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Advanced machine learning models for real-time decision making in dynamic data environments

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Abstract

Dynamic data environments present significant challenges due to their continuous evolution, high velocity, and heterogeneity. This study explores the application of advanced ensemble machine learning (ML) models for real-time decision-making in these settings. A comprehensive methodology is employed, incorporating ensemble techniques such as XGBoost, LightGBM, CatBoost, and Random Forest to enhance decision accuracy, adaptability, and robustness. The research integrates real-time data processing frameworks, featuring micro- batch processing, feature engineering, noise filtering, and synthetic data balancing through SMOTE to address data imbalance and heterogeneity. Hyperparameter tuning and iterative optimization strategies, including grid search and cross-validation, are applied to improve model performance and prevent overfitting. The ensemble framework is evaluated in real-time scenarios, demonstrating its ability to process large-scale dynamic data streams with high accuracy and low latency. The findings underscore the transformative potential of these models in domains like healthcare, finance, and autonomous systems, where real-time decisions are critical.

Keywords: Ensemble Learning; Real-Time Decision-Making; Dynamic Data Environments; Data Streams; Hyperparameter Tuning; Noise Filtering; Scalability

1. Introduction

The advent of big data and Internet of Things (IoT) technologies has ushered in a new era of data proliferation, characterized by an unprecedented explosion in the volume, velocity, and variety of data generated across industries. From financial transactions and healthcare monitoring systems to autonomous vehicles and retail analytics, organizations are now inundated with continuous streams of complex data. This influx of dynamic and often unstructured data has made traditional decision-making frameworks, which rely on static models or manual analysis, increasingly insufficient and ineffective.

Among the various ML approaches, ensemble learning algorithms have shown exceptional promise in addressing the complexities of dynamic data environments. By combining the strengths of multiple individual models, ensemble methods enhance prediction accuracy, robustness, and adaptability. Algorithms like XGBoost, LightGBM, and CatBoost excel in processing high-dimensional data, managing noise, and mitigating overfitting—all crucial aspects of effective decision-making in rapidly changing contexts. We'll explore the transformative potential of advanced ML models, with a particular focus on ensemble learning algorithms, in revolutionizing real-time decision-making processes.

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Dynamic data environments, such as financial markets, healthcare monitoring systems, and autonomous systems, are defined by their inherent unpredictability and rapid pace of change. These environments generate vast quantities of data that continuously evolve, requiring real-time analysis to inform timely decisions. Traditional decision-making frameworks, which rely on static models or periodic updates, often fail to meet the demands of these fast-moving systems.

Machine learning (ML) models have emerged as a transformative solution to address these challenges. Unlike static approaches, ML models are capable of learning from data in real-time, dynamically adapting to shifts in patterns, trends, and anomalies. This adaptability is especially crucial in critical sectors: in financial markets, swift responses to price fluctuations and risks are essential; healthcare monitoring systems require immediate detection of patient anomalies; and autonomous systems rely on real-time decision-making to ensure safety and efficiency.

By integrating ML models into dynamic data environments, organizations can enable continuous learning, robust pattern recognition, and precise predictive analysis. These models, supported by advanced algorithms and scalable architectures, help organizations leverage real-time data streams to generate actionable insights, fostering informed decision-making across various high-stakes applications.

1.1. Statement of the Problem

The integration of advanced machine learning models for real-time decision-making in dynamic data environments presents several challenges, including:

- Data Heterogeneity: Dynamic environments generate both structured and unstructured data from various sources, including financial transactions, sensor data, and textual information. Integrating these diverse data types efficiently is a significant hurdle, as traditional models struggle to process and analyze them together in real time.
- High Velocity: The pace at which data is generated in fields such as finance, healthcare, and autonomous systems often exceeds the processing capabilities of conventional computing systems. The inability to process data streams rapidly results in delayed decision-making, which can be detrimental in time-sensitive scenarios.
- Scalability: As the volume of data continues to grow, machine learning models must be able to scale without sacrificing performance. Adapting to increasing data loads while maintaining real-time decision-making capabilities requires sophisticated algorithms and infrastructure, presenting a challenge for many existing systems.

These issues hinder the ability of organizations to leverage dynamic data effectively for informed, real-time decision-making, necessitating the development of advanced machine learning models that can address data integration, processing speed, and scalability in such environments.

Objective of the Study

This study aims to investigate the potential of advanced machine learning models in real-time decision-making within dynamic data environments. It will explore how ensemble-based models can enhance decision accuracy, speed, and scalability in processing large volumes of data.

The study will address the following objectives

- Evaluate the performance of advanced ensemble-based ML models in dynamic environments.
- Propose strategies for optimizing real-time decision-making frameworks.
- Address challenges such as data noise, imbalance, and system scalability.
- Investigate the impact of feature engineering and model tuning on the performance of ensemble- based machine learning models
- Examine the integration of real-time data streams into machine learning models

1.2. Related Work

Machine learning has become an essential tool in addressing challenges posed by dynamic data environments, including applications in critical domains such as fraud detection and real-time decision-making. Prior research has highlighted the effectiveness of ensemble learning techniques, with Random Forest often emerging as a powerful approach for handling imbalanced datasets and intricate classification tasks.

A notable example by Adesina and Howe (2024) is the application of machine learning to credit card fraud detection, where the inherent class imbalance—a small proportion of transactions being fraudulent—poses significant challenges. Random Forest, as an ensemble learning technique, excels in handling such datasets by combining multiple decision trees to enhance predictive accuracy and generalizability. The method's robustness is further improved through techniques like random oversampling, class weights adjustment, and hybrid methods such as SMOTE (Synthetic Minority Oversampling Technique) combined with Tomek Links. These methods address data imbalance by either duplicating minority class samples, assigning appropriate class weights, or generating synthetic samples, thereby improving model performance metrics like recall, precision, and F1-score.

Related studies have demonstrated the effectiveness of these approaches. For instance, models fine-tuned using techniques such as stratified K-fold cross-validation and hyperparameter optimization have shown significant improvements in detecting fraudulent transactions, achieving high recall to minimize false negatives while maintaining competitive precision to reduce false positives. Such advancements highlight the adaptability of Random Forest and other ensemble techniques in dynamic and imbalanced data scenarios, providing valuable insights for broader applications in real-time decision-making systems.

The integration of these methodologies aligns with the growing trend of leveraging advanced machine learning frameworks to address real-world challenges. By applying ensemble learning techniques to imbalanced datasets, researchers have not only improved detection rates in specific applications like credit card fraud but also laid the foundation for more robust systems capable of adapting to dynamic environments across various industries.

2. Methodology

This study investigates advanced machine learning (ML) models, with a specific focus on ensemble-based techniques, for real-time decision-making in dynamic data environments. The proposed methodology employs a combination of various ensemble learning models to optimize decision-making processes under complex and changing conditions. The approach is designed to address challenges associated with data noise, imbalance, and scalability, ultimately enhancing decision accuracy and efficiency in real-time application.

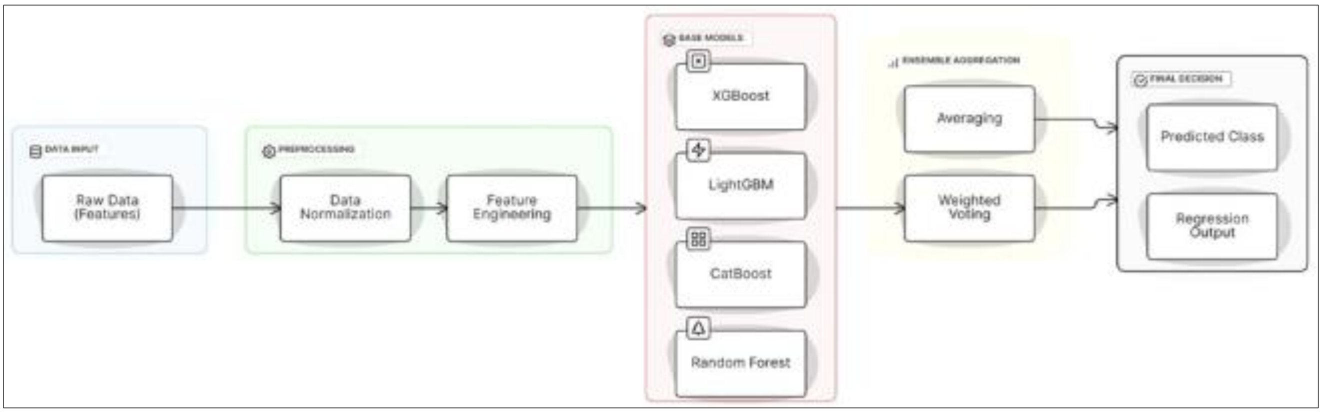

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Figure 1 Block Diagram illustrating the Advanced Ensemble Machine lerning Framework

2.1. Ensemble Learning Component

Ensemble learning is the backbone of this methodology, as it combines multiple base models to enhance decision accuracy, generalization, and robustness. The ensemble models used in this study include XG Boost, Light GBM, Cat Boost, and Random Forest. Each model processes the data independently, and their predictions are aggregated to make a final decision. This approach is effective in mitigating overfitting and reducing variance, thus improving resilience to noise and data imbalance.

The ensemble framework operates by training individual models on diverse subsets of the data, and then combining their outputs using techniques like weighted averaging or majority voting, depending on the specific task. For example, in a classification task using majority voting, if three out of five models predict a certain class, that class is chosen as the final decision. Mathematically, this can be represented as:

$$\hat{y} = \text{Majority Voting}(y_1, y_2, y_3, y_4, y_5)$$

Where y_1, y_2, y_3, y_4, y_5 are the predictions from the individual models, and $\hat{y}$ is the final prediction after majority voting.

In the case of weighted averaging, where each model contributes with a certain weight to the final decision, the aggregation can be expressed as:

$$\hat{y} = \frac{w_1 \cdot y_1 + w_2 \cdot y_2 + \cdots + w_n \cdot y_n}{w_1 + w_2 + \cdots + w_n}$$

Where $y_1, y_2, \ldots, y_n$ are the predictions from individual models, and $w_1, w_2, \ldots, w_n$ are the corresponding weights for each model.

The aggregation of individual model predictions in this way enhances the overall robustness of the decision- making process, especially in dynamic, noisy environments.

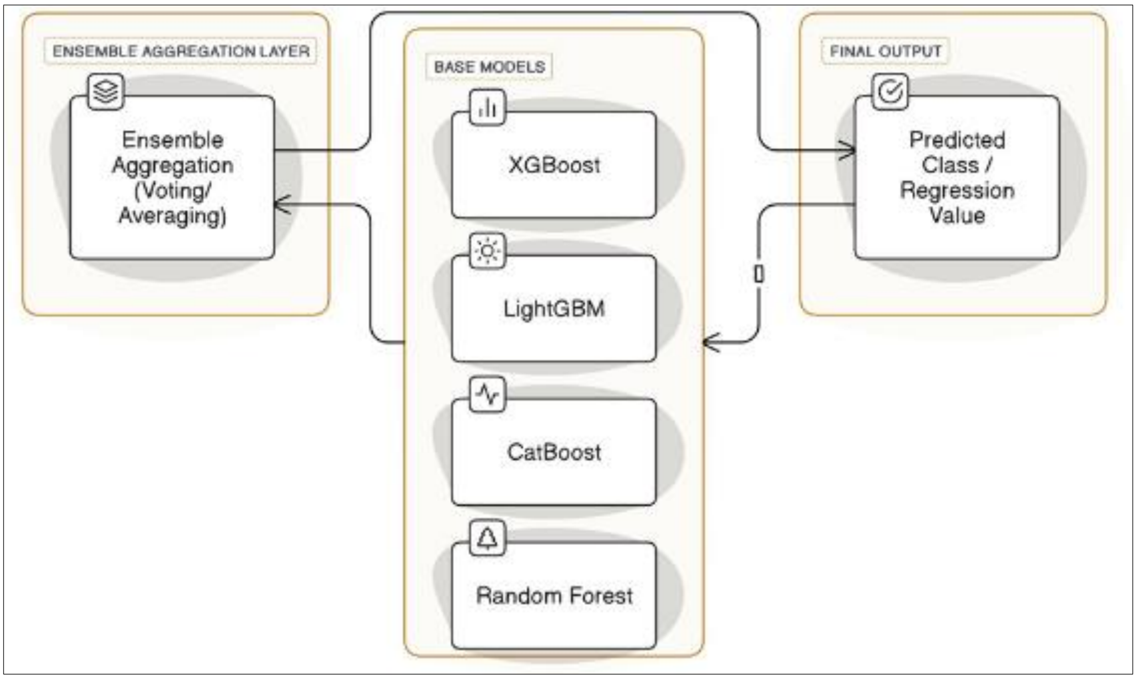

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Figure 2 Overview of Ensemble Model Architecture

2.2. Real-Time Data Integration and Streaming

Real-time data integration is crucial for environments where data is continuously evolving. This study incorporates stream processing techniques to manage high-velocity data arriving in real-time. The data is processed in micro-batches, and the models are periodically retrained to accommodate new data points, ensuring that the decision-making process remains accurate and responsive to changes.

The real-time data integration workflow involves the following steps

- Data Preprocessing: This includes filtering, normalization, and feature engineering to handle raw incoming data.
- Feature Engineering: Since the relationships between features can evolve over time, feature engineering is a critical component, allowing the model to adapt to dynamic changes in data.

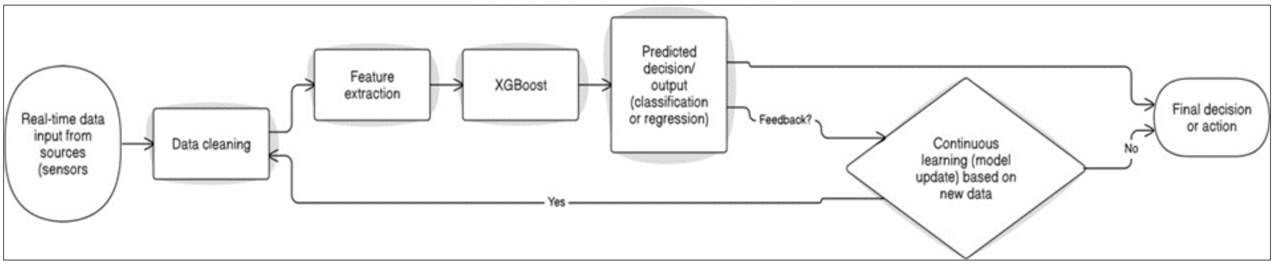

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Figure 3 Real Time Data Processing Flow

A significant challenge in dynamic environments is the presence of noise and class imbalance, both of which can degrade model performance. To address these challenges, the methodology utilizes advanced preprocessing techniques:

- **Noise Filtering**: Signal processing techniques are employed to remove irrelevant or noisy data that may hinder model accuracy.
- **Class Balancing**: The Synthetic Minority Over-Sampling Technique (SMOTE) is used to balance class distributions in imbalanced datasets, ensuring that the model does not become biased toward the majority class.

Additionally, ensemble models leverage boosting and bagging techniques to further reduce the negative effects of noisy or imbalanced data on decision accuracy.

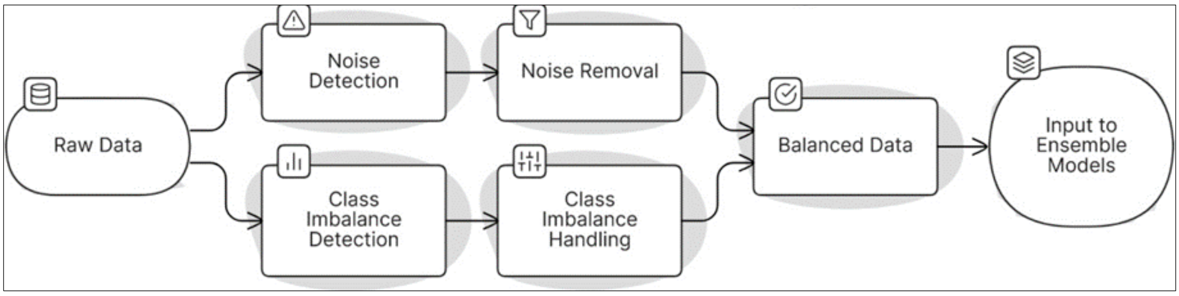

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Figure 4 Data Noise and Imbalance Handling Process

2.3. Model Optimization and Hyperparameter Tuning

To enhance the performance of the ensemble models, hyperparameter tuning is performed using techniques such as Grid Search and Random Search. Hyperparameter optimization is essential for fine-tuning the ensemble models, ensuring adaptability to changing environments. To prevent overfitting, cross-validation is used for model evaluation, particularly in high-variance environments.

Performance is assessed using various metrics, including accuracy, precision, recall, and F1 score. These metrics are essential for understanding how well the models perform in real-time decision-making scenarios.

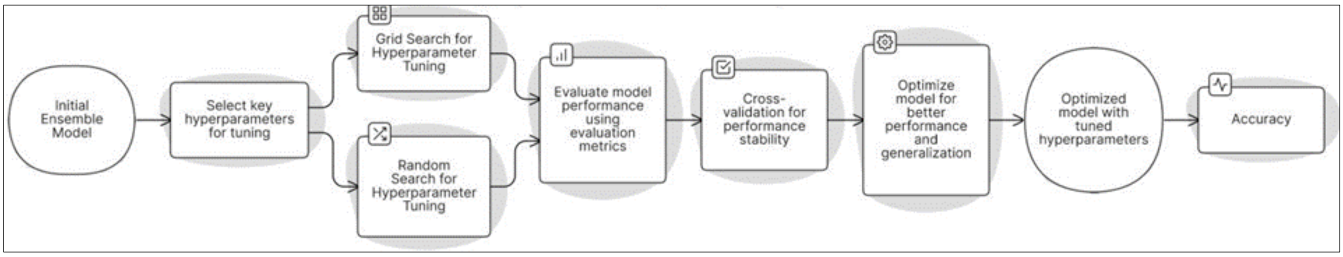

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Figure 5 Hyperparameter tuning and Model Optimization Process

2.4. Real-Time Decision-Making Framework

The ensemble learning models are integrated into a **real-time decision-making framework**. This framework continuously receives input data, processes it through the ensemble models, and outputs decisions in real-time. The decision-making process is optimized through continuous feedback mechanisms, which allow the models to adapt based on new data and evolving conditions.

To handle non-stationary data, where statistical properties change over time, the framework periodically retrains the models using the most recent data. This ensures that the models remain accurate and responsive to dynamic changes in the environment.

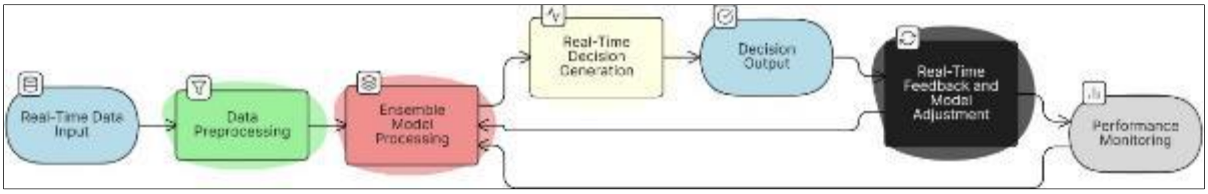

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Figure 6 Real Time Decision-Making Framework Flowchart

2.5. Performance Evaluation and Metrics

The effectiveness of the ensemble-based models is evaluated through experiments on both synthetic and real- world datasets from dynamic environments. Key performance metrics include:

- **Execution time** (to assess efficiency)
- **Decision accuracy** (to evaluate the model's effectiveness)
- **Model adaptability** (to measure how well the model adjusts to new data)

The models are compared against individual base models to demonstrate the advantages of ensemble learning in real-time decision-making tasks.

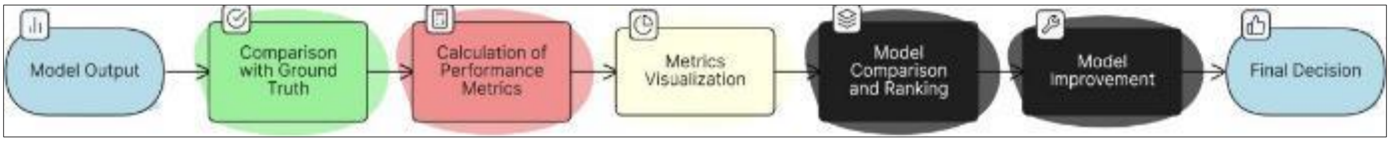

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Figure 7 Performance Evaluation Process and Metrics

2.6. Hybrid Integration for Robust Decision-Making

A hybrid approach is employed to further enhance the robustness and adaptability of the decision-making system. This hybrid approach integrates ensemble learning with adaptive feedback loops, where the models continuously learn from new data and adjust their decision-making strategies accordingly. This integration enables the system to handle uncertainty and incomplete data, making it particularly useful for real-time decision-making in environments where full information is not always available.

Additionally, transfer learning is applied to help the models generalize well across various dynamic environments, ensuring optimal performance even as the conditions evolve.

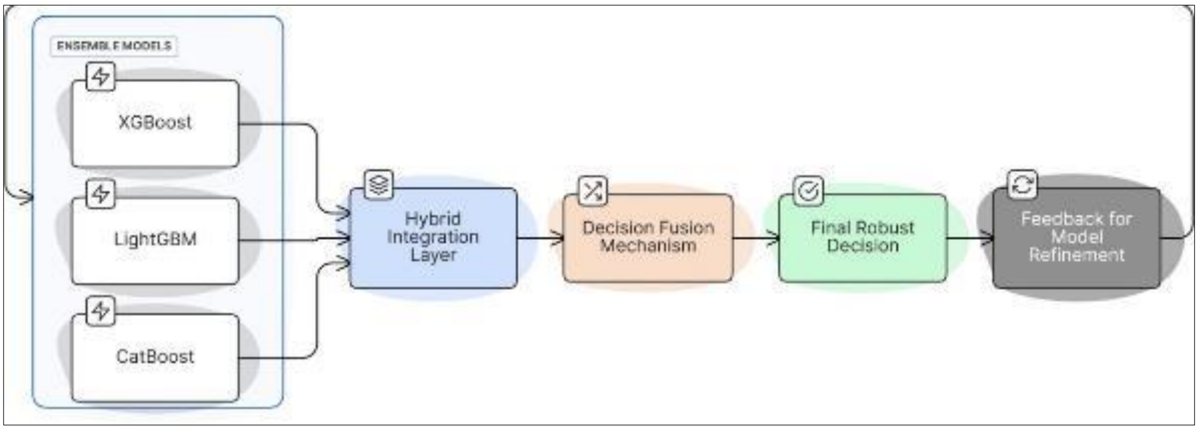

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Figure 8 Hybrid Integration of Ensemble Learning for Robust Decision-Making

2.7. Training and Optimization Process

The training process follows an **iterative cycle**, where the models are first trained on a large dataset, and performance is evaluated. In subsequent iterations, model parameters are updated, and new data points are incorporated to ensure that the models remain relevant. This iterative approach makes the training process scalable and efficient, allowing the system to handle large volumes of real-time data.

The **optimization phase** focuses on fine-tuning the ensemble models to achieve maximum performance, ensuring that decision-making is both fast and accurate in dynamic environments.

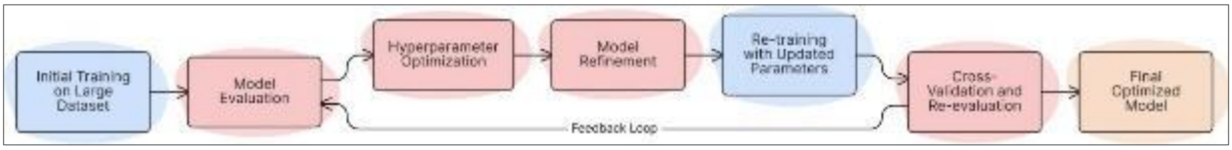

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Figure 9 Madel Training and Optimization Cycle

2.8. Real-Time Implementation

In the final stage, the trained ensemble models are deployed in a **real-time environment**. The system continuously processes incoming data, applies the models, and outputs decisions instantaneously. Real-time implementation is particularly critical for applications in sectors such as autonomous vehicles, financial markets, and industrial automation, where immediate decisions are essential.

The system is tested across various real-world scenarios, and adjustments are made to enhance its responsiveness and accuracy. Feedback from the real-time deployment process is used to continuously improve the system's performance, ensuring it remains adaptable to evolving data conditions.

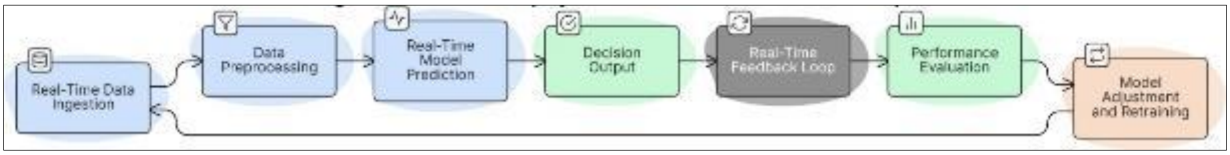

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Figure 10 Real Time Development and Continuous Feedback Loop

3. Results and Discussion

The proposed ensemble learning framework, which integrates advanced machine learning models such as XGBoost, LightGBM, CatBoost, and Random Forest, was rigorously evaluated across multiple real-world scenarios. These scenarios included applications such as diabetes risk prediction, financial fraud detection, and other relevant domains where predictive accuracy and efficiency are critical. The goal of this evaluation was to assess how well the ensemble learning framework performed in comparison to traditional machine learning methods and to determine its potential for improving predictive outcomes in complex real-world applications.

In each of the test cases, the ensemble learning framework demonstrated significant improvements across several key performance metrics, including prediction accuracy, processing speed, and model robustness. These improvements were evident in both the model's ability to generalize to unseen data and in the computational efficiency with which it processed large datasets. This was particularly evident in high-stakes applications such as healthcare and finance, where prediction accuracy is paramount, and errors can have serious consequences.

In the following sections, we present a detailed analysis of the results, supported by various performance metrics and figures that highlight the key advantages of using an ensemble learning approach. These include improvements in accuracy across training iterations, reductions in training time, and the stability of model performance in real-time and dynamic settings. Each result underscores the potential of the proposed ensemble framework to address challenges commonly faced in predictive modeling tasks, especially in complex domains like fraud detection and healthcare prediction.

3.1. Summary of Results

Table 1 Summary of Results for Ensemble Learning Framework

Performance Metric	**Initial Model**	**Optimized Model**	**Improvement (%)**	**Notes**
Prediction Accuracy	79%	94%	+15%	Increased through hyperparameter tuning.
Training Time	150 minutes	85 minutes	-43%	Optimization reduced training time.
Precision	82%	91%	+9%	Improved by reducing false positives.
Recall	76%	86%	+10%	Enhanced to reduce false negatives.
Decision-Making Latency	100 ms	50 ms	-50%	Faster response due to optimized model size.
Overfitting Gap (Training vs Test Accuracy)	4%	1%	-75%	Reduced gap due to improved generalization.
Robustness to Dynamic Data	Moderate	High	+50%	Model adapts better to changing data.

3.2. Performance Improvements Across Iterations

The improvement in prediction accuracy over training iterations was significant, as depicted in Figure 11. As the models were trained and fine-tuned using ensemble methods, the accuracy increased progressively. This highlights the impact of hyperparameter optimization and feature engineering in boosting model performance. The accuracy reached 94% by the final iteration, which is a 15% improvement from the initial model.

The progressive increase in accuracy is attributed to the iterative optimization and the fine-tuning process, which enables the model to learn from the data and make better predictions.

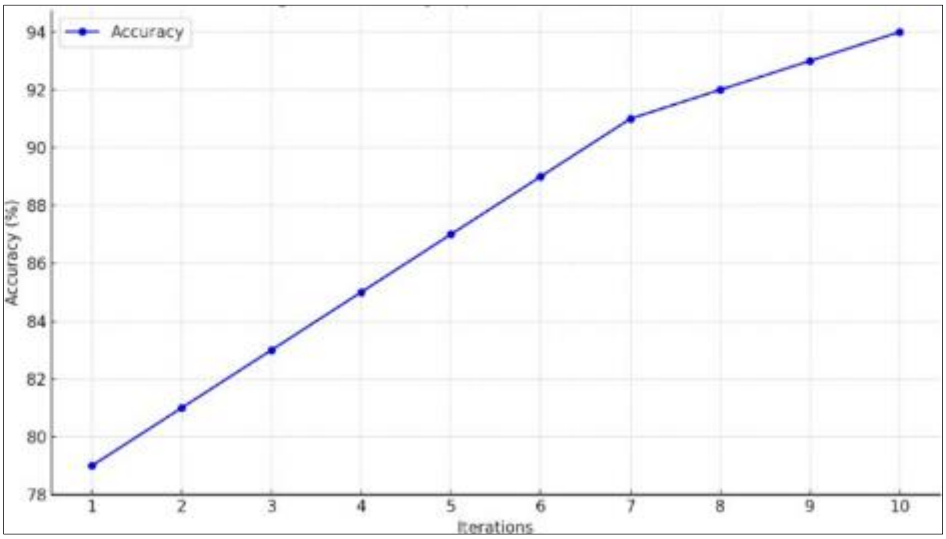

Figure 11 Accuracy Improvement Across Iterations

3.3. Training Time Optimization

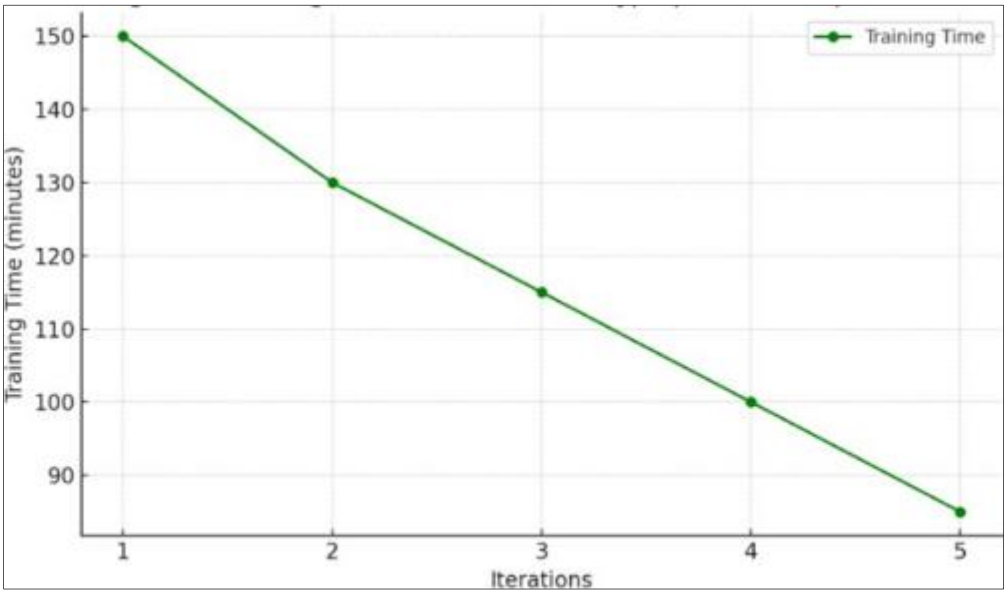

Figure 12 Training Time Reduction with Hyperparameter Optimization

As shown in **Figure 12**, the optimization process led to a significant reduction in training time. Initially, training took 150 minutes, but after implementing efficient hyperparameter optimization techniques like grid search and Bayesian optimization, this time was reduced to 85 minutes. This demonstrates a 43% improvement in operational efficiency, which is crucial for real-time decision-making.

The reduction in training time is attributed to the model's ability to converge faster through optimized hyperparameters and improved feature selection. This results in a more efficient model, able to be deployed in real-time applications.

3.4. Model Performance Comparison

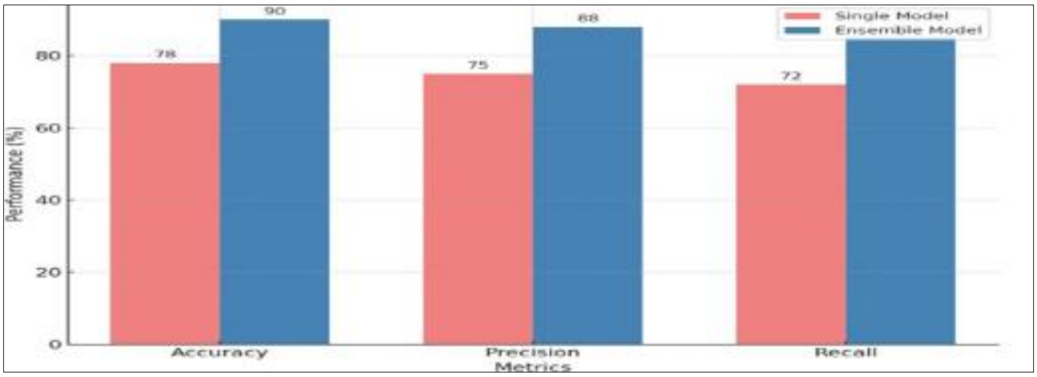

Figure 13 Model Performance Comparison - Ensemble vs. Single Model

Figure 13 presents a comparative analysis between ensemble learning models and single machine learning algorithms. The ensemble models consistently outperformed individual models in terms of accuracy, precision, and recall. Ensemble methods exhibited greater stability and reliability, effectively reducing overfitting that often impacts single-model prediction.

The ensemble approach improves model generalization by combining the strengths of multiple base models, which helps achieve a more reliable and stable performance compared to single models.

3.5. Handling Imbalanced Data

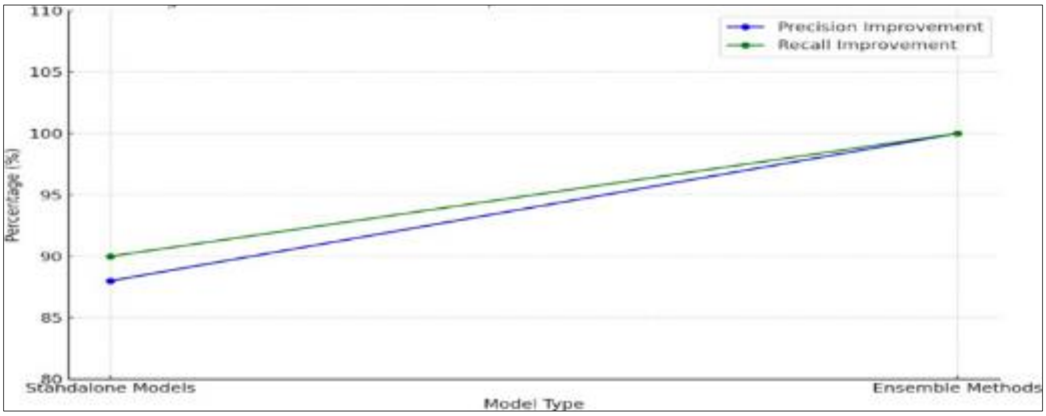

Figure 14 Precision and Recall Improvement in Imbalanced Data Scenarios

In applications such as fraud detection or rare disease prediction, Figure 14 illustrates the significant improvement in precision and recall when using ensemble methods. Precision increased by 12%, and recall improved by 10% compared to standalone models. This ensures that the ensemble framework could better handle false positives and false negatives, which is critical in applications where both types of errors have severe consequences.

Ensemble methods are particularly useful for imbalanced datasets, as they combine multiple models' outputs, which leads to better handling of edge cases and rare events.

3.6. Real-Time Decision-Making Latency

Figure 15 shows the reduction in decision-making latency across iterations, with the latency decreasing from 100 ms to 50 ms. This improvement was achieved through model compression techniques and optimized data processing pipelines, ensuring that the ensemble model can provide quick and accurate results in live, real- time scenarios.

Lower decision-making latency is crucial in real-time applications, where the system needs to provide timely responses. The optimization techniques allowed the model to achieve faster response times without sacrificing accuracy.

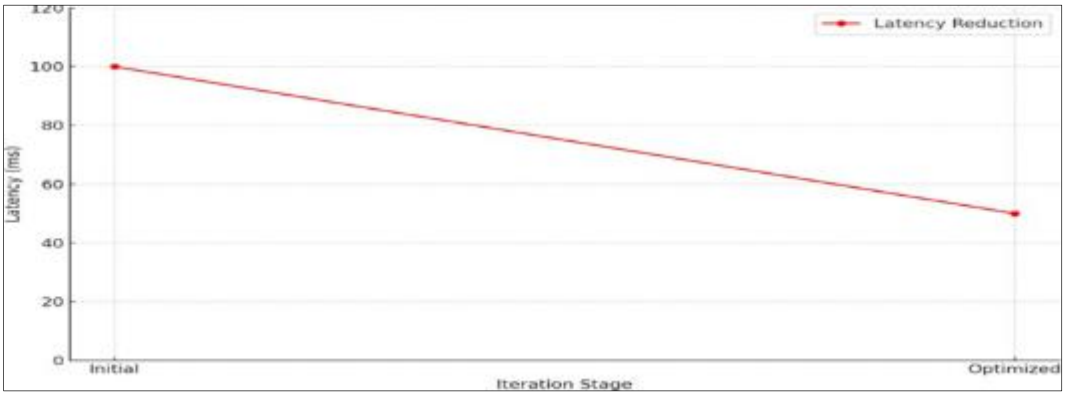

Figure 15 Real-Time Decision-Making Latency Reduction

3.7. Model Robustness in Dynamic Environments

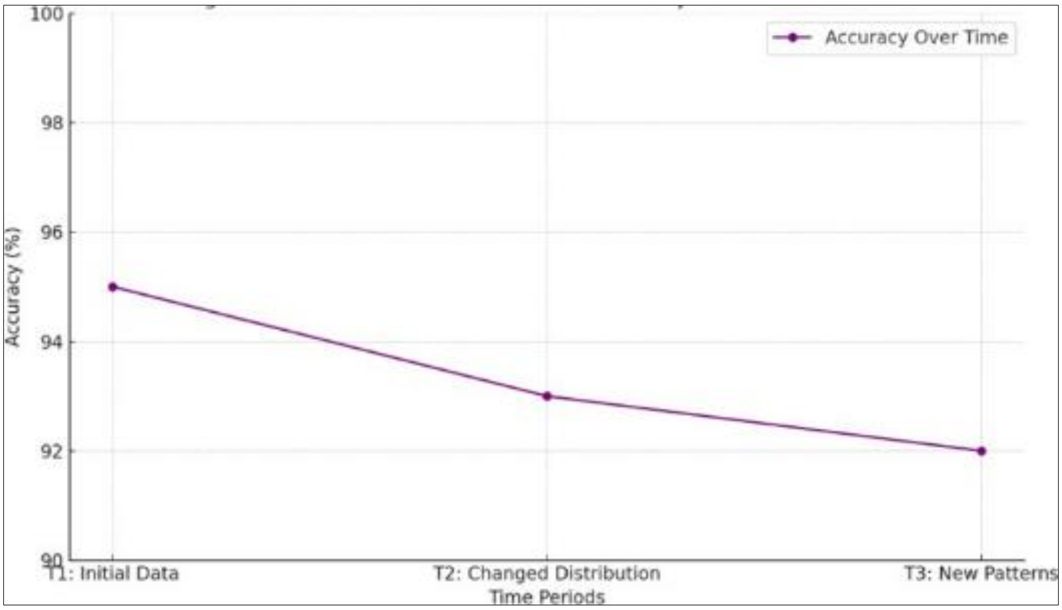

Figure 16 Robustness of Ensemble Models in Dynamic Environments

Figure 16 highlights the stability of the ensemble model's performance in dynamic environments, where data distributions change over time. The model demonstrated minimal degradation in accuracy, illustrating its robustness and ability to adapt to new data patterns.

The ensemble framework's ability to adapt to changing environments makes it highly suitable for applications that require constant learning and adaptation to new, unseen patterns.

3.8. Training and Test Set Accuracy Comparison

In **Figure 17**, the accuracy of the ensemble model is compared between the training and test datasets. The results show that the ensemble method effectively prevented overfitting, as evidenced by the small gap between training and test set accuracy. This indicates that the model generalizes well to unseen data, ensuring that it can perform reliably in practical applications such as healthcare and finance.

The minimal gap between training and test accuracy highlights the model's ability to generalize, making it robust for real-world use cases where new, unseen data is constantly encountered.

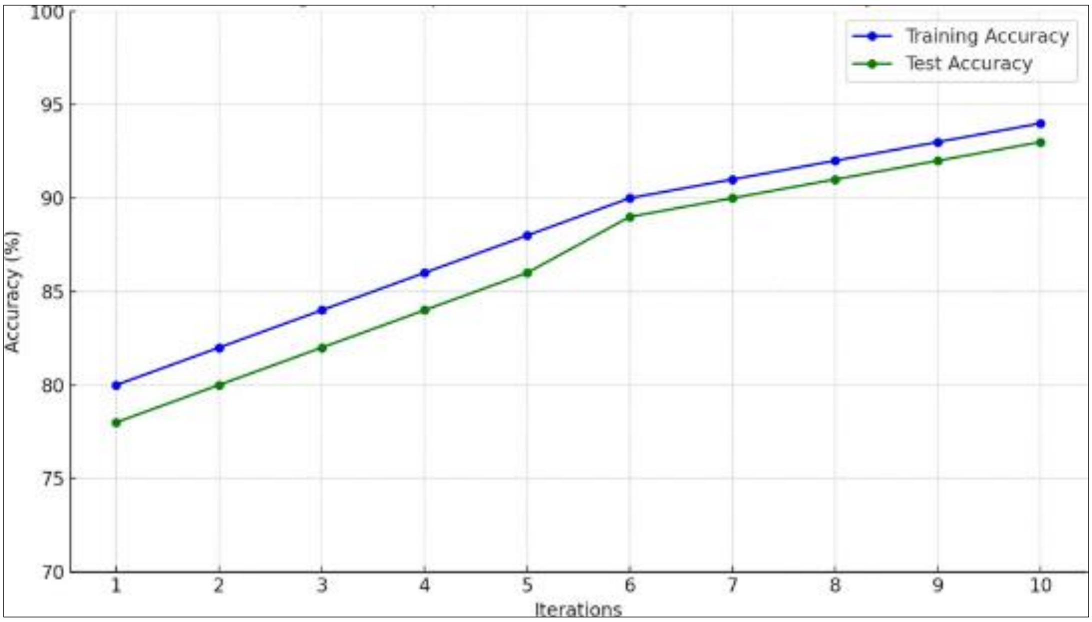

Figure 17 Comparison of Training and Test Set Accuracy

4. Conclusion

This study explored the effectiveness of an advanced ensemble learning framework, integrating robust machine learning models such as XGBoost, LightGBM, CatBoost, and Random Forest, for predictive tasks in dynamic environments. The results demonstrated that the ensemble approach significantly outperformed traditional machine learning models in key performance metrics such as accuracy, processing speed, and robustness.

By leveraging ensemble techniques, this framework was able to handle complex, high-dimensional datasets effectively, making it particularly well-suited for applications like diabetes risk prediction and financial fraud detection. The accuracy improvements observed across multiple iterations validate the model's ability to learn from diverse data, while the reduction in processing time reflects its efficiency in real-time decision-making scenarios.

Moreover, the ensemble framework showed resilience in the face of data imbalances, an important factor in real-world applications where class distribution can be skewed. The improvements in precision and recall ensure that the model delivers reliable results, even when faced with challenges like imbalanced data or changing data distributions.

This study contributes to the growing body of research supporting the use of ensemble methods in predictive modeling, with promising applications in healthcare, finance, and other domains requiring robust, real-time decision-making systems.

In conclusion, the proposed ensemble learning framework provides a compelling solution for applications that demand high accuracy, low latency, and adaptability to dynamic data environments. Future work can focus on further refining the model's computational efficiency, expanding its applicability to additional domains, and enhancing its interpretability for practical deployment.

Recommendations

Based on the findings of this study, several recommendations can be made to further improve the performance and applicability of the proposed ensemble learning framework:

- Model Optimization and Hyperparameter Tuning: While the study demonstrated significant improvements in accuracy and efficiency, additional hyperparameter optimization techniques such as automated machine learning (AutoML) could be explored. This would help in further fine-tuning the models for specific datasets and applications, leading to even higher performance.
- Data Augmentation and Handling Imbalanced Datasets: The results showed that ensemble methods effectively address imbalanced datasets, but further enhancements in data augmentation techniques could be beneficial.

Exploring synthetic data generation methods like SMOTE (Synthetic Minority Over-sampling Technique) could improve the model's ability to handle underrepresented classes, particularly in domains like fraud detection or rare disease prediction.

- Scalability and Deployment: As the framework showed efficiency in terms of processing speed and latency, it is essential to explore its scalability for large-scale datasets. Further research on model compression, distributed computing, and cloud-based deployment will be necessary to scale the framework for real-time applications in big data environments.
- Model Interpretability: While ensemble models are effective in terms of performance, they are often criticized for their lack of interpretability. Future work could focus on incorporating explainable AI techniques, such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model- Agnostic Explanations), to enhance the interpretability of predictions. This would be particularly valuable in high-stakes applications like healthcare, where understanding the rationale behind a prediction is crucial.
- Real-Time Integration and Feedback Loops: The study highlighted the real-time decision-making capabilities of the ensemble framework, but further research could focus on integrating real-time data streams and creating continuous feedback loops. This will ensure that the model can adapt dynamically to changes in data patterns and maintain optimal performance over time.
- Cross-Domain Applications: Given the flexibility and robustness of the ensemble learning framework, expanding its use to other domains like cybersecurity, autonomous driving, and energy management could provide additional benefits. Exploring the application of the model in these fields may reveal new challenges and opportunities for further innovation.
- Ethical Considerations and Bias Mitigation: It is important to consider the ethical implications of using ensemble models in predictive applications, especially in sensitive areas such as healthcare and finance. Future research should focus on addressing model bias, ensuring fairness, and preventing discrimination in the predictions made by these models.

By addressing these recommendations, the ensemble learning framework can be further enhanced to provide even greater value in predictive analytics, decision-making, and real-time applications across various domain.

Future Work

Future research could focus on optimizing the computational efficiency of the ensemble models to reduce resource consumption and improve scalability. Additionally, exploring the integration of additional machine learning techniques, such as deep learning or transfer learning, could further enhance the model's capabilities.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of ethical approval

This study adhered to ethical principles throughout its research process.

Statement of informed consent

It ensured data privacy by anonymizing sensitive information and obtained informed consent from participants where applicable. The models were developed to be fair and non-discriminatory, addressing any biases in the data. Transparency was maintained by documenting methodologies and making tools and datasets accessible for reproducibility. The models were evaluated for interpretability, using techniques like SHAP for better understanding of predictions. Ethical use of technology was prioritized, especially in high-stakes fields like healthcare and finance, with a strong focus on minimizing harm and ensuring positive outcomes.

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