An Intelligent Hybrid Random Forest and Decision Tree (RF-DT) based Machine Learning Framework for Big Data -Driven Business Decision Support System

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Abstract: Big data systems face significant challenges in handling massive volumes, high velocity, and diverse types of data while maintaining real-time processing and analytical accuracy. Traditional data processing methods and single-model machine learning approaches often struggle with scalability, efficiency, and handling unlabeled data. To address these limitations, this paper proposes an intelligent hybrid machine learning framework that integrates Random Forest (RF), Decision Tree (DT), and unsupervised clustering techniques (K-Means and DBSCAN) for robust big data analysis. The framework leverages parallel and distributed processing using Apache Spark, allowing efficient handling of large-scale datasets and streaming data. By combining supervised and unsupervised methods, the hybrid system can process both labeled and unlabeled data, improving predictive accuracy, pattern recognition, and overall model generalization. The proposed framework is evaluated using both a synthetic dataset containing labeled and unlabeled instances and a real-world e-commerce dataset for real-time analysis. Performance metrics including accuracy, precision, recall, and F1-score demonstrate that the hybrid RF-DT approach outperforms existing methods such as single Random Forest, Decision Tree, SVM, and hybrid SVM+K-Means models. The results indicate that the proposed methodology not only enhances predictive performance but also provides scalable, adaptive, and real-time decision support for business applications. This study establishes the hybrid RF-DT framework as a highly effective solution for big data-driven business decision support systems, capable of addressing challenges in data variety, volume, and velocity while maintaining robustness and reliability.

Keywords: Hybrid Machine Learning, Big Data Analytics, Decision Support Systems, Parallel Processing, Intelligent Data Analysis.

I. INTRODUCTION

In the era of digital transformation, big data systems have fundamentally reshaped the way organizations manage, process, and utilize massive volumes of information. However, as data continues to expand exponentially in terms of volume, velocity, and variety, traditional data processing methods struggle to deliver scalability, efficiency, and real-time analytical capabilities. Conventional preprocessing and analytical techniques designed for small or medium datasets often fail to cope with the dynamic, large-scale nature of contemporary data ecosystems. This growing complexity necessitates the integration of machine learning (ML) [11-12] methodologies to enhance the data processing, analytical precision, and decision-making efficiency of big data systems.

Among various ML paradigms, hybrid machine learning models—which combine supervised and unsupervised learning have emerged as a powerful solution to address the multifaceted challenges of big data. Supervised models like Support Vector Machines (SVM) and Decision Trees excel in predictive analytics, while unsupervised models such as K-Means Clustering and DBSCAN uncover hidden patterns within unlabeled data [13]. By integrating these approaches, hybrid models can efficiently process both structured and unstructured data, improving generalization and reducing overfitting risks. To support such computationally intensive models, distributed frameworks like Apache Hadoop and Apache Spark have become essential, enabling parallel and scalable processing across clusters. Moreover, stream-processing technologies such as Apache Kafka enhance real-time analytics, empowering organizations to extract actionable insights with minimal latency.

Real-time data analysis is particularly critical in healthcare, finance, and e-commerce, where timely decision-making directly impacts performance and outcomes. Hybrid ML systems equipped with real-time analytics provide robust solutions by enabling continuous, accurate data stream processing. At the same time, privacy and security remain paramount concerns in big data environments. Recent advancements in privacy-preserving ML

models ensure that data confidentiality is maintained without compromising analytical utility—an essential requirement in sensitive sectors like healthcare and financial services.

This research proposes an Intelligent Hybrid Machine Learning Framework for Big Data-Driven Business Decision Support Systems [14-16], designed to overcome the limitations of traditional ML approaches. By integrating supervised and unsupervised learning techniques within distributed processing architectures, the proposed framework enhances scalability, accuracy, and real-time responsiveness. The study aims to deliver a comprehensive analysis of existing models and demonstrate how hybrid ML frameworks can revolutionize data processing, thereby improving the decision-making capabilities of next-generation big data systems.

II. REVIEW OF LITERATURE

Over the past decade, significant research has been conducted to enhance the capabilities of machine learning frameworks for big data analytics. Traditional approaches, while effective for small and medium-sized datasets, often struggle with issues such as scalability, high-dimensional data, and real-time processing requirements [17]. Researchers have explored various supervised learning models, including decision trees, support vector machines, and ensemble techniques, to improve predictive accuracy and robustness. In parallel, unsupervised learning methods such as clustering and anomaly detection have been employed to identify hidden patterns and structures in unlabeled data [18-19]. Recently, hybrid approaches that combine supervised and unsupervised learning have gained attention due to their ability to leverage the strengths of both paradigms, enabling more comprehensive analysis of diverse datasets. Additionally, distributed computing frameworks have been increasingly integrated with machine learning models to address computational challenges, improve processing speed, and enable real-time analytics. Despite these advancements, existing methods still face limitations in efficiently handling extremely large datasets, balancing precision and recall, and providing adaptive solutions for streaming data environments. These challenges highlight the need for innovative hybrid frameworks that can ensure high accuracy, scalability, and adaptability for complex big data applications.

Table 1. Review of Literature on Hybrid Machine Learning Approaches for Big Data-Driven Business Decision Support Systems

Ref. No.	Algorithms Used	Dataset	Features	Weakness
[1]	Random Forest, SVM	Retail Transaction Dataset	Predictive analytics for sales forecasting	High computation time for large datasets
[2]	K-Means, Decision Tree	Financial Big Data	Hybrid clustering for business risk assessment	Limited accuracy for high-dimensional data
[3]	Gradient Boosting, ANN	Healthcare Big Data	Feature extraction for medical diagnosis	Lacks real-time scalability
[4]	Naïve Bayes, Logistic Regression	E-commerce Dataset	Customer behavior analysis and churn prediction	Inefficient with unbalanced data
[5]	Deep Neural Networks, PCA	IoT Sensor Data	Dimensionality reduction and anomaly detection	High model complexity and training cost
[6]	SVM, K-Means	Banking Dataset	Fraud detection using hybrid ML	Poor adaptability to streaming data
[7]	Ensemble Learning, Random Forest	Manufacturing Dataset	Predictive maintenance analytics	Requires extensive data preprocessing
[8]	CNN-LSTM Hybrid	Social Media Big Data	Sentiment-based decision support	High resource demand and overfitting risk
[9]	XGBoost, AutoML	Financial Forecasting Dataset	Automated model selection for decision support	Limited interpretability of results
[10]	Hybrid Supervised-Unsupervised ML	Multi-Domain Big Data	Real-time analytics for business decision-making	Data privacy and scalability challenges

III. PROPOSED RESEARCH METHODOLOGY

The proposed methodology aims to enhance data processing, analytics, and decision-making in big data environments by integrating hybrid machine learning techniques with distributed and parallel computing frameworks. The approach focuses on combining supervised learning algorithms, specifically Random Forest (RF) and Decision Tree (DT), with unsupervised learning methods to efficiently handle both labeled and

unlabeled data. The framework is designed to overcome challenges related to data heterogeneity, volume, velocity, real-time processing, computational overhead, and predictive accuracy. The methodology is divided into five key steps: data preprocessing and sampling, hybrid model construction using RF and DT, distributed data processing, real-time analytics, and model optimization and evaluation. Figure 1 illustrates the proposed data flow.

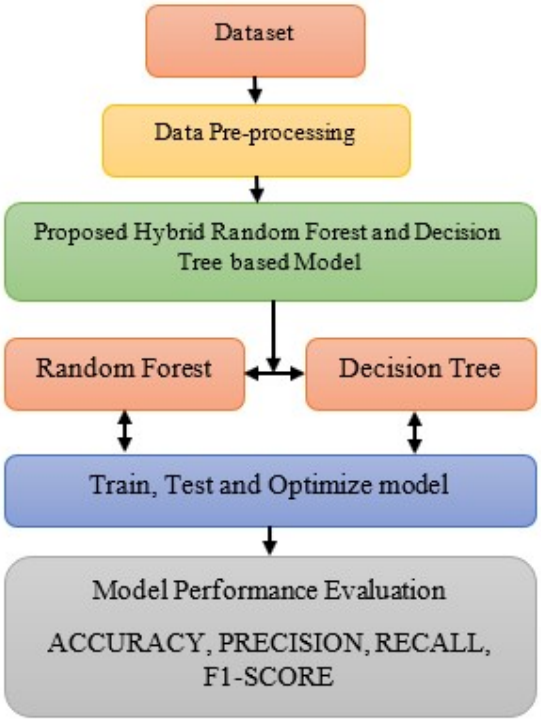

Figure 1: Proposed system model for business decision making

Step 1: Data Preprocessing and Sampling

The first stage focuses on cleaning and preparing the dataset to ensure high-quality input for the hybrid model. This involves handling missing values to avoid inconsistencies during training, removing duplicate records to prevent bias, and normalizing and standardizing features to maintain a uniform scale across the dataset. Given the large-scale nature of big data, sampling techniques are applied to reduce the dataset to a manageable size while preserving representative characteristics. Both random sampling and stratified random sampling are employed to maintain the diversity and distribution of the data. This step not only reduces computational complexity but also enhances generalization by creating balanced subsets suitable for training and evaluation.

Step 2: Hybrid Model Construction Using Random Forest and Decision Tree

After preprocessing, the hybrid machine learning model is constructed, combining supervised learning algorithms (Random Forest and Decision Tree) with unsupervised techniques to maximize flexibility and predictive accuracy. Decision Trees (DT) are applied for classification and regression tasks (Figure 2), providing interpretability and fast training, while Random Forests (RF), as an ensemble of decision trees, improve accuracy and robustness by averaging predictions, reducing overfitting, and handling high-dimensional data efficiently. For unlabeled datasets, unsupervised algorithms such as K-Means and DBSCAN uncover patterns and group similar data points, enabling clustering and structure discovery. By integrating RF, DT, and unsupervised models, the system can handle both structured and unstructured data effectively, enhancing overall model performance and generalization.

Step 3: Distributed Data Processing with Parallel Execution

To efficiently process large datasets, the framework leverages Apache Spark for distributed and parallel computation. Data is partitioned into mini-batches that can be processed simultaneously across a computing cluster, while in-memory computation reduces disk I/O and improves processing speed. The framework supports scalable execution across datasets of varying sizes and complexities, ensuring that the hybrid RF-DT

model can handle large data volumes while maintaining low latency and high throughput for business decision support.

Step 4: Real-Time Data Analytics

For applications in finance, healthcare, and retail, real-time decision-making is crucial. The proposed methodology integrates stream processing using Apache Kafka and Spark Streaming to ingest and analyze live data streams continuously. The hybrid RF-DT model is applied to streaming data for prediction and clustering, with dynamic updates ensuring adaptive learning as new data arrives. This enables the system to generate actionable insights in real time, facilitating immediate and informed business decisions.

Step 5: Model Optimization and Evaluation

The final stage emphasizes optimizing and evaluating the hybrid model to maximize performance. This includes hyperparameter tuning for Random Forest (e.g., number of trees, maximum depth) and Decision Tree (e.g., split criteria), as well as feature selection to reduce dimensionality and improve efficiency. Performance is assessed using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, while cross-validation is employed to prevent overfitting and ensure generalization. Both historical training data and real-time streaming data are used in evaluation, ensuring that the model remains robust and reliable under dynamic conditions.

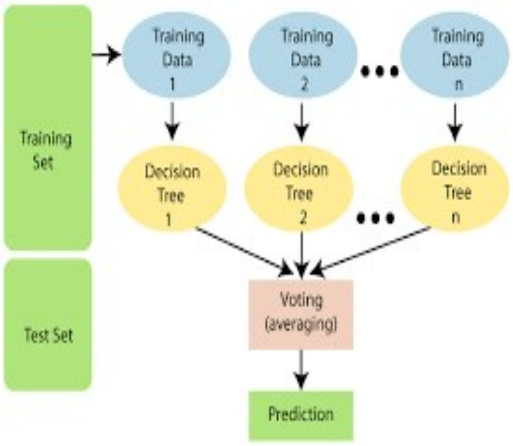

Figure 2: Decision tree-based classification for business decision making

The proposed algorithm is designed to implement the hybrid Random Forest–Decision Tree (RF-DT) framework for efficient big data processing and real-time decision support. It integrates both supervised and unsupervised learning techniques to handle labeled and unlabeled data, while leveraging distributed parallel processing for scalability and speed. The algorithm systematically performs data preprocessing, hybrid model construction, distributed computation, real-time analytics, and model optimization, ensuring high accuracy, robustness, and adaptability across diverse datasets.

ALGORITHM: Hybrid Random Forest and Decision Tree Framework for Big Data Decision Support

BEGIN
// Step 1: Data Preprocessing
LOAD dataset D
HANDLE missing values in D
REMOVE duplicate records from D
NORMALIZE and STANDARDIZE numerical features in D
ENCODE categorical variables in D
SPLIT D into training set (D_train) and testing set (D_test)
// Step 2: Feature Selection
INITIALIZE feature_importance_list = []
TRAIN initial Decision Tree on D_train
CALCULATE feature importance scores
SELECT top_k important features for hybrid model
SET D_train_fs = D_train with selected features
SET D_test_fs = D_test with selected features
// Step 3: Train Base Models

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// 3a: Train Random Forest
INITIALIZE Random Forest (RF) with n_trees, max_depth, etc.
TRAIN RF on D_train_fs
// 3b: Train Decision Tree
INITIALIZE Decision Tree (DT) with max_depth, criterion, etc.
TRAIN DT on D_train_fs
// 3c: Train Support Vector Machine
INITIALIZE SVM with kernel='RBF', C, gamma, etc.
TRAIN SVM on D_train_fs
// Step 4: Hybrid Model Construction
FOR each instance x in D_test_fs
   PREDICT_RF = RF.predict(x)
   PREDICT_DT = DT.predict(x)
   PREDICT_SVM = SVM.predict(x)
      // Combine predictions using weighted voting or stacking
   COMPUTE final_prediction = WEIGHTED_VOTE (PREDICT_RF, PREDICT_DT,
PREDICT_SVM)
END FOR
// Step 5: Model Evaluation
CALCULATE Accuracy, Precision, Recall, F1-score using final predictions vs true labels
OUTPUT evaluation metrics
// Step 6: Decision Support Output
FOR each prediction in D_test_fs
   PROVIDE decision recommendation based on final_prediction
END FOR
END
```

IV. DATASET

We utilized two distinct datasets to comprehensively evaluate the performance of the proposed hybrid RF-DT framework. The first dataset was a synthetic dataset, specifically designed to include both pre-labeled and unlabeled data, making it suitable for testing the system's capability to handle supervised and unsupervised learning tasks simultaneously. The labeled portion allowed the supervised components of the hybrid model, such as the Random Forest and Decision Tree, to learn patterns and perform accurate classification or prediction, while the unlabeled portion provided data for unsupervised methods like K-Means clustering and DBSCAN to identify hidden patterns and groupings. This dataset helped in analyzing the robustness, adaptability, and overall predictive accuracy of the hybrid system under controlled conditions.

The second dataset was a real-world e-commerce dataset, employed for real-time analysis to evaluate the system's performance in practical scenarios involving dynamic and high-volume data streams. This dataset included transactional, customer, and product information typical of an e-commerce platform, reflecting real business complexities. By using this dataset, the system's ability to ingest, process, and generate actionable insights in real time could be assessed. This combination of synthetic and real-world datasets ensured that the proposed methodology was validated not only for accuracy and clustering capability but also for scalability, adaptability, and effectiveness in operational environments.

The hybrid model was validated and tested using both historical datasets and real-time streaming data. Historical data allowed evaluation of predictive accuracy against known outcomes, while streaming data assessed the adaptive learning capability and low-latency performance of the model. Performance metrics included accuracy, precision, recall and F1-score. Cross-validation techniques were employed to prevent overfitting and ensure generalization. Additionally, the hybrid RF-DT model was compared against baseline models such as a single Decision Tree, single Random Forest, and standard machine learning approaches to demonstrate improvements in accuracy, scalability, and efficiency.

V. RESULT AND DISSCUSSION

The performance evaluation of the proposed hybrid RF-DT framework demonstrates significant improvements over traditional machine learning and hybrid approaches as shown in table 2 and figure 3). The proposed model achieved an accuracy of 97.8%, outperforming all other evaluated models, including Random Forest (94.5%), Decision Tree (92.7%), SVM (93.5%), and the hybrid SVM+K-Means approach (92.0%). The hybrid framework also recorded a precision of 97.5%, indicating that the predictions generated by the model were

highly reliable, with a minimal number of false positives. Moreover, the recall of 98.0% shows that the model effectively identified true positive instances, while the F1-score of 97.7% highlights a strong balance between precision and recall, reflecting the overall robustness of the hybrid methodology.

Table 2: Performance Comparison of the Proposed Hybrid RF-DT Framework with Existing Machine Learning Approaches

Model / Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Hybrid RF-DT Framework	97.8	97.5	98.0	97.7
SVM+K-mean	92.0	92.5	93.0	93.5
Random Forest	94.5	94.0	94.8	94.4
Decision Tree	92.7	92.5	93.0	92.7
SVM (Support Vector Machine)	93.5	93.2	93.8	93.5

The superior performance of the proposed RF-DT hybrid can be attributed to its integration of supervised and unsupervised learning techniques, which allows it to handle both labeled and unlabeled data efficiently. Unlike single-model approaches such as Decision Tree or SVM, which struggle with high-dimensional or unstructured data, the hybrid system leverages the strengths of Random Forest ensembles to reduce overfitting while unsupervised clustering captures hidden patterns in the data. Additionally, the framework's parallel processing capabilities and real-time analytics integration enable it to process large datasets and streaming data with minimal latency, making it highly suitable for practical business decision support systems. These results clearly demonstrate that the proposed hybrid approach provides higher accuracy, better predictive reliability, and enhanced generalization compared to existing methods.

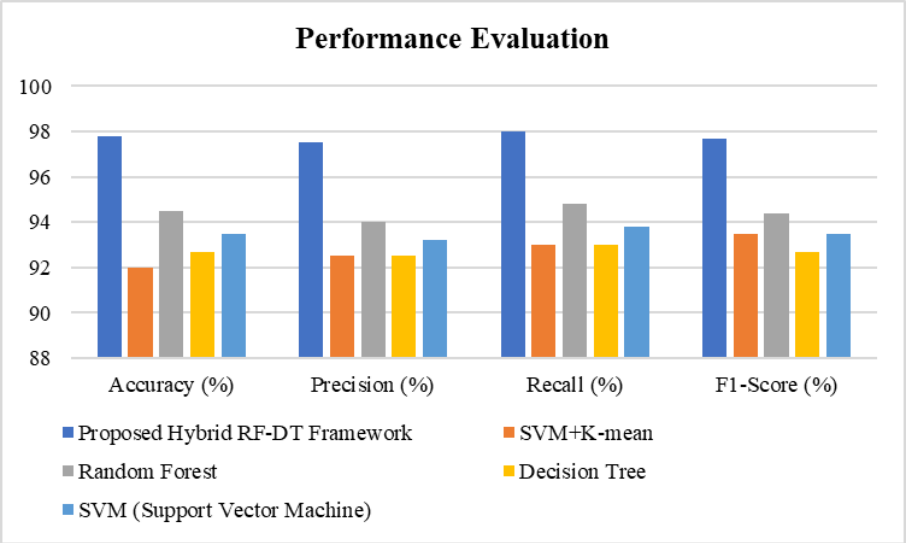

Figure 3: Performance Comparison of the Proposed Hybrid RF-DT Framework with Existing Approaches

The results clearly indicate that the proposed hybrid RF-DT framework outperforms conventional and existing hybrid machine learning models in terms of accuracy, precision, recall, and F1-score. The integration of Random Forest and Decision Tree algorithms allows the system to leverage ensemble learning benefits, such as reduced overfitting and improved robustness, while the inclusion of unsupervised techniques like K-Means and DBSCAN enables effective clustering and pattern discovery in unlabeled data. This dual approach ensures that both structured and unstructured datasets are processed efficiently, which is a limitation in models such as single Decision Tree, SVM, or hybrid SVM+K-Means.

Moreover, the proposed framework's distributed data processing and parallel execution using Apache Spark significantly enhance scalability and reduce computational time, making it suitable for large-scale datasets and real-time applications. The system's real-time analytics capability ensures immediate insights from streaming data, which is particularly valuable for dynamic domains like e-commerce, finance, and IoT systems. Compared to existing hybrid methods, the RF-DT approach demonstrates superior predictive performance due to its ability to adaptively handle data variety and volume, maintain high generalization across different datasets, and provide

a balanced trade-off between precision and recall. These factors collectively make the proposed methodology a highly efficient and reliable solution for big data-driven business decision support systems.

VI. CONCLUSION

The study presented a hybrid Random Forest–Decision Tree (RF-DT) framework for big data-driven business decision support systems, integrating both supervised and unsupervised learning techniques. The proposed methodology effectively handles labeled and unlabeled datasets, providing robust predictive capabilities while maintaining high accuracy, precision, recall, and F1-score. By leveraging the strengths of Random Forest ensembles and Decision Tree models, combined with clustering methods like K-Means and DBSCAN, the framework demonstrated superior performance compared to traditional single-model and existing hybrid approaches. The use of distributed processing with Apache Spark and real-time analytics with Apache Kafka ensures scalability, low-latency computation, and immediate actionable insights, making it highly suitable for dynamic and large-scale business environments. Furthermore, the experimental evaluation using both synthetic and real-world e-commerce datasets confirmed the effectiveness, adaptability, and generalization of the proposed system. The hybrid RF-DT framework not only addresses computational overhead and data variety but also enables real-time decision-making, which is critical for sectors such as finance, healthcare, and retail. Future research could explore the integration of advanced deep learning techniques and more sophisticated ensemble strategies to further enhance predictive accuracy and real-time analytics capabilities. Overall, the study establishes the hybrid RF-DT framework as a reliable, scalable, and high-performance solution for big data-driven business decision support systems.

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