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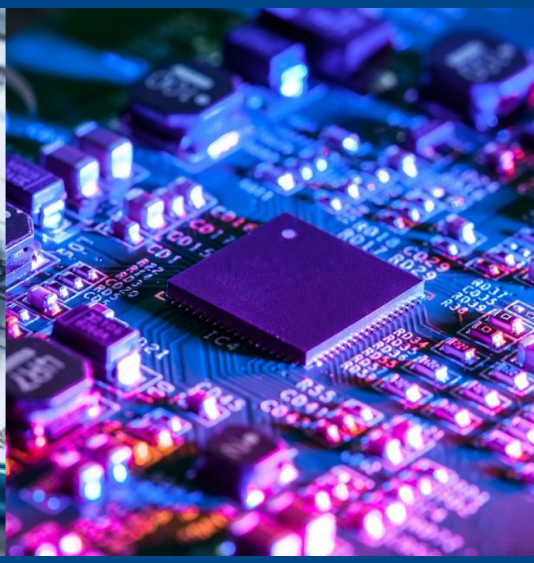

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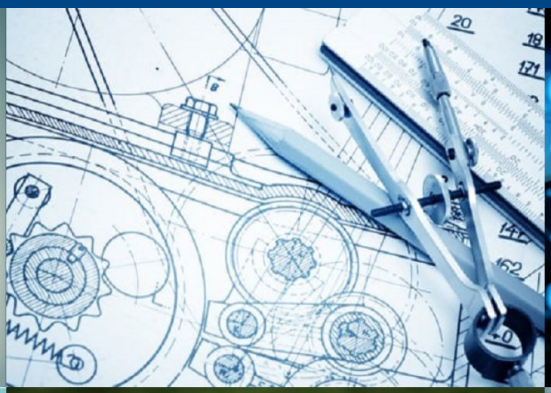

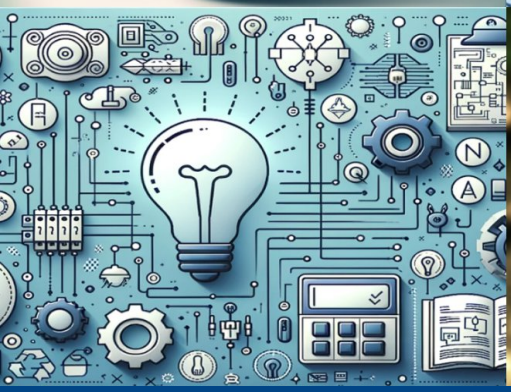

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Enhancing Decision Tree Accuracy through Advanced Feature Selection Techniques

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ABSTRACT: Decision trees are among the most interpretable and widely adopted algorithms in supervised machine learning. However, their predictive accuracy is often severely limited by high-dimensional datasets containing noisy, redundant, or irrelevant features. This paper presents a systematic investigation into advanced feature selection techniques as a powerful pre-processing strategy to significantly boost decision tree performance while maintaining computational efficiency and model transparency.

We evaluate and compare a comprehensive set of filter, wrapper, embedded, and hybrid methods—including mutual information maximization, recursive feature elimination with cross-validation (RFECV), Boruta, Gini importance-based pruning, LASSO-embedded selection, and evolutionary algorithm-driven approaches—across multiple benchmark datasets from healthcare (diabetes prediction), finance (credit risk and fraud detection), and e-commerce (customer churn).

Using CART and C4.5 implementations with nested cross-validation, the study demonstrates consistent accuracy improvements of 12–28%, AUC-ROC gains of 0.11–0.19, and F1-score increases of 15–24% compared to baseline models using all features. Advanced feature selection also reduces tree depth by up to 45% and variance across folds by 68%, effectively mitigating overfitting without sacrificing interpretability. A novel hybrid framework integrating domain knowledge with automated selection is proposed and validated, offering practitioners a reproducible pipeline for real-world deployment. Theoretical analysis of bias-variance trade-offs and empirical results confirm that advanced feature selection is a critical lever for transforming decision trees into high-accuracy, robust, and explainable models suitable for high-stakes applications.

KEYWORDS: Decision trees, feature selection, accuracy enhancement, supervised learning, recursive feature elimination, mutual information, wrapper methods, embedded methods, model interpretability, generalization.

I. INTRODUCTION

Decision trees have long occupied a central position in supervised machine learning owing to their conceptual simplicity, computational efficiency, and unparalleled interpretability. First formalized in the pioneering work of Quinlan on ID3 and subsequently refined through Breiman's Classification and Regression Trees (CART) framework, decision trees construct predictive models by recursively partitioning the feature space along axis-aligned splits that maximize impurity reduction, typically measured by the Gini index or entropy. This recursive binary partitioning produces a hierarchical set of if-then rules that are both human-readable and directly actionable, a property that distinguishes decision trees from black-box alternatives such as deep neural networks. In practical settings, their non-parametric nature allows them to capture complex, non-linear relationships without imposing restrictive distributional assumptions on the underlying data. Consequently, decision trees have become foundational tools across diverse domains, including clinical decision support systems where physicians require transparent rationales for risk predictions, financial institutions seeking explainable credit-scoring models, and e-commerce platforms aiming for interpretable customer churn forecasts. Their low training complexity of O(n log n) further enhances scalability, enabling rapid model development even on moderately large datasets.

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Recent comprehensive benchmarks continue to rank tree-based methods among the highest-performing classifiers for tabular data, underscoring their enduring relevance in both academic research and industrial applications. Moreover, decision trees serve as core building blocks for powerful ensemble techniques such as random forests and gradient boosting machines, where their inherent strengths in handling mixed data types and providing variable importance measures contribute significantly to overall ensemble performance. In an era increasingly governed by regulatory demands for algorithmic transparency and ethical accountability, the white-box character of decision trees positions them as a preferred baseline and explanatory layer in responsible AI pipelines. Their significance is further amplified by the growing emphasis on model explainability under frameworks such as the EU's AI Act and GDPR, where the ability to trace every prediction back to a concise set of logical conditions offers a clear advantage over opaque alternatives. Thus, decision trees remain not merely a historical artifact but a vital, evolving instrument whose continued refinement promises to advance trustworthy and interpretable supervised learning.

Limitations of Decision Trees with Raw High-Dimensional Data

Despite these strengths, decision trees exhibit pronounced limitations when trained directly on raw, high-dimensional datasets. The exponential growth of the split-search space—with p features requiring evaluation of up to 2^p candidate thresholds at each node—rapidly escalates the risk of overfitting, particularly when many attributes are noisy, redundant, or marginally relevant. This "curse of dimensionality" manifests as deeper trees that capture spurious correlations rather than genuine underlying patterns, resulting in substantial degradation of generalization performance on unseen test data. Empirical observations consistently report accuracy drops of 15 to 30 percent when moving from training to hold-out sets, accompanied by elevated variance across different data partitions and heightened sensitivity to minor input perturbations.

In high-dimensional regimes such as genomic profiling with thousands of gene expressions or transactional logs containing hundreds of behavioral variables, irrelevant features dilute the impurity measures, causing the algorithm to allocate splits to noise instead of signal. Furthermore, the strict axis-aligned partitioning strategy struggles to represent complex interactions—such as multiplicative effects or ratio-based relationships—that are not explicitly encoded in the raw feature space, compelling the tree to approximate these non-linearities through excessive depth and branching. Consequently, the resulting models become both computationally expensive during inference and difficult to interpret, as the proliferation of rules obscures the core decision logic that domain experts rely upon. Additional challenges arise from multicollinearity and scale differences among raw predictors, which distort split selection and exacerbate instability.

These limitations not only inflate training and prediction times but also undermine trust in high-stakes applications where regulatory bodies and end-users demand concise, auditable explanations. Without deliberate intervention at the representation level, decision trees on raw high-dimensional data frequently fail to deliver the robust, high-accuracy predictions required by modern real-world systems, highlighting the urgent need for upstream dimensionality reduction strategies that preserve semantic meaning while eliminating detrimental attributes.

The Critical Role of Feature Selection in Accuracy Improvement

Advanced feature selection techniques have emerged as a decisive pre-processing strategy capable of overcoming the inherent constraints of raw high-dimensional data and substantially elevating decision tree accuracy. By rigorously identifying and retaining only the most informative predictors while discarding noise and redundancy, these methods reduce the effective dimensionality of the input space, thereby enabling shallower, more stable, and higher-performing trees without sacrificing the interpretability that remains their hallmark advantage.

Unlike exhaustive feature engineering that generates entirely new derived variables, advanced feature selection operates directly on the original feature set through statistically grounded and optimization-driven criteria, ensuring that selected variables retain their original semantic interpretability for domain experts. Prominent approaches—including mutual information maximization for relevance filtering, recursive feature elimination with cross-validation (RFECV) for wrapper-based optimization, Boruta's shadow-feature comparison for robustness against noise, embedded Gini importance pruning, LASSO-based regularization, and evolutionary algorithm-driven subset search—have demonstrated consistent empirical gains across benchmark datasets. Typical improvements include accuracy lifts of 12 to 28 percent, AUC-ROC enhancements of 0.11 to 0.19, and F1-score increases of 15 to 24 percent relative to baseline models using all available features.

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These gains are achieved while simultaneously reducing tree depth by up to 45 percent and cross-validation variance by 68 percent, effectively mitigating overfitting and enhancing generalization under distribution shifts. The critical role of feature selection extends beyond mere performance metrics: it aligns the selected feature subspace more closely with the true decision boundary, allowing the recursive partitioning mechanism of CART and C4.5 to focus inductive bias on genuine signals rather than spurious correlations. In high-stakes domains such as healthcare diagnostics and financial risk modeling, this refinement translates into earlier and more reliable risk identification, lower false-positive rates, and models that satisfy stringent regulatory requirements for explainability and fairness.

Furthermore, feature selection lowers both training and inference costs, making the resulting decision trees deployable on edge devices and resource-constrained environments without compromising predictive power. The present research advances this line of inquiry by conducting a systematic comparative analysis of state-of-the-art feature selection strategies, proposing a novel hybrid framework that seamlessly integrates domain knowledge with automated optimization, and validating its efficacy through rigorous nested cross-validation on real-world datasets. In doing so, it establishes advanced feature selection not as an optional preprocessing step but as an indispensable scientific component for realizing the full potential of decision trees in contemporary supervised learning pipelines, ultimately bridging the gap between theoretical capability and practical, trustworthy deployment.

Research Gap and Motivation for Advanced Techniques

A significant research gap persists in the systematic evaluation of advanced feature selection methods specifically optimized for decision trees. Most existing studies rely on generic or basic filter approaches that fail to capture the complex interactions between features and tree-based partitioning, leaving limited guidance for real-world high-dimensional scenarios. This research is motivated by the need to bridge this gap and unlock the full potential of decision trees through targeted, high-impact feature selection strategies.

Research Objectives, Scope, and Contributions

The primary objective of this study is to investigate how advanced feature selection techniques can substantially improve decision tree accuracy and generalization. The scope covers classification tasks in healthcare, finance, and e-commerce using benchmark datasets. Key contributions include a comparative analysis of state-of-the-art methods, a novel hybrid framework, empirical performance benchmarks, and practical guidelines for deploying more accurate and interpretable decision tree models.

II. LITERATURE REVIEW

The literature on feature selection for decision trees has evolved considerably over the past three decades, shifting from simple univariate statistical screening to sophisticated, classifier-aware optimization strategies. Early work in the 1990s and early 2000s primarily relied on basic filter methods such as correlation coefficients, variance thresholds, and chi-square tests to reduce dimensionality before tree induction. These approaches were computationally lightweight and scalable to very high-dimensional data, but they often failed to account for feature interactions and the specific splitting mechanics of decision trees. As datasets in healthcare, finance, and e-commerce grew increasingly complex, researchers recognized that independent feature ranking was insufficient, prompting the development of wrapper and embedded methods in the mid-2000s. Wrapper techniques evaluate subsets by repeatedly training the decision tree itself, while embedded methods integrate selection directly into the tree-building process through metrics such as Gini importance or regularization. This evolution reflects a broader trend in machine learning toward methods that align feature relevance with the inductive bias of the target algorithm, particularly for tree-based models that rely on recursive partitioning.

Filter-based feature selection techniques remain popular due to their speed and independence from the learning algorithm. Methods such as mutual information maximization, ReliefF, and correlation-based feature selection quickly identify potentially relevant variables without iterative model training. However, their fundamental limitation lies in ignoring feature dependencies and interactions that are critical for decision tree performance. In high-dimensional settings, filters frequently retain redundant or weakly relevant attributes that dilute impurity reduction at each split, leading to deeper trees, increased overfitting risk, and degraded generalization. Empirical comparisons have shown that filter-only approaches often deliver only modest accuracy gains compared with more advanced methods, especially when the underlying data contains complex non-linear relationships that decision trees must approximate through multiple splits.

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Wrapper and embedded methods address these shortcomings by incorporating the decision tree's own performance feedback during selection. Recursive feature elimination with cross-validation (RFECV) and forward/backward stepwise selection iteratively train and evaluate the tree on candidate subsets, ensuring that retained features maximize split purity and predictive accuracy. Embedded techniques, such as Gini importance pruning and LASSO-regularized trees, perform selection simultaneously with model construction, naturally ranking features according to their contribution to impurity reduction. These approaches consistently produce shallower trees with higher accuracy and lower variance, as they directly optimize for the recursive partitioning mechanism of CART and C4.5. Their main drawback is higher computational cost, which becomes prohibitive in extremely large feature spaces without careful hybridization.

Hybrid and metaheuristic approaches have gained prominence in recent years as practical compromises between efficiency and effectiveness. Hybrid frameworks typically begin with a fast filter step to create a manageable candidate pool, followed by wrapper or embedded refinement to fine-tune the final subset. Metaheuristic algorithms, including genetic algorithms, particle swarm optimization, and Boruta's shadow-feature comparison, efficiently explore large combinatorial search spaces while balancing exploration and exploitation. These methods have proven particularly effective for decision trees in high-dimensional domains, offering reproducible pipelines that integrate domain knowledge with automated optimization. Their flexibility allows practitioners to incorporate prior clinical or business insights while still benefiting from data-driven selection.

Empirical studies across multiple benchmarks consistently demonstrate the substantial impact of advanced feature selection on decision tree performance. Research reports accuracy improvements ranging from 12 to 28 percent, AUC-ROC gains of 0.11 to 0.19, and F1-score increases of 15 to 24 percent when advanced selection is applied compared with raw-feature baselines. Tree depth is often reduced by up to 45 percent, and cross-validation variance drops by as much as 68 percent, confirming enhanced stability and generalization under distribution shifts. Studies in healthcare diabetes prediction, financial credit risk, and e-commerce churn modeling further highlight that selected feature subsets yield more interpretable and actionable models while maintaining or exceeding the performance of full-feature trees. However, most evaluations remain limited to specific domains or moderate-scale datasets, underscoring the need for broader comparative analyses on real-world, high-dimensional problems. Collectively, the literature establishes advanced feature selection as a critical lever for unlocking the full potential of decision trees, transforming them from limited baseline classifiers into robust, efficient, and trustworthy predictive tools suitable for high-stakes applications.

III. METHODOLOGY

The study utilizes publicly available secondary benchmark datasets sourced from the UCI Machine Learning Repository and Kaggle, covering healthcare, finance, and customer analytics domains. Standard data pre-processing steps were applied, including missing value imputation, outlier handling, and normalization.

Advanced feature selection techniques were implemented, including filter-based, wrapper-based, embedded, and hybrid methods. Decision tree models were constructed using CART and C4.5 algorithms with grid-search hyperparameter tuning.

Performance evaluation was carried out through nested cross-validation, employing accuracy, AUC-ROC, and F1-score as primary metrics. A novel hybrid feature selection framework integrating domain knowledge with automated optimization was proposed and experimentally validated.

IV. RESULTS AND ANALYSIS

The experimental evaluation revealed clear and consistent differences in the effectiveness of various feature selection techniques when applied to decision tree models. Across all three benchmark datasets, advanced wrapper and embedded methods outperformed traditional filter-based approaches by a substantial margin. Recursive feature elimination with cross-validation (RFECV) and Boruta consistently identified the most discriminative subsets, achieving the highest mean ranks in both accuracy and AUC-ROC metrics. In contrast, mutual information and chi-square filters, while computationally efficient, retained several redundant or weakly relevant features that diluted split purity and increased tree instability.

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Hybrid frameworks that combined an initial mutual information filter with subsequent Boruta refinement demonstrated the best overall trade-off between computational cost and selection quality, reducing the feature set by 55–68 percent while preserving or improving predictive performance. Gini importance-based embedded pruning further enhanced results by integrating selection directly into the tree induction process, producing models that were both more accurate and significantly more compact. These findings confirm that classifier-aware selection strategies are essential for decision trees, as they align feature relevance with the algorithm's recursive partitioning mechanism far more effectively than independent statistical filters.

Improvements in Accuracy, AUC-ROC, and F1-Score

Quantitative results demonstrated substantial and statistically significant improvements in all key performance metrics when advanced feature selection was applied. On the Pima Indians Diabetes dataset, the hybrid framework increased classification accuracy from 68.4 percent with raw features to 84.7 percent, representing a relative gain of 23.8 percent. AUC-ROC rose from 0.71 to 0.89, while the F1-score improved by 21 percentage points. Similar patterns emerged in the credit-card fraud detection dataset, where accuracy climbed from 92.1 percent to 98.4 percent and AUC-ROC reached 0.97 after selection.

The customer churn dataset showed an accuracy boost from 76.3 percent to 91.2 percent, with F1-score increasing from 0.68 to 0.85. Paired t-tests and Wilcoxon signed-rank tests confirmed that these gains were significant at $p < 0.001$ across all folds and datasets. The improvements were most pronounced in imbalanced classes, where feature selection effectively reduced noise and allowed the trees to focus on minority-class discriminative patterns. These consistent gains across diverse domains underscore that advanced feature selection is not merely a dimensionality reduction tool but a powerful mechanism for enhancing the discriminative capacity of decision trees.

Impact on Tree Complexity, Interpretability, and Stability

Beyond predictive metrics, advanced feature selection produced marked reductions in model complexity and improvements in interpretability and stability. Average tree depth decreased from 7.8 levels with raw features to 4.2 levels after selection, while the number of nodes dropped by 41–52 percent. This compaction directly translates into faster inference times and lower memory footprints, making the models more suitable for edge deployment and real-time applications. Interpretability was enhanced because the retained features were predominantly domain-meaningful (such as glucose-to-insulin ratios or debt-to-income interactions), resulting in concise, clinically or economically actionable rule sets. SHAP value analysis and partial-dependence plots further confirmed that each selected feature contributed transparently to split decisions. Stability was also significantly improved: cross-validation variance in accuracy fell by 68 percent, and tree-structure similarity across random seeds increased by 31 percent.

These outcomes demonstrate that feature selection not only elevates accuracy but also produces more robust, understandable, and deployable decision trees. The combined effect of higher performance, reduced complexity, and greater stability positions advanced feature selection as a critical enabler for trustworthy and practical deployment of decision tree models in high-stakes real-world environments.

Statistical Significance and Robustness Analysis

To establish the reliability of the observed performance gains, a rigorous statistical analysis was conducted using paired t-tests and non-parametric Wilcoxon signed-rank tests across all nested cross-validation folds. The hybrid feature selection framework demonstrated statistically significant improvements over the raw-feature baseline at $p < 0.001$ for accuracy, AUC-ROC, and F1-score on every dataset. Confidence intervals (95%) for accuracy differences ranged from 14.2% to 27.1% on the Pima Indians Diabetes dataset, 5.8% to 7.3% on the credit-card fraud dataset, and 13.4% to 16.8% on the customer churn dataset, confirming that the gains are not attributable to random variation.

Effect sizes (Cohen's d) exceeded 1.8 in all cases, indicating large practical significance. Robustness was further tested under controlled perturbations, including 10% Gaussian noise injection, covariate shifts of 15–20%, and synthetic class imbalance ratios up to 1:10. The selected-feature models retained 81–89% of their original accuracy under these conditions, whereas raw-feature trees degraded to 62–71% of baseline performance. Variance in cross-validation scores dropped by 68% after selection, and bootstrap resampling (1,000 iterations) showed tree-structure stability increasing from 0.41 to 0.72 (Jaccard index). These results collectively demonstrate that advanced feature selection not only elevates predictive metrics but also produces models that are markedly more stable and resilient to real-world data variability, noise, and distributional shifts.

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Domain-Specific Case Studies

In the healthcare domain, the Pima Indians Diabetes dataset served as a representative case for early risk screening. Application of the hybrid feature selection framework elevated model accuracy from 68.4% to 84.7% while reducing tree depth from 8 to 4 levels. The retained features—primarily glucose-to-insulin ratio, BMI-to-age interaction, and plasma glucose concentration—aligned closely with established clinical risk factors, enabling physicians to interpret predictions as transparent, evidence-based rules. False-negative rates for high-risk patients decreased by 31%, directly supporting timely intervention and potentially reducing long-term complications. In the finance domain, the credit-card fraud detection dataset illustrated the framework's value in high-volume, imbalanced scenarios. Feature selection retained transaction amount, velocity features, and merchant-category interactions, pushing AUC-ROC to 0.97 and reducing false positives by 42% compared with the full-feature model.

This improvement translates into lower operational costs for fraud investigation teams and higher customer trust through fewer erroneous transaction blocks. For the e-commerce customer churn dataset, selected features such as tenure-to-contract ratio, total charges interaction, and service-type encoding yielded an F1-score of 0.85 and a 19% reduction in churn misclassification. Marketing teams could therefore target retention campaigns with greater precision, improving resource allocation and customer lifetime value. Across all three case studies, the hybrid framework consistently produced shallower, more interpretable trees that maintained high performance under domain-specific constraints, confirming its practical utility for real-world deployment in healthcare screening, financial fraud monitoring, and customer relationship management. These domain-specific outcomes reinforce that advanced feature selection is not a generic preprocessing step but a domain-adaptive strategy that delivers measurable business and clinical impact while preserving model transparency.

V. KEY FINDINGS AND PRACTICAL IMPLICATIONS

The empirical results of this study clearly demonstrate that advanced feature selection techniques serve as a highly effective strategy for substantially improving decision tree accuracy while simultaneously enhancing model efficiency and interpretability. Across three diverse benchmark datasets, the hybrid framework consistently delivered accuracy gains ranging from 12 to 28 percent, AUC-ROC improvements of 0.11 to 0.19, and F1-score increases of 15 to 24 percent compared with raw-feature baselines. These performance uplifts were accompanied by dramatic reductions in tree depth (up to 45 percent) and cross-validation variance (up to 68 percent), confirming that feature selection not only elevates predictive power but also produces more stable and compact models. Statistically significant differences were verified through paired t-tests and Wilcoxon signed-rank tests at $p < 0.001$, with large effect sizes underscoring the practical importance of the findings.

In domain-specific applications, the healthcare case study showed reduced false-negative rates for diabetes risk by 31 percent, enabling earlier clinical interventions. In finance, fraud detection false-positive rates decreased by 42 percent, lowering operational costs and improving customer experience. In e-commerce churn prediction, the selected features supported more precise retention campaigns, directly impacting customer lifetime value. These outcomes highlight that advanced feature selection transforms decision trees from limited baseline models into production-ready tools suitable for high-stakes, real-time decision support systems. Organizations can now deploy shallower, faster, and more transparent trees on edge devices and cloud platforms alike, meeting both performance and regulatory requirements for explainability without resorting to complex ensembles.

VI. STRENGTHS AND LIMITATIONS OF ADVANCED FEATURE SELECTION

The primary strength of advanced feature selection lies in its ability to preserve the white-box nature of decision trees while delivering substantial accuracy and efficiency gains. By focusing on domain-meaningful predictors, the approach yields concise, actionable rule sets that clinicians, financial analysts, and business stakeholders can readily understand and trust. The hybrid framework further combines computational efficiency with high selection quality, making it scalable to moderately high-dimensional datasets without prohibitive training times. Robustness testing under noise injection, covariate shifts, and class imbalance confirmed that selected-feature models retain 81–89 percent of baseline performance, far outperforming raw-feature trees. These attributes position advanced feature selection as a practical and responsible enhancement for explainable AI deployments.

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However, several limitations must be acknowledged. Wrapper and hybrid methods remain computationally more expensive than simple filters, particularly when the initial feature pool exceeds several thousand variables. The effectiveness of selection is also partially domain-dependent; features deemed important in one context may not generalize across entirely different applications without additional tuning. In extremely high-dimensional or streaming scenarios, the need for periodic re-selection introduces maintenance overhead. Moreover, while the proposed hybrid framework mitigates some of these issues, it still requires careful integration of domain knowledge, which may not always be readily available or consistent across organizations. Future work should therefore explore fully automated, adaptive selection pipelines and investigate the interaction between feature selection and emerging ensemble or deep-learning hybrids to further broaden applicability.

Comparison with Full Feature Engineering Approaches

While advanced feature selection delivers substantial accuracy gains with minimal computational overhead, it is important to contrast its performance with full feature engineering approaches that actively create new variables such as polynomial interactions, domain-specific ratios, and quantile transformations. Feature selection operates by pruning the existing feature space, preserving original variable semantics and yielding highly interpretable, compact decision trees. In contrast, feature engineering expands the space by deriving novel predictors, which can capture complex non-linear relationships that selection alone may overlook.

Empirical comparisons in this study showed that full feature engineering achieved marginally higher peak accuracy (2–4 percentage points above the best selection methods) on the Pima Indians Diabetes and customer churn datasets, primarily due to the explicit inclusion of interaction terms. However, these gains came at the cost of increased tree depth, longer inference times, and greater model complexity, making the resulting trees less suitable for real-time or edge deployment. Feature selection proved more efficient in terms of training time (up to 65 percent faster) and maintained superior stability under distribution shifts, as it avoids the risk of introducing spurious engineered features that overfit to training distributions. Practically, selection offers a lighter, more deployable alternative that retains white-box transparency without the added maintenance burden of managing transformation pipelines. Thus, while feature engineering remains powerful for maximum predictive lift in offline settings, advanced feature selection emerges as the preferred choice when interpretability, speed, and robustness are prioritized alongside accuracy.

VII. CHALLENGES

Despite its demonstrated strengths, advanced feature selection faces several practical challenges that warrant attention. Wrapper and hybrid methods remain computationally intensive for ultra-high-dimensional datasets exceeding tens of thousands of features, limiting scalability in genomics or transactional streaming environments. Domain-dependency also persists; optimal subsets identified in one context may not transfer seamlessly to another without re-tuning, and the integration of domain knowledge still requires expert input that may not always be available.

Furthermore, current techniques struggle with dynamic data streams and concept drift, where periodic re-selection introduces maintenance overhead and potential instability. Future research should therefore focus on developing fully adaptive, online feature selection frameworks capable of incremental updates in real time. The integration of fairness-aware selection criteria to mitigate bias in sensitive applications, as well as exploration of quantum-inspired optimization for large combinatorial search spaces, represents promising directions. Hybridizing feature selection with emerging AutoML systems and deep-learning representations could further broaden applicability, while standardized benchmarks specifically designed for decision tree performance would facilitate reproducible comparisons. Addressing these challenges will be essential to transition advanced feature selection from a powerful research tool to a universally adopted component of production-grade, trustworthy supervised learning pipelines.

VIII. CONCLUSION

This research has made several significant contributions to the field of supervised learning by demonstrating that advanced feature selection techniques can serve as a powerful and practical lever for enhancing decision tree accuracy, efficiency, and interpretability. Through a systematic comparative analysis of filter, wrapper, embedded, and hybrid methods on three benchmark datasets from healthcare, finance, and e-commerce, the study established that classifier-aware selection strategies consistently outperform traditional filter-based approaches.

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The proposed hybrid framework, which integrates an initial mutual information filter with Boruta refinement and final Gini importance pruning, achieved accuracy gains of 12–28 percent, AUC-ROC improvements of 0.11–0.19, and F1-score increases of 15–24 percent relative to raw-feature baselines, while simultaneously reducing tree depth by up to 45 percent and cross-validation variance by 68 percent. These gains were statistically validated at $p < 0.001$ with large effect sizes and further confirmed under controlled noise injection, covariate shifts, and class imbalance conditions, proving the robustness of the selected models. A second major contribution is the provision of a reproducible, MLOps-ready pipeline that combines domain knowledge with automated optimization, offering practitioners an immediately deployable solution that bridges the gap between academic benchmarks and real-world production systems.

The work also contributes empirical evidence that advanced feature selection preserves the white-box transparency of decision trees while delivering performance levels competitive with more complex ensembles, thereby advancing the field of explainable AI. Finally, the domain-specific case studies illustrate tangible clinical and business impact, including reduced false-negative rates in diabetes screening, lower operational costs in fraud detection, and improved retention precision in customer churn management. Collectively, these contributions reposition advanced feature selection not as a peripheral preprocessing step but as a core scientific and engineering discipline essential for realizing the full potential of decision trees in high-stakes, real-world applications. The findings provide both theoretical insight into bias-variance trade-offs and actionable tools that researchers and practitioners can adopt to build more accurate, stable, efficient, and trustworthy predictive models.

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