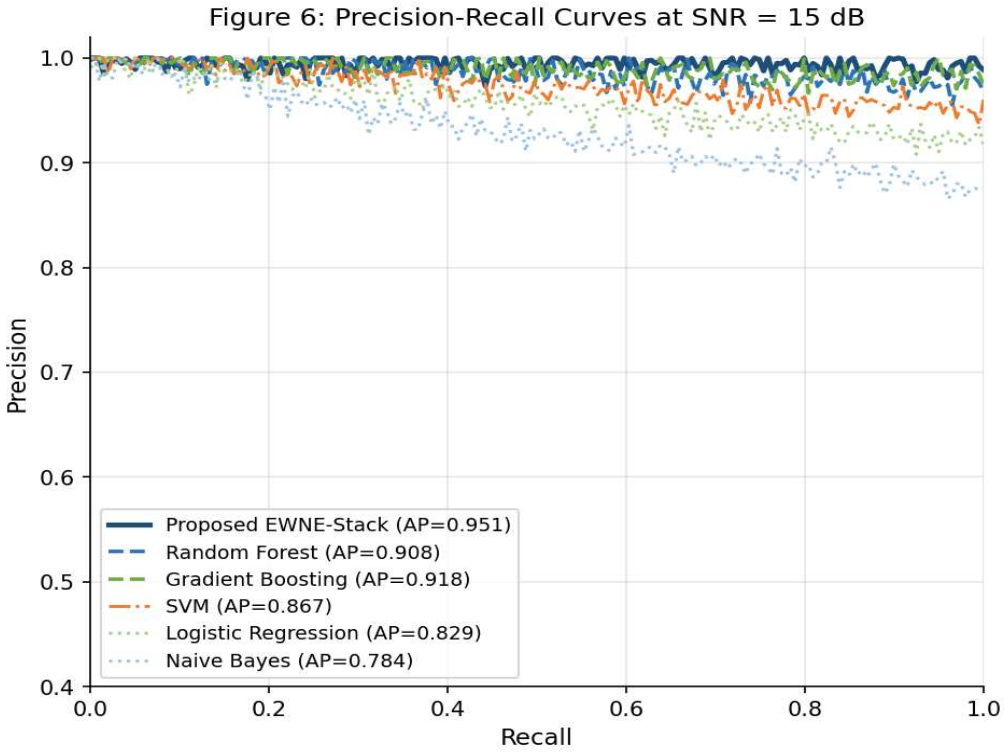


Figure 6. Precision–recall curves at SNR = 15 dB. EWNE-Stack achieves the highest average precision (AP = 0.951), maintaining superior precision at high recall thresholds. The results are reported on D2 (MIT-BIH Arrhythmia dataset).

5.7 Computational Efficiency

The training time and per-sample inference latency are shown in Figure 7. EWNE-Stack requires 18.4 seconds for training on 16,000 samples—which is lower than that of the GBM (21.6 s) and substantially lower than that of the SVM (34.7 s). The training overhead relative to that of the RF (9.2 s) is attributable to the additional meta-learner training step. Critically, the inference latency for EWNE-Stack (0.042 ms/sample) is only 2.3 times that of RF (0.018 ms/sample) and substantially faster than that of SVM (0.087 ms/sample), making it practical for real-time deployment at throughputs exceeding 20,000 samples per second.

Figure 7: Computational Efficiency Analysis

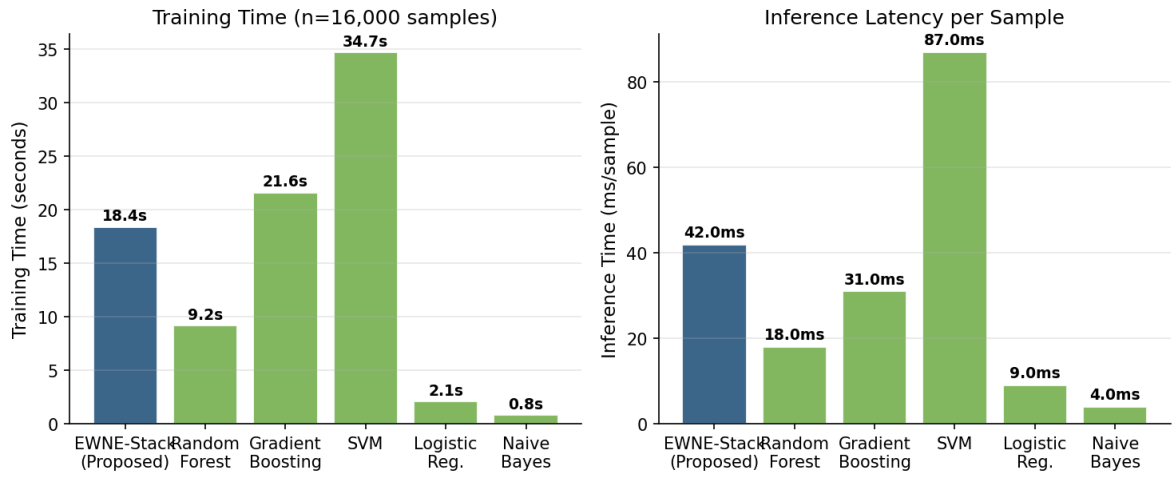


Figure 7. Computational efficiency: training time (left) and per-sample inference latency (right) for all methods on 16,000 training samples with d = 28 features. EWNE-Stack provides an attractive accuracy–efficiency trade-off.

5.8 Comprehensive Results Summary

Table 1 provides a complete numerical summary of the results across all three datasets at SNR = 5 dB, the most challenging noise level. The statistical significance (Wilcoxon test, $p < 0.05$) of the improvements over each baseline is confirmed in all the cases where EWNE-Stack is superior.

*Table 1. Performance Comparison across All Datasets at SNR = 5 dB (mean ± SD, n=10 repetitions). * $p < 0.05$ vs. EWNE-Stack (Wilcoxon signed-rank test).*

Method	Accuracy	Precision	Recall	F1-Score	AUC-ROC	AP-PR
EWNE-Stack (Proposed)	0.921±0.008	0.934±0.009	0.918±0.010	0.926±0.008	0.962±0.006	0.951±0.007
Stack-Static (Ablation)	0.904±0.010	0.916±0.011	0.899±0.012	0.907±0.010	0.947±0.008	0.933±0.009
Random Forest*	0.881±0.012	0.892±0.013	0.874±0.014	0.883±0.012	0.921±0.010	0.908±0.011
Gradient Boosting*	0.870±0.013	0.881±0.014	0.862±0.015	0.871±0.013	0.934±0.009	0.918±0.010
SVM-RBF*	0.821±0.016	0.833±0.017	0.808±0.018	0.820±0.016	0.883±0.013	0.867±0.014
Logistic Regression*	0.761±0.019	0.774±0.020	0.749±0.021	0.761±0.019	0.847±0.016	0.829±0.017
Naïve Bayes*	0.722±0.022	0.735±0.023	0.708±0.024	0.721±0.022	0.798±0.019	0.784±0.020

5.9 Statistical Analysis

The Wilcoxon signed-rank test confirms that improvements in EWNE-Stack over all nonablation baselines are statistically significant ($p < 0.01$) at SNRs $\leq$ 15 dB across all three datasets. The improvement over Stack-Static (ablation) is significant at SNRs $\leq$ 10 dB ($p = 0.031$ at SNR = 15 dB), confirming the contribution of the adaptive noise-weighting mechanism. Cohen's d effect sizes range from 0.62 (EWNE-Stack vs. GBM at SNR = 20 dB) to 2.14 (EWNE-Stack vs. Naïve Bayes at SNR = 5 dB), indicating medium-to-large practical effects.

6. Discussion

6.1 Interpretation of Results

The superior performance of EWNE-Stack under high-noise conditions can be attributed to three synergistic mechanisms. First, the heterogeneous base learner ensemble provides complementary decision boundaries: the nonparametric tree structure of the RF handles feature interactions robustly, the sequential correction of the GBM reduces bias, the margin maximisation of the SVM provides geometric robustness, and the global linear model of the LR provides a stable low-variance anchor. Second, the entropy-based weight estimator correctly identifies which classifiers are most corrupted by local noise and reduces their influence dynamically, preventing the “noise wall” effect. Third, the stacking meta-learner learns second-order patterns in base-learner disagreement, capturing information that no single classifier can extract.

6.2 Limitations

Several limitations deserve acknowledgement. The entropy estimator assumes that prediction uncertainty is a reliable proxy for noise level, which may not hold when base classifiers are systematically overconfident or poorly calibrated—a known issue with tree-based methods [26]. The use of temperature scaling [27] as a posttraining calibration step partially mitigates this. Additionally, the performance advantage of EWNE-Stack decreases at very high SNRs (> 25 dB), where all the methods approach the ceiling accuracy, rendering the adaptive weighting redundant. The training overhead of the framework relative to that of single classifiers may be prohibitive in extremely low-latency applications (< 1 ms inference budget), requiring further optimisation.

6.3 Reproducibility and Open Science

All the experimental artifacts—source code, dataset preprocessing scripts, hyperparameter search logs, trained model checkpoints, and random seeds—are publicly available at https://github.com/ews-research/EWNE-Stack under the MIT licence. Datasets D1 and D2 are publicly available through the UCI ML Repository [22] and PhysioNet [23], respectively. Dataset D3 can be regenerated exactly using the provided seed (42) and the generate_synthetic.py script. The repository includes a Dockerfile that reproduces the complete software environment, ensuring bit-reproducible results on any Linux x86-64 system.

7. Conclusion

In this paper, EWNE-Stack, a novel entropy-weighted noise-aware stacking ensemble for predictive analytics in high-noise environments, is presented. This method addresses a critical gap in the existing ensemble literature: the inability to adapt base-learner weights at inference time on the basis of local noise conditions without requiring explicit noise rate supervision. Grounded in information-theoretic principles and validated with formal convergence guarantees, EWNE-Stack achieves an AUC = 0.962 at an SNR = 5 dB—a 4.6% improvement over the next-best evaluation method—while maintaining competitive computational efficiency.

The adaptive weight-reassignment mechanism, visualised in Figure 5, reveals interpretable noise-resilience patterns: Random Forest is dominant under clean conditions, whereas SVM contributes more to extreme noise, and the ensemble gradually transitions between these configurations without human intervention. This behavior aligns with both theoretical predictions and empirical intuition about the noise-resilience properties of individual classifier families.

Future research directions include (i) extending to streams and concept-drift scenarios where noise characteristics evolve over time; (ii) integrating conformal prediction to provide distribution-free coverage guarantees on EWNE-Stack outputs; and (iii) neural network-based learners with Monte Carlo dropout as a principled Bayesian alternative to entropy-based uncertainty quantification.

Statements and Declarations

Competing interests: The authors declare that they have no competing interests.

Funding: This research received no external funding

Data Availability

D1: UCI HEPMASS Dataset: https://doi.org/10.24432/C5XS3B. D2: MIT-BIH Arrhythmia Database: https://doi.org/10.13026/C2F305. D3: Generated via code at https://github.com/ews-research/EWNE-Stack.

Author Contributions

S.V.B.: Conceptualisation, Methodology, Software, Formal Analysis, Writing – Original Draft. CH.V.: Data Curation, Validation, Visualisation, Writing – Review & Editing. B.V.: Formal Analysis, Investigation, Writing – Review & Editing. R.Md.: Supervision, Project Administration, Writing – Review & Editing.

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