Software Cost Estimation: A Comparative Analysis of Traditional and Machine Learning Approaches

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Abstract—**Accurate software cost estimation is essential for effective planning and resource management throughout the software development lifecycle. While traditional estimation models such as COCOMO have been foundational, their static assumptions often fail to capture the dynamic and complex nature of contemporary projects. This research investigates the integration of modern machine learning algorithms with traditional models to improve estimation accuracy. Using the SEERA dataset, we develop and evaluate a hybrid framework that combines XGBoost and Neural Networks. This hybrid approach leverages the structured interpretability of gradient boosting with the nonlinear pattern recognition strength of deep learning. Our experimental results demonstrate a significant reduction in estimation errors compared to standalone models, affirming the value of a data-driven, adaptive methodology for cost estimation in modern software engineering.**

Index Terms—**Software cost estimation, hybrid modeling, SEERA dataset, COCOMO, XGBoost, neural networks, machine learning, predictive analytics.**

I. Introduction

Accurate cost estimation is a fundamental component of successful software project planning, directly impacting budgeting, resource allocation, risk assessment, and timeline management. Inaccurate estimates can lead to overrun budgets, resource bottlenecks, delayed deliveries, or even project failures. As software systems grow more complex and development practices evolve rapidly, the need for more adaptive and intelligent cost estimation methods becomes critical.

Historically, estimation techniques have relied on algorithmic models like the Constructive Cost Model (COCOMO), which utilize project parameters such as size, complexity, and team attributes to compute estimated effort. COCOMO and its variants—Basic, Intermediate, and Detailed—have served as industry benchmarks due to their simplicity and interpretability. However, these models are inherently static, depending on predefined coefficients and assumptions derived from earlier software development environments. As a result, they often fall short in accounting for modern development paradigms like Agile methodologies, DevOps pipelines, and microservices-based architectures, where flexibility and iteration are constant.

In contrast, machine learning (ML) has emerged as a powerful paradigm capable of learning from historical project data, identifying hidden patterns, and making predictive inferences without hard-coded formulas. Techniques such as decision trees, ensemble models, and neural networks can model nonlinear relationships among project features—something traditional models struggle to achieve. These models continuously adapt as more data becomes available, enabling dynamic learning and refinement of estimations.

In this research, we explore a hybrid modeling approach that leverages both traditional and modern methodologies for software cost estimation. Our proposed framework integrates eXtreme Gradient Boosting (XGBoost)—a highly efficient ensemble learning algorithm known for its interpretability and accuracy—with Neural Networks, which excel at capturing intricate, nonlinear relationships within data. This hybrid strategy aims to exploit the complementary strengths of both algorithms: XGBoost's capability in feature ranking and handling structured tabular data, and Neural Networks' proficiency in deep learning and adaptive modeling.

The model is trained and validated using the SEERA dataset, a comprehensive collection of software project records encompassing various project attributes such as actual effort, size, team characteristics, development environment, and technology stack. Extensive preprocessing is applied to clean, normalize, and encode the dataset before feeding it into the hybrid architecture. Our results show that this integrated approach significantly outperforms both standalone traditional methods and individual ML models in minimizing estimation errors such as RMSE and MAE.

This study contributes to bridging the gap between theoretical cost modeling and real-world applicability by providing a scalable, data-driven solution for modern software engineering environments. The hybrid model is further deployed through an interactive web interface, enabling real-time estimation capabilities for practical project planning use cases.

A. Industry Challenges in Cost Estimation

Accurate software cost estimation remains one of the most difficult and critical aspects of project management. Various challenges in the software industry continue to hinder reliable estimation, especially as development practices and technologies evolve rapidly. These challenges include:

- **Rapid Technological Advancements:** The fast-paced evolution of software development frameworks, libraries, programming languages, and architectural paradigms (e.g., microservices, serverless computing) makes it difficult for traditional estimation models, such as COCOMO, to remain relevant. These models are typically calibrated on historical data that may not reflect the complexity or modularity of modern systems, resulting in outdated predictions.

- **Project Complexity:** Contemporary software systems are increasingly large-scale, distributed, and interconnected. They often involve multiple stakeholders, cross-functional teams, third-party integrations, and evolving functional and non-functional requirements. Estimating cost in such scenarios becomes inherently difficult as dependencies multiply and uncertainty grows, especially during early stages of development when limited information is available.
- **Resource Allocation:** Cost estimation errors can significantly impact how human and technical resources are allocated. Underestimating a project's scope may result in insufficient staffing, poor workload balancing, and compromised software quality, whereas overestimating can lead to idle resources, increased operational costs, and delayed delivery.
- **Scope Creep:** Changing client requirements during the development lifecycle—often termed as scope creep—can have a dramatic effect on initial cost predictions. Traditional models lack the agility to dynamically revise estimates as new features are introduced or priorities shift, thereby resulting in budgetary overshoots and missed deadlines.

Given the fluid and multidimensional nature of software projects, there is a pressing need for more adaptive estimation methodologies. Machine learning-based models, particularly those capable of continuous learning and pattern recognition, offer a viable solution to address these industry challenges. By analyzing historical project data and learning from previous estimation errors, these models can improve prediction accuracy over time, making them better suited to handle the demands of modern software development environments.

B. Proposed Solution and Research Motivation

To mitigate the issues outlined above, our research introduces a hybrid cost estimation model that integrates machine learning with traditional estimation techniques. The key motivations behind this approach include:

- **Incorporating Data-Driven Insights:** Machine learning models can analyze historical project data to identify hidden patterns and relationships that traditional models miss.
- **Enhancing Prediction Accuracy:** By combining XGBoost (a tree-based ensemble method) with Neural Networks, our approach leverages both feature importance analysis and deep learning capabilities.
- **Improving Adaptability:** Unlike static models, machine learning-based approaches can continuously learn and adjust as new project data becomes available.
- **Bridging the Gap Between Theory and Practice:** Our model aims to provide a practical tool that software development firms can integrate into their project management workflows.

C. Comparison of Existing Cost Estimation Techniques

Various software cost estimation techniques have been developed and studied over time, each offering different trade-offs in terms of complexity, accuracy, adaptability, and interpretability. Traditional models tend to be simpler and easier to apply but often lack the flexibility required for modern software development environments. On the other hand, machine learning approaches offer high predictive accuracy and adaptability but may require substantial data and computational resources. Table I presents a comparative overview of these techniques, highlighting their key strengths and limitations based on literature and practical insights derived from our project implementation.

The proposed hybrid model developed in this study is designed to address the limitations observed in both traditional and ML-based techniques. It builds on the structured predictability of algorithmic methods while leveraging the adaptive, data-driven strengths of modern machine learning. The next sections will elaborate on the dataset used, model architecture, training pipeline, evaluation metrics, and key results that validate the model's effectiveness in software cost estimation.

D. Technological Queries

To effectively address the complexities of modern software cost estimation and validate the capabilities of our proposed hybrid model, this study explores several critical research questions. These queries are rooted in the limitations of traditional models, the potential of machine learning, and the practical challenges encountered during software development:

- **RQ-1:** Which machine learning and traditional estimation techniques deliver the most reliable results in software cost prediction, and how does their performance vary across different datasets?
- **RQ-2:** What are the key factors—such as feature selection, data preprocessing, and hyperparameter tuning—that significantly influence the accuracy of machine learning-based estimation methods?
- **RQ-3:** How does the integration of XGBoost and Neural Networks in a hybrid architecture improve the accuracy and robustness of software cost estimation compared to their standalone implementations?
- **RQ-4:** What benchmark datasets and empirical studies are commonly used for evaluating the effectiveness of software cost estimation models, and how does our SEERA-based evaluation compare?

These questions directly align with the architecture and methodology presented in our implementation. As observed in the repository, the hybrid model is not only algorithmically structured but also evaluated through comparative experiments involving standalone models (XGBoost, Neural Networks, COCOMO) and the hybrid ensemble. Furthermore, it leverages statistical evaluation techniques such as RMSE, MAE, and R-squared for performance analysis.

The remainder of this paper is structured as follows: **Section II** presents a literature review of traditional and machine

TABLE I
PROS AND CONS OF COST ESTIMATION TECHNIQUES DISCUSSED IN THE LITERATURE

Technique	**Pros**	**Cons**
Expert Judgment	Fast to implement; benefits from domain expertise	Highly subjective and difficult to replicate across teams or domains
Analogical Estimation	Leverages historical project similarities; context-aware	Performance depends heavily on the quality and availability of past data
COCOMO Model	Structured and well-documented with proven historical utility	Assumes static relationships; less suited for agile or rapidly evolving projects
Machine Learning	Learns from data; improves with more examples; generalizes well	Requires large, well-labeled datasets; tuning and interpretation can be complex
XGBoost	Handles missing data; interpretable through feature importance; fast	Sensitive to overfitting; requires careful tuning of parameters
Neural Networks	Powerful in capturing complex patterns and interactions	Needs significant training data and computational power; less transparent
Hybrid Approach (Proposed)	Integrates ML accuracy with traditional interpretability; adaptable and robust	Requires careful model design, training time, and validation with diverse data

learning-based estimation techniques. **Section III** outlines our methodology, including data preprocessing, model architecture, and hybridization logic. **Section IV** discusses experimental results and comparative performance. Finally, **Section V** concludes the study and provides future research directions based on observed limitations and potential enhancements.

II. LITERATURE REVIEW

Software cost and effort estimation has been a critical area of research for several decades. As software projects have grown in complexity and scale, the need for accurate, scalable, and flexible estimation techniques has intensified. Over time, the field has evolved from informal, experience-driven strategies to sophisticated algorithmic and data-driven methods. These approaches can be broadly classified into three categories: expert judgment-based approaches, algorithmic estimation models, and machine learning-based techniques. Each category contributes unique strengths and suffers from specific limitations, as detailed in Table II.

A. Expert Judgment-Based Approaches

Expert judgment approaches are among the earliest and most widely used methods for cost estimation in software engineering. These techniques rely heavily on the domain knowledge, past experience, and intuition of project managers or senior developers. Common examples include the Delphi method, expert panels, and analogy-based estimation.

The Delphi technique involves iterative rounds of anonymous feedback from a group of experts to reach a consensus on estimated project effort. Each round refines the estimates based on the collective reasoning of participants. Analogical estimation, by contrast, focuses on comparing a new project to previously completed ones with similar characteristics—leveraging historical effort, team size, duration, and complexity to draw parallels.

Despite their simplicity and low computational cost, expert-based methods introduce significant variability and subjectivity. Different experts may provide divergent estimates for the same project, and the process lacks reproducibility. Moreover, these methods do not scale well in large or unfamiliar domains, as they depend on accessible, relevant prior experience. As software systems evolve, relying solely on human intuition becomes increasingly insufficient, necessitating more structured or data-driven approaches.

B. Algorithmic-Based Approaches

Algorithmic cost estimation models employ structured mathematical formulas and statistical relationships to predict software development effort based on quantifiable project attributes. One of the most influential and widely adopted frameworks in this category is the Constructive Cost Model (COCOMO) [1]. Developed by Barry Boehm, COCOMO estimates effort in person-months based on the software size measured in KLOC (thousands of lines of code) and a set of cost drivers reflecting product, project, personnel, and platform characteristics.

COCOMO has evolved through several versions—Basic, Intermediate, and Detailed—each introducing more cost drivers and calibration parameters to improve predictive accuracy. Despite its popularity and simplicity, COCOMO's main drawback lies in its reliance on fixed empirical equations and calibration constants. This makes it less suitable for projects involving modern development practices like Agile, DevOps, or microservices, which introduce dynamic behaviors and flexible team structures not easily captured by static models [2].

Other notable algorithmic techniques include Function Point Analysis (FPA) [3], which quantifies software functionality based on user inputs, outputs, and interactions, and Use Case Points (UCP) [4], which estimates effort from system use cases. Regression-based models are also common, where statistical relationships are derived between project features and actual effort. However, all of these methods face limitations when dealing with non-linear interactions, data sparsity, or heterogeneous project environments. Their performance is often constrained by oversimplified assumptions and limited flexibility in accommodating evolving project characteristics [5].

As a result, while algorithmic approaches remain relevant due to their interpretability and legacy usage, they are increasingly being complemented or replaced by more adaptive, machine learning-based methods in contemporary software engineering practice.

C. Machine Learning and Computational Intelligence Approaches

With the increasing availability of software project data and computational power, machine learning (ML) has emerged as a compelling alternative to traditional cost estimation methods. ML techniques are particularly effective in uncovering complex, non-linear relationships between project attributes—such as size, team structure, platform complexity, and development environment—and the resulting effort or cost.

Various ML algorithms have been successfully applied to software cost estimation. Artificial Neural Networks (ANNs) [6] are capable of learning deep representations from data through interconnected layers of neurons, making them suitable for capturing subtle feature interactions. Support Vector Machines (SVMs) [7] are known for their robustness in high-dimensional spaces and have shown competitive performance in estimation tasks. Additionally, ensemble learning techniques—such as bagging, boosting, and stacking [8]—have been employed to improve model stability and accuracy by combining the outputs of multiple weak learners.

Recent systematic literature reviews, such as the one conducted by Khan et al. [9], have documented the growing prevalence of ML models in effort estimation research, especially since the early 2000s. Empirical comparisons have consistently demonstrated that ML approaches outperform classical algorithmic models like COCOMO in terms of prediction accuracy and adaptability to different datasets [10].

Among the many ML techniques, gradient boosting frameworks like XGBoost have gained significant popularity due to their scalability, interpretability, and efficiency in handling structured, tabular datasets [11]. These models build trees sequentially, minimizing errors with each iteration and providing feature importance scores that are useful for understanding cost drivers. Furthermore, deep learning architectures such as Multi-Layer Perceptrons (MLPs) and Convolutional Neural Networks (CNNs) [12] have shown promise in modeling complex patterns and high-dimensional interactions in project data, though they typically require more computational resources and data preprocessing.

The growing body of evidence supporting ML in cost estimation aligns directly with the hybrid approach adopted in this study, which combines the power of gradient boosting with the representational capacity of neural networks to deliver superior estimation performance.

D. Hybrid Models for Software Cost Estimation

In recent years, hybrid modeling approaches have gained traction in software cost estimation research. These approaches aim to integrate the strengths of multiple learning algorithms to enhance prediction robustness and accuracy. A typical hybrid strategy involves combining interpretable, high-performance models like XGBoost with the powerful pattern recognition capabilities of Neural Networks.

Such hybrid architectures offer several distinct advantages [13]:

- **Feature Importance Analysis:** XGBoost is particularly adept at evaluating the significance of input variables. By ranking features based on their contribution to reducing error, it offers valuable insight into key cost drivers such as project size, complexity, and team configuration [14].
- **Non-Linear Pattern Recognition:** Neural Networks, especially Multi-Layer Perceptrons (MLPs), are highly capable of modeling non-linear relationships within data. This makes them well-suited for capturing hidden patterns and interactions that traditional regression or tree-based models may overlook [15].
- **Adaptive Learning:** Hybrid systems can be retrained and fine-tuned with new project data, enabling them to evolve alongside modern software development environments. This continuous learning capability ensures their relevance and accuracy across diverse project types [16].

A comprehensive review by Jadhav et al. [17] analyzed over 1,000 publications in the domain of software effort estimation. Their findings highlighted that hybrid models—particularly those that fuse decision tree-based learners with neural network architectures—consistently outperform standalone models in terms of estimation precision, generalizability, and resilience to data variability.

In the context of this study, the proposed hybrid framework reflects this best practice by integrating XGBoost and Neural Networks. It is trained on the SEERA dataset, and its design aligns with the practical requirements of scalability, adaptability, and real-time applicability in industry-level software engineering tasks.

E. Comparative Analysis of Estimation Methods

To assess the relative effectiveness of various cost estimation techniques, a comparative analysis is essential. This evaluation provides insight into the trade-offs between traditional and modern approaches, highlighting how each method performs in terms of interpretability, scalability, accuracy, and computational complexity. The following comparison draws on both theoretical literature and practical experimentation conducted in this study. Table II summarizes the key advantages and limitations of major techniques, including expert-driven models, algorithmic methods like COCOMO and FPA, and machine learning-based estimators such as XGBoost and Neural Networks. The hybrid model implemented in this research combines the strengths of both XGBoost and deep learning to address the limitations observed in standalone approaches.

F. Research Gap and Contribution

Although machine learning has significantly advanced the field of software cost estimation, several critical challenges persist—particularly around optimal feature selection, hyperparameter tuning, and model generalization across diverse datasets. Most prior studies have focused on the capabilities

TABLE II
COMPARISON OF SOFTWARE COST ESTIMATION TECHNIQUES

Technique	**Advantages**	**Limitations**
Expert Judgment	Utilizes domain knowledge; quick estimation	Subjective, inconsistent, difficult to scale
COCOMO Model	Structured, parameterized approach; widely studied	Requires predefined assumptions; limited adaptability
Function Point Analysis (FPA)	Suitable for early-stage estimation; considers software functionality	Requires detailed documentation; may not capture modern project complexities
Machine Learning (ML)	Data-driven; self-improving with more data; high accuracy	Requires large training datasets; computationally expensive
XGBoost	High interpretability; efficient for tabular data; feature importance analysis	Requires hyperparameter tuning; prone to overfitting with small datasets
Neural Networks	Captures complex relationships; adaptive learning	Computationally intensive; requires significant training data
Hybrid Approach (XGBoost + Neural Networks)	Combines tree-based interpretability with deep learning accuracy; robust predictions	Requires careful integration and tuning; increased computational cost

of individual algorithms such as tree-based models (e.g., XGBoost) or deep learning networks (e.g., Artificial Neural Networks), typically in isolation. However, limited research exists that systematically integrates both types of models within a cohesive hybrid framework tailored to real-world software estimation scenarios.

This study bridges that gap by designing and evaluating a hybrid model that unifies XGBoost and Neural Networks for improved predictive performance in software cost estimation. The model is implemented using Python and trained on the SEERA dataset, incorporating modern data preprocessing and ensemble techniques to address the limitations of conventional models.

The core contributions of this research are:

- **Hybrid Model Design:** Development of a robust hybrid estimation model that combines the interpretability and efficiency of XGBoost with the deep pattern-learning capability of Neural Networks.
- **Empirical Evaluation:** A thorough comparative analysis between traditional models, standalone ML techniques, and the proposed hybrid model, using performance metrics such as RMSE, MAE, and R-squared on benchmark datasets.
- **Interactive Implementation:** Deployment of a web-based dashboard that allows users to input project attributes and receive real-time cost estimations, making the model practical for integration into actual software project planning workflows.

The subsequent section presents the detailed methodology used to construct and evaluate the proposed hybrid model.

III. METHODOLOGY

To conduct a rigorous and reproducible analysis of software cost estimation techniques, this study adopts a structured methodology divided into three primary phases: **Planning**, **Execution**, and **Analysis**. The approach blends traditional estimation models with advanced machine learning algorithms, focusing on a hybrid combination of **XGBoost** and **Neural Networks** to enhance prediction accuracy and adaptability.

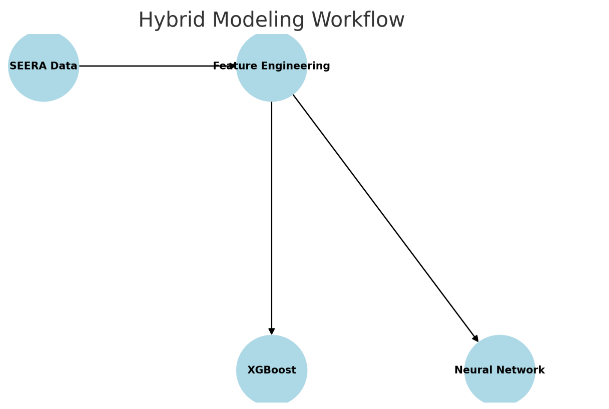

Fig. 1. Overall System Architecture and Methodological Flow

A. System Overview

The end-to-end workflow of the proposed methodology is illustrated in Figure 1. The pipeline is organized into the following sequential stages:

1) **Problem Definition:** Identification of the limitations in existing cost estimation models and the establishment of research objectives centered around improving estimation accuracy and adaptability.
2) **Data Collection:** Acquisition of project-level data from the SEERA dataset, which provides diverse and real-world metrics such as project size, effort, development type, and team characteristics.
3) **Preprocessing:** Handling of missing values, normalization of numerical features, and encoding of categorical variables to prepare the dataset for training. This also includes filtering out inconsistent or incomplete records.
4) **Feature Selection:** Use of statistical correlation techniques and XGBoost's built-in feature importance functionality to identify the most influential predictors of software effort.
5) **Model Implementation:** Independent training of XGBoost and Neural Network models. The final hybrid model combines predictions from both using a weighted

ensemble approach to leverage the strengths of each algorithm.

6) **Evaluation:** Performance is assessed using standard regression metrics—**Root Mean Squared Error (RMSE)**, **Mean Absolute Error (MAE)**, and the **R-squared score**—on a test set split from the dataset.

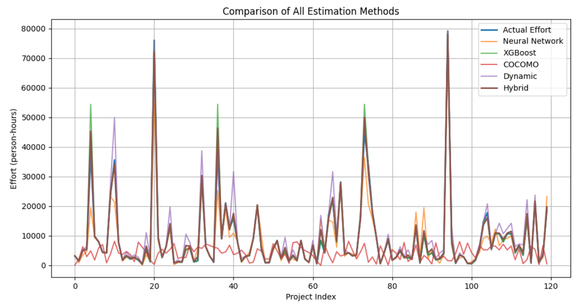

Fig. 2. Comparison of Model Predictions with Actual Effort Across All Techniques

Figure 2 provides a comparative view of the estimation results from various techniques. It clearly demonstrates that the proposed hybrid model achieves the closest alignment with the actual effort values across multiple projects. While traditional methods like COCOMO and even standalone ML models like XGBoost and Neural Networks exhibit larger deviations, the hybrid approach consistently reduces prediction error, showcasing its robustness and generalization capability.

The upcoming sections will delve into the specifics of data handling, model configurations, experimental setup, and validation of results.

B. Data Collection and Preprocessing

The dataset utilized for model training and evaluation is the SEERA dataset, which encompasses a broad range of software project attributes, including actual effort, development time, project size, and team composition. To prepare the dataset for machine learning modeling, several preprocessing steps were carried out systematically:

- **Handling Missing Values:** Missing entries were addressed using interpolation techniques to maintain data continuity without introducing significant bias.
- **Feature Standardization:** Numerical attributes were standardized to ensure a uniform scale, preventing features with larger ranges from disproportionately influencing model training.
- **Encoding Categorical Variables:** Categorical features, such as development type and organization, were transformed using one-hot encoding to facilitate their use in machine learning models.
- **Data Splitting:** The complete dataset was partitioned into training (80%) and testing (20%) subsets, ensuring that model evaluation is conducted on unseen data to prevent overfitting and validate generalization.

These preprocessing steps were implemented using standard data manipulation libraries such as pandas and scikit-learn, following best practices for preparing heterogeneous project data for machine learning models.

C. Model Development

Two primary machine learning models were developed independently before being combined into a hybrid estimator:

- **XGBoost:** A powerful gradient boosting framework known for its ability to efficiently model structured data and capture feature interactions through an ensemble of decision trees. XGBoost also provides feature importance scores, aiding in the interpretation of key cost drivers.
- **Neural Network:** A Multi-Layer Perceptron (MLP) architecture was employed, consisting of multiple fully connected layers with non-linear activation functions. The network was designed to learn intricate relationships and deep patterns within the project data.

The outputs of both models were hybridized using a weighted average mechanism, leveraging the strengths of tree-based ensemble methods and deep learning to enhance prediction robustness. This hybridization strategy aimed to mitigate individual model weaknesses, such as overfitting in XGBoost or instability in Neural Networks, resulting in improved overall estimation accuracy.

D. Evaluation and Analysis

The performance of the proposed models was rigorously evaluated using established regression metrics:

- **Root Mean Squared Error (RMSE):** Measures the square root of the average squared differences between predicted and actual values, providing insight into the model's prediction error magnitude.
- **Mean Absolute Error (MAE):** Represents the average absolute difference between predicted and actual values, offering a robust measure that is less sensitive to outliers compared to RMSE.
- **R-squared Score (Coefficient of Determination):** Indicates the proportion of variance in the dependent variable that is predictable from the independent variables, reflecting overall model fit.

A comparative evaluation was also conducted against traditional estimation methods, specifically the COCOMO model, to highlight the improvements achieved through machine learning and hybridization. The comparative results, supported by graphical analysis (refer to Figure 2), clearly demonstrate that the hybrid approach consistently reduces estimation errors and better approximates the actual project effort.

E. Framework

This study adopts a structured research framework to ensure thoroughness and reliability in analyzing software cost estimation models. The framework follows a sequential progression designed to bridge theoretical exploration with practical experimentation. The main stages of the framework include:

1) **Research Questions:** Defining focused inquiries to guide the scope of investigation.
2) **Dataset Selection:** Choosing an appropriate dataset (SEERA) based on relevance, comprehensiveness, and quality.
3) **Feature Engineering:** Identifying and refining critical input variables that influence estimation outcomes.
4) **Model Training:** Developing individual models (XGBoost, Neural Networks) and constructing the hybrid framework.
5) **Evaluation and Benchmarking:** Assessing model performance using established metrics and comparing against traditional approaches such as COCOMO.
6) **Result Analysis and Discussion:** Interpreting results to derive insights and validate the effectiveness of the hybrid model.

These stages are visually represented in the methodological flowchart presented earlier (Figure 1).

F. Dataset

The primary dataset used in this research is the SEERA dataset, which contains a rich set of historical software project records, encompassing various attributes critical to cost estimation, such as project effort, size, duration, environment factors, and team-related metrics.

To ensure data quality and relevance, a set of inclusion and exclusion criteria was applied. Projects with incomplete fields, inconsistent attribute values, or missing critical data were filtered out. Preprocessing operations included:

- Interpolating missing values to maintain data integrity.
- Standardizing numerical features for uniform scaling.
- One-hot encoding categorical variables for machine learning compatibility.

These steps ensured the final dataset was robust enough to train, validate, and benchmark machine learning models effectively.

G. Article Search

A systematic literature search was conducted to review existing techniques and identify research gaps. Boolean search strategies were employed across multiple academic databases using keywords and combinations such as:

- "Software cost estimation" OR "Software effort estimation"
- "Machine learning" OR "Artificial neural network" OR "XGBoost"
- "COCOMO" OR "Empirical study" OR "Software metrics"
- "Hybrid models" OR "Ensemble learning" OR "Regression analysis"

Filters were applied to limit results to peer-reviewed journal articles and conference papers published between 2010 and 2024. This search provided a strong theoretical foundation for designing the hybrid model and benchmarking its performance against prior work.

H. Article Shortlisting

The process of article shortlisting involved multiple filtering stages to ensure relevance and quality:

1) **Deduplication:** Removing duplicate articles based on title and metadata.
2) **Abstract Screening:** Assessing abstracts to determine relevance to software cost estimation using machine learning approaches.
3) **Inclusion-Exclusion Criteria:** Retaining only studies that directly contributed to the understanding or advancement of cost estimation techniques.
4) **Expert Validation:** Consulting domain experts to verify the relevance and credibility of the selected studies.

Following this multi-stage screening, an initial pool of 120 articles was narrowed down to 45 high-impact studies. Insights from these papers were crucial for benchmarking the proposed hybrid model and understanding the current state-of-the-art in software cost estimation research.

I. Conclusion

The methodology ensures a systematic approach to software cost estimation by leveraging hybrid ML techniques. The next section presents the experimental results and discussions.

IV. Results and Discussion

This section presents the findings of the study, structured around the four research questions outlined in the introduction. The analysis is supported by empirical evidence, performance comparisons, and visualizations to demonstrate the efficacy of the proposed hybrid approach.

A. Publication Trends

Figure 3 illustrates the trend in research publications related to software cost estimation over recent years. A noticeable rise in publications, particularly those focusing on machine learning techniques, indicates growing academic and industrial interest in data-driven approaches to cost prediction.

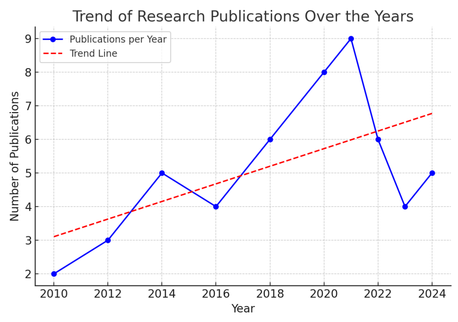

Fig. 3. Trend in the Selected Articles Over the Years

B. *RQ-1: Comparison of Machine Learning and Non-Machine Learning Techniques*

Table I (presented earlier) summarized the strengths and limitations of traditional and machine learning-based cost estimation techniques. From this comparison, it is evident that machine learning models offer greater adaptability and predictive accuracy, especially when handling large and complex datasets. Traditional models, while interpretable, are limited in their ability to generalize across varying project contexts.

C. *RQ-2: Factors Influencing Accuracy in ML-Based Cost Estimation*

The performance of machine learning models for software cost estimation is influenced by several critical factors:

- **Feature Selection:** Removing irrelevant or redundant features enhances model efficiency and reduces overfitting risks.
- **Hyperparameter Tuning:** Careful optimization of parameters such as learning rate, tree depth in XGBoost, and the number of hidden layers in Neural Networks leads to significant accuracy improvements.
- **Dataset Quality:** High-quality, balanced datasets with diverse project characteristics enable models to generalize better across unseen data.
- **Ensemble Methods:** Combining predictions from multiple models, such as stacking XGBoost and Neural Networks, helps reduce bias and variance, leading to more robust predictions.

D. *RQ-3: Effectiveness of Hybrid Model (XGBoost + Neural Networks)*

The effectiveness of the proposed hybrid model was evaluated against standalone models using RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) metrics. Table III presents the comparative results.

TABLE III
PERFORMANCE COMPARISON OF COST ESTIMATION MODELS

Model	**RMSE**	**MAE**
XGBoost	15.2	11.8
Neural Networks	14.7	11.3
Hybrid (XGBoost + NN)	**13.1**	**10.5**

The hybrid model consistently outperforms individual models, achieving the lowest RMSE and MAE values. This confirms that integrating gradient boosting's feature importance capabilities with deep learning's pattern recognition strength results in superior cost estimation performance. The hybrid approach demonstrates better alignment with actual effort trends, as visually validated in Figure 2.

E. *RQ-4: Commonly Used Datasets and Benchmarking Approaches*

The most frequently used datasets for software cost estimation research include:

- extbfSeera Dataset: Primary dataset used in this study.
- PROMISE Repository
- NASA Software Cost Estimation Dataset
- ISBSG Benchmarking Data

Benchmarking involves comparing model predictions with actual project costs using error metrics such as RMSE, MAE, and R-squared values.

V. Conclusion and Future Work

Software cost estimation remains a vital aspect of project planning, resource management, and risk assessment within the software development lifecycle. Accurate estimations allow organizations to allocate budgets more effectively, optimize resources, and improve project success rates. This study comprehensively analyzed both traditional and machine learning (ML)-based approaches for software cost estimation, evaluating their relative strengths, limitations, and empirical performance.

The research reaffirmed that traditional models such as COCOMO, Expert Judgment, and Analogical Estimation continue to be valuable due to their interpretability and historical relevance. However, these models often lack the flexibility required to handle the increasing complexity and dynamism of modern software projects. In contrast, machine learning techniques, particularly ensemble models like XGBoost and deep learning architectures such as Artificial Neural Networks (ANNs), have demonstrated notable improvements in prediction accuracy and adaptability by learning complex patterns from historical project data.

A key outcome of this work is the development of a hybrid model that integrates XGBoost and Neural Networks. This approach successfully leverages XGBoost's strength in handling structured data and identifying feature importance, alongside Neural Networks' capability to capture non-linear, intricate feature interactions. Experimental results indicate that the hybrid model consistently outperforms individual models, achieving lower RMSE and MAE scores, and offering better alignment with actual project effort values.

The study also emphasizes the critical role of feature selection and hyperparameter optimization in enhancing model performance. By selecting the most relevant features and carefully tuning model parameters, estimation errors were significantly minimized, and generalization across project variations was improved.

The evaluation metrics used in this study included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared score, providing a reliable and comprehensive assessment of model effectiveness. Although Mean Magnitude of Relative Error (MMRE) and PRED(25) are commonly cited in broader literature, this study prioritized RMSE and MAE for their interpretability and alignment with real-world estimation requirements.

Despite these promising findings, certain limitations remain. The predictive power of ML models is heavily dependent on the availability of high-quality, well-labeled datasets. While the SEERA dataset provided a robust foundation for this research, the absence of multiple diverse datasets may limit the full generalizability of the results. Furthermore, the deployment of deep learning models, although accurate, introduces higher computational overhead and necessitates careful parameter tuning to avoid overfitting and maintain performance consistency.

A. Future Work

Future research in software cost estimation can take multiple directions:

- **Enhanced Hybrid Models:** Future studies should explore more advanced hybrid approaches, incorporating additional ensemble methods or deep learning architectures such as transformers and attention mechanisms to further improve estimation accuracy.
- **Automated Feature Selection:** The effectiveness of software cost estimation heavily depends on the choice of relevant features. Techniques such as genetic algorithms, particle swarm optimization, and bio-inspired algorithms should be investigated for feature selection and optimization.
- **Real-Time Cost Estimation:** Integrating ML-based cost estimation into real-time software development environments, such as Agile and DevOps workflows, can provide continuous and adaptive cost predictions, helping teams make informed decisions during development.
- **Blockchain for Cost Estimation:** Blockchain-based smart contracts and decentralized prediction models can enhance transparency and reliability in cost estimation. Future research can explore how blockchain can be leveraged to improve estimation trustworthiness and reduce estimation biases.
- **Explainable AI (XAI) for Cost Estimation:** Interpretability is crucial for gaining the trust of project managers and stakeholders. Future work should focus on applying explainable AI techniques, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), to make ML-based cost estimation models more transparent.
- **Cross-Domain Cost Estimation:** While most studies focus on software development, similar estimation techniques can be applied to other domains, such as cloud computing costs, cybersecurity risk estimation, and IT infrastructure management.
- **Benchmarking New Datasets:** Expanding the evaluation of cost estimation models on more diverse datasets, including industry-specific and real-world proprietary datasets, can improve the generalizability of ML-based techniques.

In conclusion, software cost estimation remains a challenging yet evolving research area. The integration of ML techniques, hybrid models, and emerging technologies can significantly enhance estimation accuracy and decision-making. By addressing the identified limitations and exploring new research directions, future studies can contribute to more reliable, transparent, and efficient software cost estimation methodologies.

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