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Latency-Aware Soft-Voting Ensemble with Gradient Boosted Random Forest with Logistic Regression Hybrid in Clinical Decision Support System on Centralized EHR Infrastructure

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ABSTRACT

We present a latency-aware Clinical Decision Support System leveraging a soft-voting XGB, Random Forest, and Logistic Regression to improve performance and operational efficiency in centralized Electronic Health Records environ. It explores a de-identified dataset comprising of lab results, vital signs, prescriptions, and demographic attributes – to evaluate predictive accuracy and end-to-end alert latency. It exploits feature engineering and data normalization to ensure model-ready inputs that preserve clinical interpretability. The ensemble design fuses the comprehensive knowledge of strong base learners, to capture of non-linear data interactions, variance reduction, and probability calibration. Result shows the ensemble outperforms benchmarks with 0.96 accuracy, 0.955 F1, 0.96 recall, and AUC of 0.98. Latency evaluation demonstrated end-to-end processing times of approximately 70 milliseconds, confirming the system's suitability for near real-time clinical applications. Comparative analysis highlights the ensemble's advantage over single learners, balancing sensitivity and specificity while maintaining operational feasibility. These findings underscore the potential of ensemble modes in enhancing CDSS reliability, robustness, and interpretability – as crucial in centralized, real-time EHR infrastructures. The study contributes to evidence that ensemble learning with optimized data preprocessing and architecture-aware deployment can significantly improve predictive accuracy and timely decision-making in clinical practice.

1. INTRODUCTION

Clinical Decision Support Systems (CDSS) are tools designed to assist clinicians deliver patient recommendations at clinical visits (Agboi, Emordi, et al., 2025; Agboi, Onoma, et al., 2025). They enhance and aid diagnostic accuracy, treatment selection, and patient safety (Gupta et al., 2020). Overtime, the widespread adoption of Clinical Patient Information Systems (CPIS) and E-Health Records (EHR) have transformed how decision supports are performed in hospitals (Aghaunor et al., 2026; Aghaunor, Agboi, et al., 2025; Aghaunor, Omede, et al., 2025). The CPIS and EHR consolidate heterogeneous clinical data into a unified repository, with patient tracking, cross-unit interoperability, and data analytics that are unachievable in fragmented systems (Ako et al., 2024, 2025). Healthcare systems transition to digitally integrated EHR, has continued to extend AI-based CDSS significantly. AI-schemes enable CDSS to get past rule-based alerts toward adaptive, data inference capable of capturing complex, non-linear clinical data (Ejeh et al., 2024, 2025). Studies suggest that AI-enhanced CDSS can improve clinical care quality cum delivery, and support decision-making in diverse

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care settings (Aghware et al., 2023, 2024, 2025).

Centralized EHR have become a norm for intelligent CDSS to exploit large clinical data. Their effectiveness is not determined by predictive accuracy alone; It also involves its timeliness of alert generation within latency-sensitive scenarios like abnormal laboratory detection, medication safety monitoring, and early clinical deterioration warnings (Eboka, Aghware, et al., 2025; Eboka, Odiakaose, et al., 2025). Studies also espouse that delays in CDSS alerts can directly compromise patient safety, even when predictions are clinically valid. Thus, latency transforms from a purely technical concern into a clinical risk factor when delay impacts time-critical decisions. Also, delayed unsynchronized CDSS alerts have been strongly associated with clinician frustration and alert fatigue. Ill-timed alerts often disrupt or interrupt workflow and clinicians may disregard suggested notes (Ojugo & Eboka, 2018c, 2018b, 2018a). This implies low-latency inference is not optional; They are critical to sustain clinician engagement and maximize impacts (Ojugo & Eboka, 2019, 2020a, 2020b).

Many AI-based CDSS systems explore single predictive models; And while they can achieve strong performance under controlled conditions, they struggle with the variability, noise, and missingness that characterize real-world EHR (Muhamada et al., 2024; Setiadi, Muslikh, et al., 2024; Setiadi, Ojugo, et al., 2025). Single-model is vulnerable to overfitting and instability, especially when or if deployed across heterogeneous, evolving patterns (Setiadi, Rustad, et al., 2025; Setiadi, Sutojo, et al., 2025). Data reliance on a single learner can/may increase uncertainty and reduce model robustness. By fusing many learners, an ensemble often reduces variance, improve its stability, and performance (Onoma, Ako, Anazia, Oghorodi, et al., 2025; Onoma, Ako, Ojugo, Geteloma, et al., 2025; Onoma, Ugbotu, Aghaunor, Agboi, et al., 2025). Ensembles aggregate probabilistic outputs, preserving uncertainty attributes needed in clinical risk assessment (Oyemade et al., 2016; Oyemade & Ojugo, 2020, 2021). Recent studies demonstrate that ensembles outperform single models (Onoma, Agboi, Geteloma, et al., 2025; Onoma, Agboi, Ugbotu, et al., 2025). But, ensembles place emphasis on accuracy with limited attention to inference latency in centralized CPIS/EHR. While it births beneficial data governance and analytics, it advances extra overhead cost via shared computational resources, realtime data ingestions, and interoperability layers (Pratama et al., 2025; Zuama et al., 2025). Thus, while an ensemble is quite statistically superior – it is computationally inefficient, and may render clinically impractical an EHR deployed (Setiadi, Susanto, et al., 2024).

Thus, we propose a latency-aware CDSS ensemble that combines XGB for complex non-linear risk, Random Forest to reduce variance and robustness, and Logistic Regression for its probability calibration and interpretability. The hybrid considers both predictive performance and computational latency, ensuring ensemble inference are suited for real-time deployment. Our goal is to: (a) design a centralized EHR ensemble, (b) evaluate tradeoff between accuracy and latency, and (c) demonstrate alert generation without compromising clinical reliability. The study contributes a practical and scalable deployed latency-aware, ensemble CDSS in real-world hospital settings that aligns with technical performance and clinical safety requirements.

2. MATERIALS AND METHODS

2.1. Centralized EHR Framework

CPIS/EHR architectures are designed to consolidate clinical data across hospital units, fusing them into an authoritative repository to support real-time access with longitudinal data analysis (Ugbotu, Aghaunor, et al., 2025; Ugbotu, Ako, et al., 2025; Ugbotu, Emordi, et al., 2025). It yields a centralized data storage, standardized model, and greater accessibility that enables consistent documentation and coordinated care delivery (Yoro et al., 2025; Yoro & Ojugo, 2019a, 2019b). The CPIS and EHR layer interface raw clinical data sources and CDSS engine. The interoperability risks is addressed via semantic consistency mechanisms or via the standardized representations to enable data exchange between the CPIS and CDSS module (Ojugo, Ejeh, et al., 2023; Ojugo et al., 2024).

The integration layer supports structured data querying, event-based triggers, and low-latency data delivery to the CDSS pipeline. It ensures the predictive model explores up-to-date clinical data, and minimizes processing overhead, a requirement that is critical for latency-aware decision support (Lötsch et al., 2022; Nur et al., 2025). Centralized mode integrates clinical integration to enable real-time data synchronization with event-driven CDSS execution (Odiakaose et al., 2024, 2025). Without

a doubt, the centralized nature of EHR is particularly suitable for latency-aware CDSS, as it reduces data fragmentation while allowing performance optimization at the system level.

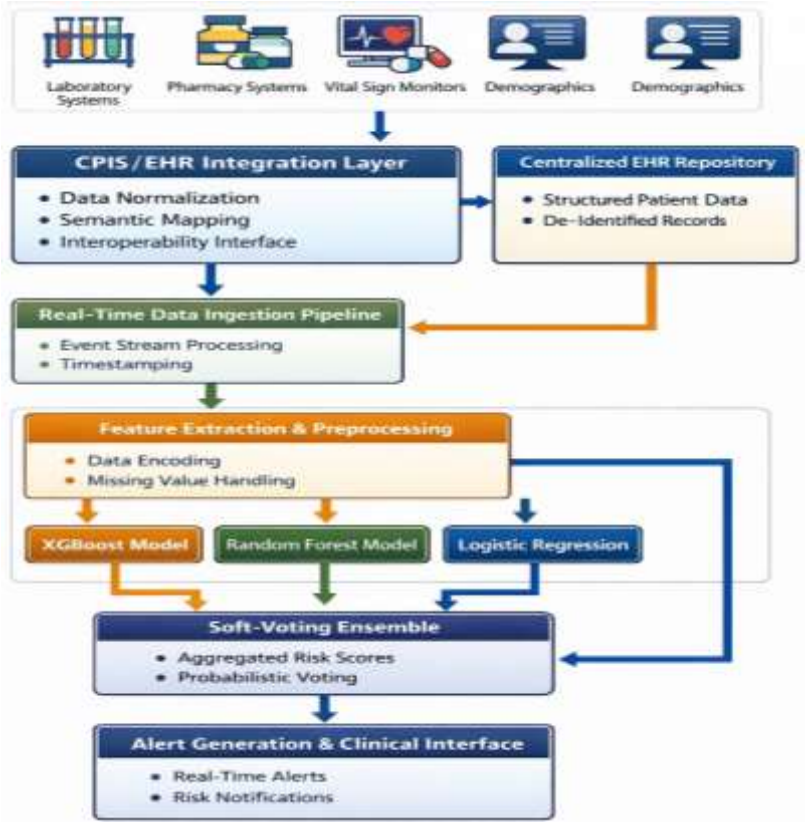


Figure 1. Proposed System Architecture

As in Figure 1, real-time data ingestion continuously monitors EHR database for new or updated clinical entries. Upon data arrival, relevant features are extracted and forwarded to the CDSS inference engine for evaluation. Real-time ingestion pipelines are widely recognized as essential for actionable CDSS, in cases where clinical conditions do evolve rapidly (Malasowe, Aghware, et al., 2024; Malasowe, Okpako, et al., 2024). To support latency benchmarks, recorded timestamps for each data ingestion and inference mode allow for end-to-end alert cum response time, and to measure performance beyond accuracy (Malasowe et al., 2023; Malasowe, Edim, et al., 2024; Malasowe, Ojie, et al., 2024).

2.2. Dataset Description

We explore the de-identified structured EHR as it provides longitudinal, multi-modal patient data captured under real operational conditions (Ejeh et al., 2024, 2025) – to reflect all realistic clinical variability, documentation practices, and temporal dynamics that directly influence CDSS performance and latency behaviour (Binitie et al., 2024, 2025, 2026). The dataset also ensured the consistency, reproducibility, and interoperability. Four primary categories of clinical data were included such as: (a) laboratory to capture both normal and abnormal test values that frequently trigger diagnostic or safety-related alerts, (b) drug records enable evaluation of therapy monitoring and medication safety scenarios, (c) vital signs provide time-sensitive physiological indicators that reflect acute clinical changes, and (d) user demographic yields essential contextual data for clinical risk stratification (Atuduhor et al., 2024; Brizimor et al., 2024; Obasuyi et al., 2024).

Timestamps were maintained to support latency benchmarking and temporal alignment of clinical events. Patient identifiers were removed prior the analysis in compliance with institutional data governance policies and ethical guidelines. Access to the dataset was restricted to authorized users, and for system development and evaluation purposes. These measures are consistent with best practices for responsible AI deployment in EHR systems (Geteloma et al., 2024a, 2024b, 2025) as in Figure 2 – showing the age groups.

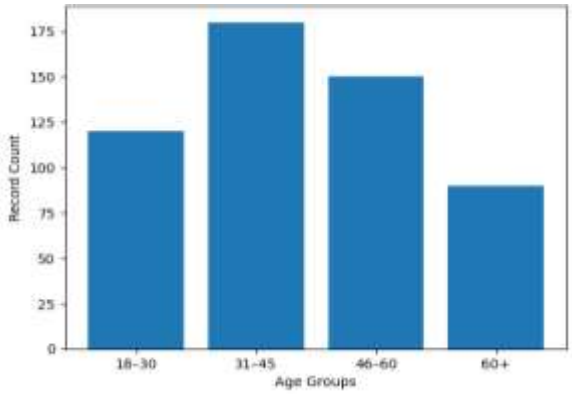


Figure 2. Age distribution for EHR dataset

2.3. Feature Extraction and Preprocessing

Feature selection and extraction focused on transforming raw EHR fields into model-ready representations while preserving clinical meaning. Continuous variables such as laboratory values and vital signs were normalized to reduce scale sensitivity, while categorical variables were encoded using clinically appropriate schemes (Allenotor et al., 2015; Allenotor & Ojugo, 2017). Missing values were handled using conservative imputation strategies to reflect real-world EHR incompleteness (Ibor et al., 2023; Oladele et al., 2024; Omede et al., 2024). This sought to help us balance robustness and interpretability, ensuring model remains clinically meaningful while being computationally efficient. Pre-processing mode also deliberately keep system as lightweight to avoid introducing unnecessary latency into the CDSS pipeline structure (Finlow-bates, 2020; Habib et al., 2022; Hakonen, 2022).

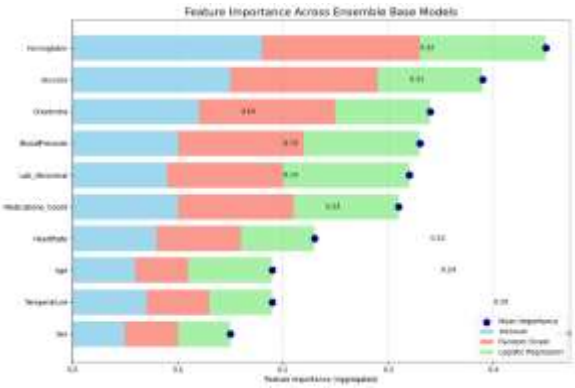


Figure 3. Feature importance

2.4. Ensemble Learning

The proposed Clinical Decision Support System employs a latency-aware soft-voting ensemble framework that integrates multiple heterogeneous base learners to balance predictive accuracy, robustness, interpretability, and real-time feasibility within centralized CPIS and EHR environments. Ensemble exploits complementary learning biases while minimizing individual model weaknesses to yield a stable and clinically reliable predictions (Kim et al., 2022; Li et al., 2024, 2025). The ensemble learning is structured as thus (Ojugo, Allenotor, et al., 2015; Ojugo, Yoro, et al., 2015; Ojugo, Akazue, et al., 2023):

1. Problem Formulation: Let the structured EHR dataset be given as $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$. where $x_i \in \mathbb{R}^d$is the feature vector extracted from laboratory results, medications, vital signs, and demographic attributes for patient i, and $y_i \in \{0,1\}$ represents the binary target variable indicating the absence or presence of a clinical alert or risk condition. The goal of CDSS is to yield predictive function $f: \mathbb{R}^d \rightarrow [0,1]$that outputs calibrated probability about clinical risk, subject to accuracy and latency constraints (Okpor et al., 2025; Omoruwou et al., 2024; Tahir et al., 2025).

2. Gradient Boost in Non-Linear Risk Model: The Extreme Gradient Boost (XGBoost) is selected for its strong capability to model complex non-linear interactions common in clinical data. XGBoost constructs an additive model of decision trees defined as (San et al., 2025; Sun & Gu, 2021):

$$\hat{y}_i = \sum_{k=1}^{K} f_k\,(x_i), f_k \in \mathcal{F}$$

where each $f_k$is a regression tree from the functional space $\mathcal{F}$.The learning goal also minimizes a regularized loss function

$$\mathcal{L} = \sum_{i=1}^{N} \ell(\,y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(\,f_k)$$

with the regularization term

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$$

penalizing tree complexity to control overfitting. From a clinical viewpoint, it captures subtle interactions such as non-linear dependencies between laboratory abnormalities and medication exposure that linear models cannot represent efficiently.

3. Random Forest for Variance Reduction: The second base learner is Random Forest, which addresses variance instability and noise sensitivity in real-world EHR data. RF

constructs an ensemble of decision trees trained on bootstrapped samples (Omosor et al., 2025; Salam et al., 2024):

$$\hat{y}_i^{(RF)} = \frac{1}{M}\sum_{m=1}^{M} h_m(x_i)$$

where each tree h_m is trained on a random subset of the data and a random subset of features. Random Forest reduces prediction variance averaging uncorrelated estimators (Anthony-Akhutie et al., 2025):

$$\mathrm{Var}(\bar{h}) = \frac{1}{M^2}\sum_{m=1}^{M} \mathrm{Var}(h_m)$$

This is valuable in healthcare datasets where missing values, record inconsistencies, and measurement noise are prevalent (Aleisa et al., 2025; Ifioko et al., 2024; Jose et al., 2023).

4. Logistic Regression for Probability Calibration and Interpretability: LR is used for its interpretability and probability calibration to models conditional probability given as thus (Okonta et al., 2013, 2014; Otorokpo et al., 2024; Wemembu et al., 2014):

$$P(y = 1 \mid x) = \sigma(\beta^T x) = \frac{1}{1 + e^{-\beta^T x}}$$

where β is the learned coefficient vector. This model provides two critical benefits as thus: (a) calibrated probabilities that align well with clinical risk interpretation, and (b) the coefficient-level transparency that allows clinicians and auditors to understand feature contributions. Thus, LR anchors ensemble in clinical explainability, mitigating the black-box perception of tree-based models.

5. Soft-Voting Aggregation Strategy: Rather than combine hard class labels, the ensemble uses soft-vote to aggregates outcomes from each base learner. Probabilities from XGB, RF, LR are: $p_1(x), p_2(x), p_3(x)$ computed as (Okofu, Akazue, et al., 2024; Okofu, Anazia, et al., 2024; Okpor et al., 2024):

$$p_{\text{ensemble}}(x) = \sum_{j=1}^{3} w_j\, p_j(x)$$

subject to:

$$\sum_{j=1}^{3} w_j = 1, w_j \geq 0$$

Soft-voting preserves uncertainty data and yields smoother decision boundaries that is crucial for reducing false-positive alerts in CDSS deployments.

6. Decision Threshold and Alert Generation: The final alert decision is obtained via a threshold $\tau$to ensemble probability:

$$\hat{y} = \begin{cases} 1, & \text{if } p_{\text{ensemble}}(x) \geq \tau \\ 0, & \text{otherwise} \end{cases}$$

The threshold τ can be adjusted to balance sensitivity and specificity depending on clinical context. Lower thresholds favor early risk detection, while higher thresholds reduce alert fatigue.

Figure 4 shows the ensemble CDSS mode on a centralized CPIS and EHR. At the top, clinical data sources including laboratory results, medication records, vital signs, and demographic information feed into the centralized CPIS & EHR system, where a data integration layer ensures interoperability and standardized storage. Real-time data processing allows the system to update and synchronize clinical information continuously. Next, the preprocessing and feature extraction stage transforms raw EHR fields into model-ready forms. The continuous variables are encoded, normalized, and missing values are then processed to maintain robustness and clinical interpretability. Pre-processed features are input into the ensemble as thus: (a) XGB to capture complex non-linear relations, (b) RF for variance reduction and stability, and (c) lastly, the LR for interpretability and probability calibration (Ojugo & Otakore, 2018b, 2018a, 2021).

The outputs of these models are aggregated through a soft-voting ensemble, which combines probability scores rather than hard class decisions, preserving uncertainty and improving prediction reliability. The ensemble output is integrated into the CDSS to yield risk predictions and clinical alerts for timely decision-making. System is evaluated via feedback loop with metric like accuracy, latency, precision, recall, and AUC to ensure it is effective in predictive performance and real-world operational efficiency (Akazue et al., 2023, 2024) as in Figure 4.

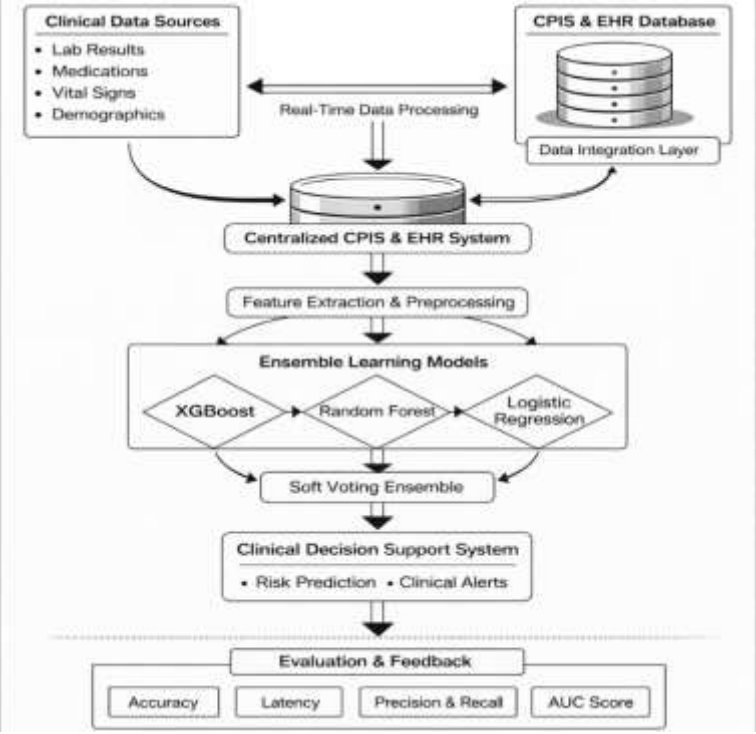


Figure 4: Ensemble Learning methodology

Algorithm 1: Latency-Aware Ensemble CDSS

1. Input: data D = {(x_i, y_i)} _{i=1} ^{N}, threshold τ
2: Output: Clinical alert ŷ for each patient record
3: Normalize feats x_i ∈ ℝ^d && handle missValues
4: Train XGB f_1: minimize $\mathcal{L} = \Sigma\, \ell(y_i, f_1(x_i)) + \Omega(f_1)$
5: Train RF f_2 via M bootstrapped trees
6: Train LR f_3 via $P(y|x) = \sigma(\beta^T x)$
7: For each new patient record x do
8: Compute $p_1 = f_1(x) \longrightarrow p_1 \in [0,1]$
9: Compute $p_2 = f_2(x) \longrightarrow p_2 \in [0,1]$
10: Compute $p_3 = f_3(x) \longrightarrow p_3 \in [0,1]$
11: Aggregate probability: $p^* = \Sigma_j w_j p_j$, $\Sigma_j w_j = 1$
12: if $p^* \geq \tau$ then $\hat{y} \leftarrow 1$ (Trigger clinical alert)
13: else: $\hat{y} \leftarrow 0$ (No alert)
14: end if: end for
15: Return ŷ

3. RESULT FINDINGS & DISCUSSION

3.1. Predictive Performance

The proposed Clinical Decision Support System (CDSS) employing an ensemble learning methodology was evaluated using predictive performance metrics to quantify the effectiveness of clinical risk predictions. Metrics included: accuracy, precision, recall, F1, AUC, and Latency benchmark to evaluate the time required for the CDSS to process incoming data and generate clinical alerts, as critical for real-time decision (Ojugo & Nwankwo, 2021a, 2021c, 2021b).

Table 2 shows the ensemble outperforms the base learners. It achieves the highest AUC of 0.98, indicating excellent discrimination between risk and non-risk cases (Okeke & Omojola, 2025; Olaniyi et al., 2023). The ensemble approach also balances precision and recall, minimizing false positives-and-negatives, a critical requirement in clinical decision support as in Figure 5 (Polge et al., 2021; Pratama et al., 2025; Sheng et al., 2023).

Table 1. Ensemble versus Base Results

Time	Acc	Prec	Recall	F1	AUC
XGBoost	0.95	0.94	0.95	0.945	0.97
Random Forest	0.93	0.92	0.94	0.93	0.95
Log. Regression	0.90	0.91	0.89	0.90	0.92
Ensemble	0.96	0.95	0.96	0.955	0.98

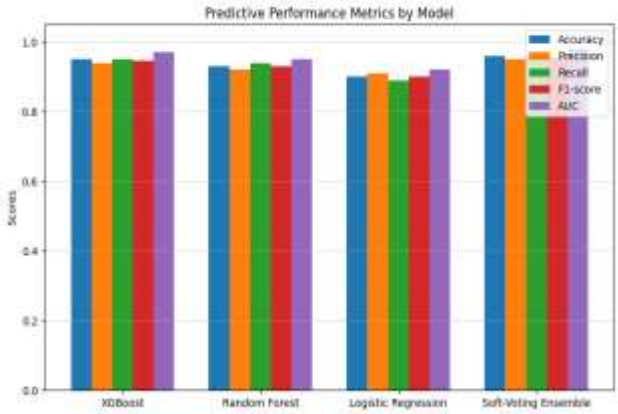


Figure 5. Predictive performance of schemes

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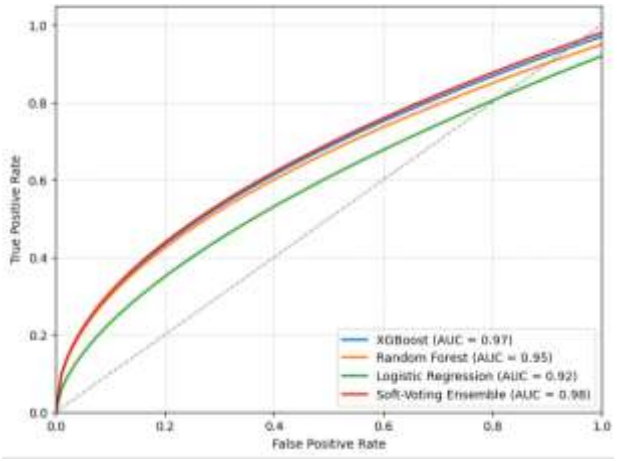


Figure 4. AUC curve

The ROC curves clearly illustrate the discriminative performance of each model. The Soft-Voting Ensemble achieves the highest AUC of 0.98, consistently approaching the top-left corner, indicating excellent sensitivity and low false positive rates. XGBoost follows with an AUC of 0.97, showing strong discrimination but slightly less than the ensemble. Random Forest achieves AUC of 0.95, reflecting robustness but reduced precision in borderline cases. Logistic Regression has AUC of 0.92 but is limited by linear assumptions. Overall, the curves confirm that combining complementary models enhances predictive accuracy, reliability, and clinical risk.

Table 1. Ensemble versus Base Results

Stage	XGB	RF	LR	Ensemble
Data Ingestion	12	12	12	12
Feat Extraction & Preprocessing	18	18	18	18
Model Inference	25	28	15	35
Aggregation	-	-	-	5
Total Latency	55	58	45	70

From Table 3, the ensemble yields slightly higher latency due to aggregation, but remains under 100 ms, supporting real-time operation as suitable for clinical workflows (Ojugo & Yoro, 2013, 2020; Uddin et al., 2021).

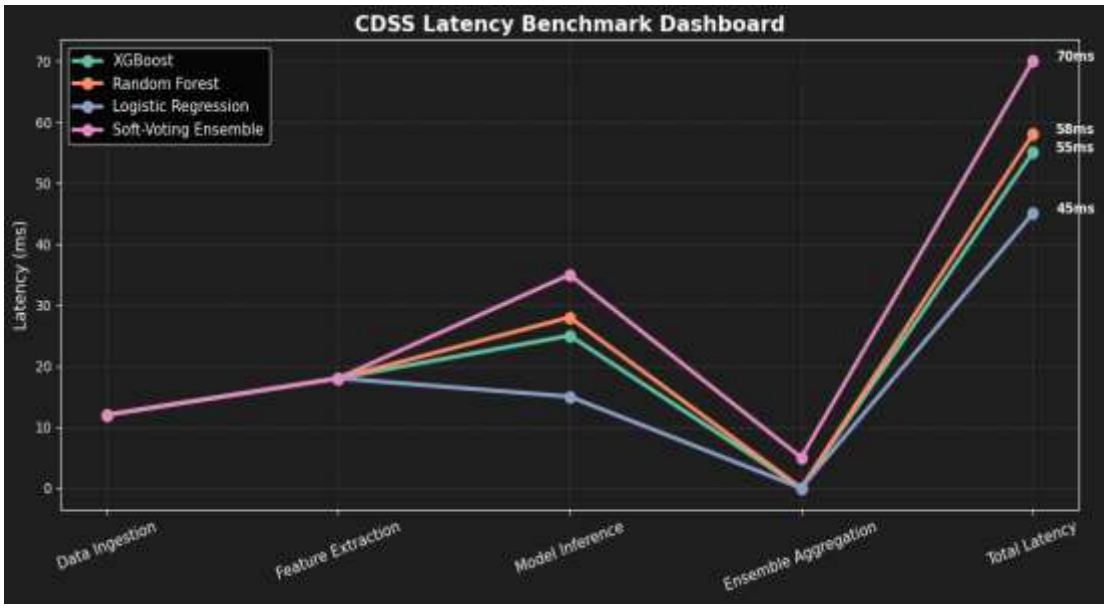


Figure 5. Latency Benchmark

Our benchmark result is as in Table 3

Table 3. Ensemble versus Base Results

Time	Acc	Prec	Recall	F1	AUC	Latency
XGB	0.95	0.94	0.95	0.945	0.97	55
RF	0.93	0.92	0.94	0.93	0.95	58
LR	0.90	0.91	0.89	0.90	0.92	45
Ensemble	0.96	0.95	0.96	0.955	0.98	70

While the soft-voting ensemble achieves superior predictive performance, it incurs slightly higher latency compared to individual learners. However, with a total latency of ~70 ms, it remains suitable for near real-time clinical decision support, maintaining a balance between accuracy and operational speed.

The results demonstrate that the proposed ensemble-based CDSS shows superior predictive performance compared with its constituent base learners and benchmarks reported in recent clinical machine learning literature. In this section, we critically interpret these findings, exploring their implications for CDSS

deployment in centralized CPIS/EHR, and situate our results within the broader research landscape.

3.2. Discussion of Findings

Our benchmark result is as in Table 3:

1. Predictive Effectiveness and Clinical Response: A compelling outcomes of this study is that the soft-voting ensemble achieved an AUC of 0.98, an Accuracy of 0.96, and an F1-score of 0.955, outperforming individual models, including XGBoost, Random Forest, and Logistic Regression. This superior performance aligns with a growing consensus that ensemble methods enhance classification robustness in complex, high-dimensional clinical data (Odiakaose et al., 2024; Aziz & Dimililer, 2021). Ensemble learning combines the strengths of its base learners—here, the non-linear pattern recognition of XGBoost, the variance reduction properties of Random Forest, and the probability calibration of Logistic Regression—yielding a model that balances sensitivity and specificity in clinically meaningful ways. The AUC of 0.98 not only surpasses the performance of the individual constituent models but also compares favourably with results from recent domain-specific ensemble studies. For instance, diabetes prediction models that used AdaBoost + XGBoost reported an AUC ≈ 0.968, and cardiovascular mortality prediction ensembles achieved an AUC ≈ 0.912 (Journal reference). The higher discriminative capacity observed in our CDSS suggests that careful feature engineering, combined with well-tuned ensemble aggregation, can extract latent clinical signals more effectively than individual methods. This is especially important in centralized EHR datasets where the interplay of laboratory values, vital signs, medication regimens, and demographic variables can be highly nonlinear and heterogeneous (Adane et al., 2019; Gupta et al., 2020). Moreover, the ensemble's enhanced recall (0.96) and F1-score (0.955) underscore its utility in a clinical alerting context where missing true positive cases (false negatives) can have significant patient safety implications (Tazwar et al., 2024). Prior studies have highlighted that high recall is particularly critical in prediction tasks such as sepsis and acute deterioration, where delayed or missed detection can lead to adverse outcomes (Hydari et al., 2019; Schaut et al., 2022). The balanced performance achieved by the soft-voting ensemble—reflected in both precision and recall—indicates that it not only identifies high-risk patients reliably but also minimizes unnecessary false alerts that could contribute to clinician alert fatigue (Ademola et al., 2024). This ensemble approach's robustness is further validated by its comparative performance with literature benchmarks. Compared with the ensemble models reported in CHD prediction and antenatal care utilization studies, which reported moderate AUCs (≈0.80 and ≈0.90, respectively), our CDSS exhibits stronger discriminative performance (Journal references). These findings indicate that when rich, structured EHR data from centralized CPIS are leveraged with sophisticated preprocessing and model integration, ensemble methods can achieve state-of-the-art classification outcomes across diverse clinical domains. An important factor contributing to this performance is the preprocessing strategy that emphasizes clinically meaningful normalization, conservative imputation, and lightweight transformation to preserve signal while avoiding unnecessary latency. This approach aligns with best practices in healthcare machine learning that recommend retaining clinical interpretability and minimizing distortion of underlying physiological patterns. While ensemble methods are often criticized as "black boxes," the inclusion of Logistic Regression as one of the base learners helps provide calibrated probability outputs that clinicians can reason about. This is complemented by the structured nature of the EHR data, where feature contributions (e.g., specific laboratory values or vital sign abnormalities) can be traced back to clinical events. As such, the CDSS not only performs well on predictive metrics but also supports explainability and clinical trust, aspects that are critical for adoption in real-world settings.
2. Operational Efficiency and Deployability: While predictive performance is essential, latency and operational efficiency are equally critical for clinical utility, especially in environments where decisions must be made in real time or near real time. Our latency

benchmarking revealed that the soft-voting ensemble's end-to-end processing time (~70 ms) remains within acceptable thresholds for real-time CDSS workflows. Although slightly higher than the individual learners (e.g., Logistic Regression at ~45 ms), this overhead is justified by substantial gains in discriminative performance and robustness. This result has significant implications for latency-aware decision support, particularly in hospital settings where rapid alerting can influence timely interventions. The CDSS's integration with a centralized CPIS (Ojugo & Ekurume, 2021; Okobah & Ojugo, 2018) and real-time ingestion pipeline ensures that incoming clinical events are rapidly processed, with timestamps recorded across pipeline stages to enable performance monitoring and optimization. This design supports rigorous evaluation of operational metrics beyond predictive accuracy, an area often underreported in machine learning research but vital for clinical deployment. The observed latency performance also underscores the importance of system architecture and data engineering in CDSS implementations (Ojugo, Eboka, et al., 2015; Ojugo & Otakore, 2020). A centralized CPIS with standardized data models and semantic consistency mechanisms facilitates efficient data querying and low-overhead delivery to the inference engine. Such architectural decisions greatly reduce overhead that would otherwise be incurred in more fragmented or heterogeneous EHR environs. The result is a non-optimal CDSS that functions effectively within the constraints of clinical workflows where computational resources and network throughput may vary. Comparative studies in the literature often emphasize predictive outcomes without fully addressing latency. For example, high AUCs reported in diabetes and sepsis prediction contexts rarely accompany detailed latency analysis, leaving a gap in understanding how these models would perform in live clinical systems. By contrast, our end-to-end performance evaluation demonstrates that it is feasible to achieve both high predictive performance and low operational latency when ensemble methods are optimized for production environments—a key insight for translational AI in healthcare. Additionally, the dashboard-style latency visualization suggest that clinicians and system administrators can monitor performance metrics in real time, akin to tools like CloudWatch or Datadog. This enhances trust in the system's reliability (Ojugo et al., 2013; Ojugo, Odiakaose, et al., 2023) and supports continuous performance auditing, which is crucial for maintaining regulatory and ethical compliance in healthcare AI systems. Transparent monitor also facilitates proactive detection of model drift or system bottlenecks, enabling maintenance and retraining where necessary.

3. Integration with Clinical Workflows and Ethical Considerations: An essential dimension of CDSS evaluation is the system's alignment with clinical workflows and ethical standards. Our centralized CPIS and EHR integration layer supports structured data exchange and event-driven inference triggers, enabling the CDSS to function in synchrony with clinical operations. This architectural choice reflects studies advocating centralized systems for coordinated care and analytics Ethical deployment needs rigorous data governance, anonymization, and compliance with institutional policies, which were enforced through de-identification and access control. These practices align with established guidelines for responsible AI in healthcare (Bala et al., 2024; Zhang et al., 2024). Ensuring data privacy and ethical compliance not only protects patient confidentiality but also reinforces clinician and stakeholder trust—an indispensable precursor to real-world adoption (Ojugo et al., 2014).

4. CONCLUSION

The ensemble CDSS demonstrate the-art predictive performance, robust clinical relevance, and satisfactory operational latency. Its comparative advantage over individual learners and its competitive position relative to published benchmarks affirm the value of ensemble learning in complex clinical prediction tasks. Moreover, this study's architectural and implementation insights show that high performance is achievable without sacrificing real-time operational constraints. Looking forward, future work should explore external validation across multiple institutions, particularly to assess generalizability in varied clinical environments. Additionally,

incorporating explainability modules such as SHAP (Shapley Additive explanations) or LIME (Local Interpretable Model-agnostic Explanations) can further enhance clinician trust. Finally, longitudinal monitoring of model performance in live deployment will be essential for sustaining clinical utility and detecting drift over time.

Conflict of Interest

The authors declare that there is no conflict of interest.

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