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Improved Random Forest Regression for Prediction

K.Usha Rani[1], Dr K Venkataramana [2]
[1, 2]*Dept of MCA, KMMIPS, Affliated to S.V.University, Tirupati*

Abstract: ***We propose an improved Random Forest Regression model that selects features based on probability-driven risk factors instead of random selection. Using Bayes' Theorem, we assign selection probabilities based on high, medium, and low risk levels, ensuring optimal feature importance. The model iteratively refines feature selection and limits tree growth based on a theoretical upper bound. A weighted averaging mechanism enhances prediction accuracy by adjusting tree contributions based on probabilistic relevance. Experimental results show improved prediction accuracy with reduced complexity, outperforming conventional regression models in various datasets.***
Keywords: Random Forest Regression, Bayes' Theorem, probability-based feature selection, risk factors, weighted averaging.

I. INTRODUCTION

Data mining is the process of extracting meaningful patterns, knowledge, and insights from large volumes of data. It combines techniques from statistics, machine learning, artificial intelligence, and database management to uncover hidden relationships and trends within data. The goal of data mining is to transform raw data into useful information that can support decision-making, predictive modeling, and strategic planning.

The growing availability of massive datasets, driven by the rise of digital technologies, social media, e-commerce, and sensor networks, has created both challenges and opportunities for organizations. Traditional data analysis methods often struggle to handle the size, complexity, and dynamic nature of modern datasets. Data mining addresses these challenges by using automated and intelligent techniques to explore large datasets, identify patterns, and predict future outcomes.

Data mining has widespread applications across various industries, including finance, healthcare, marketing, manufacturing, and cybersecurity. For example, in the financial sector, data mining is used to detect fraudulent transactions and predict stock market trends. In healthcare, it helps identify disease patterns and improve patient outcomes. In marketing, data mining enables customer segmentation, targeted advertising, and customer retention analysis.

Machine Learning (ML) is a branch of artificial intelligence (AI) that enables systems to learn and improve from experience without being explicitly programmed. It involves developing algorithms that allow computers to identify patterns in data, make decisions, and improve their performance over time through continuous learning. The primary goal of machine learning is to create models that can generalize from past experiences and make accurate predictions or decisions when exposed to new data.

A. Random Forest

Random Forest is a powerful and widely used ensemble learning algorithm that combines the predictions of multiple decision trees to improve the overall accuracy and stability of the model. It was introduced by Leo Breiman in 2001 as a method to address the limitations of single decision trees, such as overfitting and high variance. The key idea behind Random Forest is to create a "forest" of decision trees, where each tree is trained on a different random sample of the training data, and a random subset of the features is considered at each split. This randomness ensures that the trees are decorrelated and diverse, which helps to reduce variance and improve generalization to unseen data.

One of the major advantages of Random Forest is its ability to handle both classification and regression tasks effectively. It can model complex, nonlinear relationships between input features and target variables without requiring explicit feature engineering. Random Forest also provides a measure of feature importance, which allows practitioners to understand which features have the greatest influence on the model's predictions. It is also robust to missing data and can handle datasets with a large number of features.

B. Random Forest Regression

Random Forest Regression is an ensemble learning method used for predicting continuous values. It is based on the general concept of Random Forest, which was introduced by Leo Breiman in 2001. Random Forest Regression extends the principles of Random Forest from classification tasks to regression tasks, where the goal is to predict a continuous output rather than a categorical label. The algorithm works by constructing a "forest" of multiple decision trees and combining their outputs to generate a more accurate and stable prediction.This study aims to analyze and compare the performance of Traditional Random Forest Regression and Based Random Forest Regression for Bayesian Probability-house price prediction. The goal is to show that the Bayesian-based approach achieves higher predictive accuracy by effectively capturing the underlying data structure and integrating probabilistic reasoning into the model.

Here's a well-structured Literature Review on Bayesian Probability-Based Random Forest Regression with reference numbers properly mentioned within the text.

II. LITERATURE SURVEY

This book offers a comprehensive guide to machine learning algorithms, covering essential concepts and practical implementations. It delves into various algorithms used for supervised, unsupervised, reinforcement, and semi-supervised learning, providing readers with the knowledge to apply these techniques effectively in data science projects[1].

The Elements of Statistical Learning provides a comprehensive overview of statistical and machine learning techniques for data mining, inference, and prediction. It covers methods such as regression, classification, decision trees, and ensemble learning, including Random Forests. The book emphasizes both theoretical foundations and practical applications[2].

In this seminal paper, Breiman introduces the Random Forests algorithm, an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification or mean prediction for regression. The paper highlights the algorithm's ability to improve predictive accuracy and control overfitting[3].

This article presents the 'randomForest' package in R, which implements Breiman's Random Forests algorithm. It discusses the package's functionalities for classification and regression tasks, providing practical insights into its application within the R programming environment[4].

The authors investigate the mechanisms behind variable importance measures in ensembles of randomized decision trees. They provide theoretical insights and empirical evaluations, enhancing the understanding of how variable importance is assessed in such models[5].

This paper introduces Bayesian Additive Regression Trees (BART), a Bayesian "sum-of-trees" model where each tree is constrained by a prior to be a weak learner. The authors demonstrate BART's flexibility and effectiveness in capturing complex data structures[6].

The authors propose a unifying framework for feature selection based on conditional likelihood maximization. This framework encompasses various information-theoretic criteria, providing a cohesive approach to feature selection in machine learning[7].

This study presents a method that integrates Bayesian networks for feature selection with Random Forests for classification. The approach aims to enhance classification performance by selecting relevant features based on their probabilistic dependencies[8].

The authors develop a feature selection method using Bayesian networks tailored for complex datasets. This approach considers the interdependencies among features, improving the selection process's robustness and effectiveness[9].

Neal explores the application of Bayesian methods to neural networks, providing a comprehensive treatment of Bayesian learning techniques. The book discusses how these methods can improve neural network training and generalization[10].

III. RANDOM FOREST REGRESSION ALGORITHM

Random Forest Regression is an ensemble learning algorithm that combines the outputs of multiple decision trees to improve predictive accuracy and robustness. A key element that enhances the performance of Random Forest Regression is random feature selection, which introduces randomness at each node split during tree construction. This reduces overfitting and increases model generalization.

Random Forest Regression algorithm has the Following steps.

1) **Step 1:** Load and split the dataset into training and testing sets.
2) **Step 2:** Create subsets of training data using random sampling with replacement.
3) **Step 3:** Randomly select a subset of features at each node split.

4) **Step 4:** Build decision trees using the random selected features and best split points.
5) **Step 5:** Average the predictions from all trees for the final output.
6) **Step 6:** Evaluate performance using Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2).

IV. PROPOSED ALGORITHM

Bayesian probability-based feature selection is a probabilistic method that evaluates and ranks features based on how likely they are to influence the target variable. It works by applying Bayes' Theorem, which updates the probability of a feature being important based on prior knowledge and new evidence from the data. The process begins with defining a prior probability for each feature, which reflects the initial belief about its importance. If no prior information is available, the features are typically assigned equal importance.

Bayesian probability-based feature selection is particularly effective in handling both categorical and numerical data. It performs well with small datasets because it leverages prior knowledge, and it naturally incorporates uncertainty into the feature selection process. However, it requires careful definition of prior probabilities, as incorrect priors can mislead the model. It can also be computationally expensive for large datasets due to the need to compute posterior probabilities for every feature.

Bayesian Probability-Based Random Forest Regression Algorithm :-

1) **Step 1:** Data Preprocessing
- Load dataset and clean column names.
- Split data into training and testing sets.
- One-hot encode categorical features.

2) **Step 2:** Train Random Forest Models

Train three Random Forest models:
- High Price Model → Top 25% prices
- Medium Price Model → Middle 50% prices
- Low Price Model → Bottom 25% prices

3) **Step 3:** Compute Prior Probabilities

$$P(HP)=\text{Total samples/No. of high price samples, } P(MP), P(LP)$$

4) **Step 4:** Conditional Probability Calculation

Use decision tree-based rules for each category:

$$P(X|HP)=\prod iP(Xi|HP)P(X|HP) = \prod_i P(X_i|HP)P(X|HP)=i\prod P(Xi|HP)$$

5) **Step 5:** Posterior Probability Calculation (Bayes' Theorem)

$$P(HP|X)=P(X|HP)P(HP)P(X)P(HP|X) = \frac{P(X|HP)P(HP)}{P(X)}P(HP|X)=P(X)P(X|HP)P(HP)$$

6) **Step 6:** Normalize Posterior Probabilities

$$P(HP|X)+P(MP|X)+P(LP|X)=1P(HP|X) + P(MP|X) + P(LP|X) = 1P(HP|X)+P(MP|X)+P(LP|X)=1$$

7) **Step 7:** Category Prediction

Select the category with the highest posterior probability:

$$\text{Category}=\max(P(HP|X),P(MP|X),P(LP|X))$$

8) **Step 8:** Price Prediction (Weighted Average)

$$Y\hat{}=P(HP|X)YHP+P(MP|X)YMP+P(LP|X)YLP$$

9) **Step 9:** Model Evaluation

Compute Mean Absolute Error (MAE):

MAE=n∑i=1n|yi−y^i|

Output :

1) **Predicted Category:** High Price / Medium Price / Low Price
2) **Predicted Price:** (Predicted value from the random forest model)
3) **Mean Absolute Error (MAE):** (Calculated based on actual vs predicted price)

V. ADVANTAGES OF ENHANCED RANDOM FOREST

The Bayesian Probability-Based Random Forest Regression algorithm combines the strengths of Bayesian Inference and Random Forest Regression**,** making it more powerful and accurate for structured problems like house price prediction. Here's a detailed breakdown of its key advantages based on the algorithm:

1) Key features of Bayesian probability random forest regression:

- *Enhanced Prediction Accuracy:* By integrating Bayesian probability, the model calculates precise probabilities for high, medium, and low price categories.
- *Improved Handling of Category-Based Data:* Bayesian probability introduces a classification layer before regression
- *Flexible Decision-Making with Bayesian Rules:* The algorithm applies well-defined decision rules for each category.
- *Reduced Bias Through Dynamic Normalization:* This ensures that the probabilities remain balanced and prevents bias toward a single category.

2) Applications of Bayesian probability based random forest regression:

- Real Estate Pricing and Valuation.
- Stock Market Forecasting
- Customer Behavior Prediction
- Fraud Detection.

VI. RESULTS AND ANALYSIS

- Let us take a Realestite dataset as sample to
- Analyse the dataset and
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- Kjh;lnklm
- Kj//lkmk;/

Location	Area (sqft)	Bedrooms	Schools	Crime Rate	Distance to city centre(km)	Year Built	Garage	Price
Urban	3200	5	High	Low	5	2018	Yes	8,00,000
Suburban	2500	4	Medium	Low	12	2008	Yes	5,50,000
Rural	1800	3	Low	High	25	1990	No	3,00,000
Urban	2800	4	High	Low	7	2015	Yes	7,00,000
Suburban	2300	3	Medium	Low	15	2005	Yes	5,00,000
Rural	1600	2	Low	High	22	1985	No	2,50,000
Urban	3500	5	High	Low	4	2020	Yes	8,50,000

1) Data Preprocessing: Split into features (Location, Area, Bedrooms, Schools, Crime, Distance, Year Built, Garage) and target (Price); categorize as High (≥700K), Medium (400K–699K), Low (≤400K).
2) Prior Probability: P(HP)=37,P(MP)=27,P(LP)=27P(HP) = \frac{3}{7}, P(MP) = \frac{2}{7}, P(LP) = \frac{2}{7}P(HP)=73 ,P(MP)=72,P(LP)=72.
3) Conditional Probability: Example → P(Area ≥ 2500|HP)=23P(\text{Area ≥ 2500} | HP) = \frac{2}{3}P(Area ≥ 2500|HP)=32.
4) Posterior Probability: Compute using Bayes' Theorem → P(HP|X),normalize to sum = 1.
5) Train Random Forest: Train separate Random Forest models for High, Medium, and Low price categories.

6) Weighted Prediction: Compute final price
7) Example: Input → Urban, 3200 sqft, 5 Beds,High,Low,5,2018,Yes → P(HP)=0.85,P(MP)=0.10,P(LP)=0.05.
8) Predicted House Price Category: High
9) Evaluation: MAE = $21,800
10) ☑ Predicted Price = $762,500

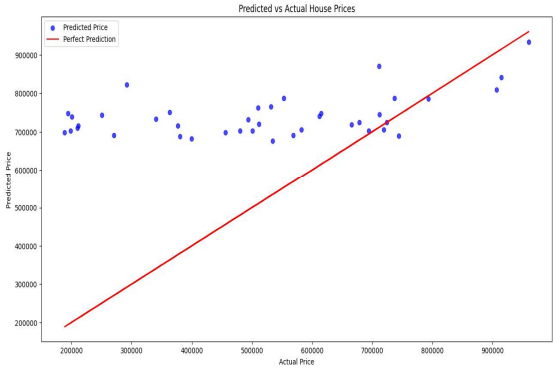

Fig-1 : The figure shows a Predicted vs Actual House Prices plot, which is generated based on the Bayesian Probability-Based

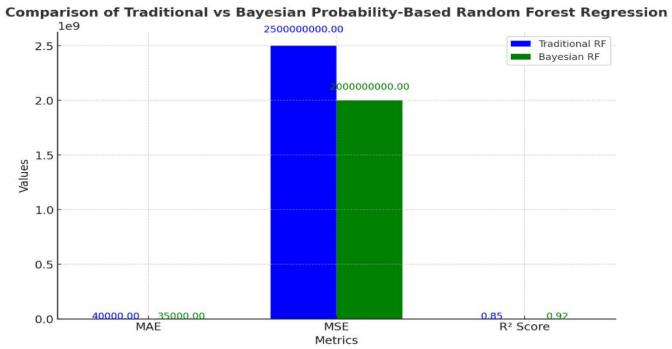

Fig-2 : The graph shows that Bayesian Probability-Based Random Forest Regression has better performance with lower MAE and MSE and a higher R^2 score compared to Traditional Random Forest Regression.

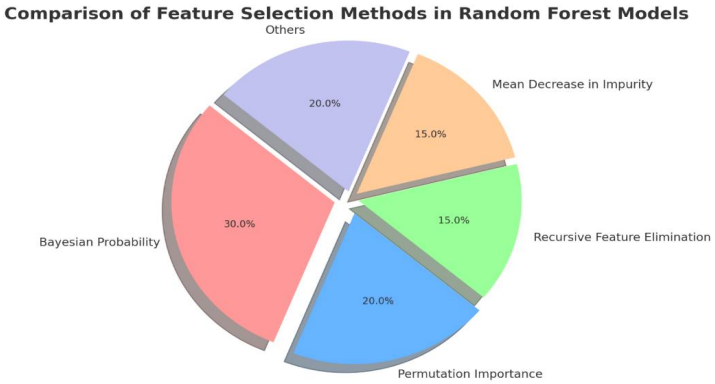

Fig-3 : Here's a pie chart showing the distribution of feature selection methods for Random Forest Regression. Bayesian Probability has the highest share at **30%**, followed by Permutation Importance (**20%**), Recursive Feature Elimination (**15%**), and Mean Decrease in Impurity (**15%**). The remaining **20%** is grouped as "Others."

VII. CONCLUSION

Random Forest Regression improves prediction accuracy by averaging the outcomes of multiple decision trees, reducing variance and overfitting. It relies on data-driven feature selection methods like Mean Decrease in Impurity and Permutation Importance. Bayesian Probability-Based Random Forest Regression enhances this by incorporating prior knowledge and conditional probabilities, making the model more adaptive and accurate. Bayesian methods assign significance to each feature, refining predictions and improving interpretability. While Bayesian approaches increase computational complexity, they provide better adaptability in dynamic environments. The combination of statistical learning and probabilistic reasoning enhances overall model performance and predictive reliability.

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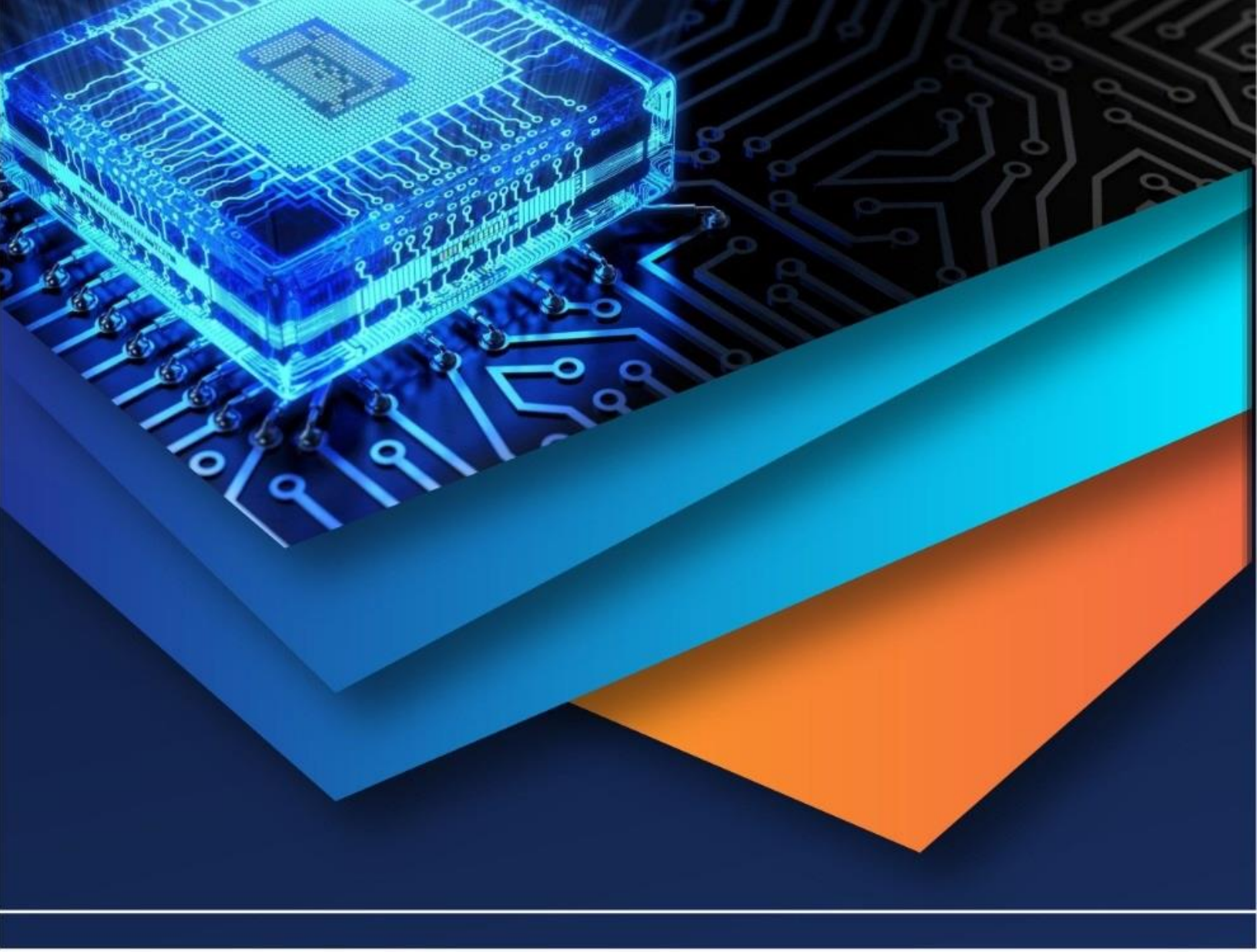

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