Cracking the Clock: Unlocking Smart Predictions for Effortless Task Completion

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Abstract—**Accurate effort estimation at the task level is essential for effective project planning, resource allocation, and meeting delivery timelines in software development. While traditional approaches have focused primarily on project-level estimation, limited research exists on predicting the duration of individual tasks. This paper proposes a novel approach for task effort estimation using a combination of Google's Gemini API and Facebook's Prophet time series model. The model takes task-specific features such as task name, priority, complexity, labels, and starting date as input to predict the expected completion time. By leveraging both semantic understanding and temporal modeling, our approach addresses the limitations of conventional estimation techniques. Experimental results demonstrate the feasibility and practical utility of the proposed method in forecasting task durations with promising accuracy. This work contributes to bridging the gap between high-level project estimation and fine-grained task-level forecasting, offering a data-driven solution to support dynamic planning in agile development environments.**

Index Terms—**Task Prioritization, Workflow Optimization, Predictive Task Analytics, Team Collaboration, Productivity Tracking, Project Lifecycle Management, Performance Monitoring, Real-Time Task Insights, Project Forecasting, Task Automation.**

I. Introduction

In the evolving landscape of software development, intelligent project management tools have become indispensable. Traditional dashboards often fall short, focusing primarily on task assignment and progress tracking, while real-world development environments are characterized by dynamic factors such as delays, shifting priorities, and concurrent task execution. These complexities significantly hinder effective project planning.

Popular tools such as Jira and Trello lack intelligent recommendation systems and fail to learn from historical performance data, resulting in suboptimal planning outcomes. Pasuksmit et al. [1] critique Agile estimation methods like planning poker for their inherent subjectivity and inconsistency. Classic models such as COCOMO [2] and Function Point Analysis [3], [4] also fall short, especially in accounting for human-centric and team-dynamic variables, as emphasized by Jørgensen and Shepperd [5]. The inadequacy of static models in modern, fluid environments has led to the growing interest in adaptive, ML-based approaches.

Recent work underscores the potential of machine learning for software effort estimation. Kocaguneli et al. [6] advocate personalized models, while Rahman et al. [7] demonstrate ML's success in issue tracking systems. Similarly, Mockus and Weiss [8], and Menzies et al. [9] reveal the value of learning from past defects and code attributes. Uc-Cetina [10] explores ML models in Agile contexts, and Chen and Zhou [11] leverage reinforcement learning for feature selection in effort estimation. Tran and Le [12] propose hybrid models for greater predictive accuracy, while Kumar and Srinivas [13] use optimization-driven analogies.

Deep learning has also shown promise, with Garcia and Lopez [14] conducting comparative analyses, and Ahmed et al. [15] employing BERT-based textual representations. Moreover, Wang and Zhao [16] apply prompt learning, Singh et al. [17] investigate the role of large language models (LLMs), and Li and Sun [18] explore few-shot learning for low-data scenarios.

To address the limitations of existing tools, this paper proposes a novel machine learning–driven system that integrates with Jira, processes historical task data, and predicts completion times. A key innovation of our system is its ability to generate accurate estimates even when story points are absent—bridging a critical gap in current project management solutions by leveraging state-of-the-art techniques in software effort prediction.

A. Our Contribution

We develop an intelligent system capable of predicting task effort estimations based on historical project data without relying on predefined story points.

We introduce a novel hybrid model that combines the strengths of **Prophet** and the **Gemini API**, achieving superior prediction accuracy compared to traditional machine learning models.

We design and implement a fully functional web-based platform that seamlessly connects with Jira, applies machine learning predictions, and displays results through an interactive and user-friendly dashboard.

II. Background

Traditional project dashboards like Jira and Trello focus primarily on task assignment and progress tracking. However, in real-world software development, plans often change due to shifting priorities, delays, and multitasking. These fluctuations complicate estimation and tracking [19]. Inaccurate effort and cost estimation is a common cause of project failure, especially when relying on expert judgment or simplistic models.

Agile methods, while popular, also introduce new estimation challenges. Tools like planning poker are widely used but often lead to inconsistent estimations and require frequent re-adjustments [20]. These methods may work for small iterations but fail to generalize across diverse team dynamics and task complexities. As noted by Uc-Cetina [21], existing models often lack adaptability and context-awareness.

Traditional estimation models like COCOMO [2], Function Points [22], and Use Case Points [23] were not designed for Agile or distributed development. They do not consider team dynamics, concurrent tasks, or frequent context switching, all of which significantly affect effort estimation accuracy. In global software engineering, additional variables such as time zone differences and communication barriers introduce further complexity [24].

Recent research has shifted toward machine learning (ML)-based estimation. ML models can automatically learn from historical project data to predict task effort with greater accuracy. Unlike traditional approaches, ML models do not rely on predefined formulas or expert calibration. Instead, they can incorporate task descriptions, user stories, team assignments, and even code-level features [25], [26].

ML's predictive capabilities have shown success across various estimation strategies. Reinforcement learning, deep learning, and ensemble models such as Random Forests and XGBoost have demonstrated higher accuracy compared to expert-driven methods [27], [28], [29]. These approaches also reduce estimation bias and improve planning reliability in Agile settings [30], [31].

A. Decision Tree (DT)

Decision Tree (DT) algorithms build predictive models by recursively splitting data based on feature values, forming a hierarchical tree structure. Each node represents a decision based on a particular attribute, and each path leads to a predicted outcome.

DTs are particularly appealing due to their interpretability. Managers and analysts can easily trace how the model arrived at a prediction, making DTs suitable for effort estimation in software projects [32]. However, without proper pruning, DTs can overfit, especially in high-dimensional or noisy datasets. This can be mitigated through tree depth limitation and post-pruning techniques [33].

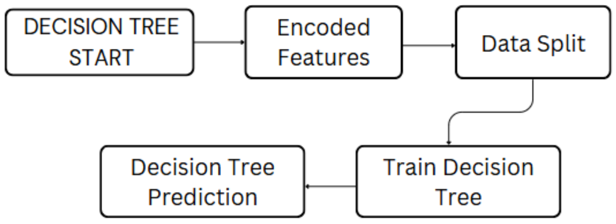


Fig. 1: Illustration of Decision Tree methodology

This diagram outlines the decision tree modeling workflow. It begins with preparing the dataset, followed by encoding categori- cal features into numeric values. The data is then split into training and testing sets. The training set is used to train the decision tree model. Once trained, the model uses selected predictors (features) to make deci- sions or predictions. The side node, "Deci- sion Tree Predictors," highlights the important features contributing to the model's de- cisions.

B. Random Forest (RF)

Random Forest (RF) is an ensemble method that constructs multiple decision trees using different data samples and aggregates their predictions to achieve more robust and accurate results. RF is less prone to overfitting compared to a single decision tree and performs well even when many irrelevant features are present.

This approach has been widely used for effort estimation in both traditional and Agile projects due to its robustness and ability to capture complex relationships among features [21], [27]. In comparison to manual estimation or classical models, RF has demonstrated superior performance across multiple studies [34].

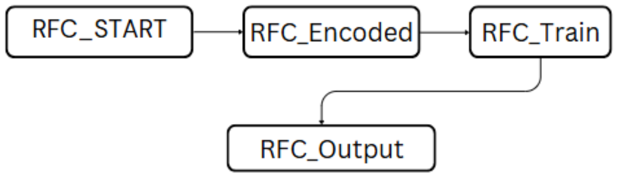


Fig. 2: Visualization of Random Forest technique

This diagram represents the workflow of building and using a Random Forest Classi- fier (RFC) model. It starts with data collec- tion and setup (RFC Start), followed by en- coding categorical features into numeric for- mat (RFC Encoded). The encoded data is then used to train the Random Forest model (RFC Train). Finally, the trained model pro- duces predictions or classification results (RFC Output).

C. Extreme Gradient Boosting (XGB)

Extreme Gradient Boosting (XGBoost) is an advanced boosting algorithm that combines many weak learners (typically decision trees) into a strong predictor through a process of error correction. It is known for its high speed and performance, making it suitable for complex estimation tasks.

XGBoost iteratively minimizes the loss function, enabling it to model intricate patterns that single models may miss. In the context of software effort estimation, XGBoost has been applied with success in recent studies [27], [35]. However, the model's complexity demands careful tuning of hyperparameters like learning rate, depth, and regularization to avoid overfitting.

Its ability to handle missing data, heterogeneous features, and multicollinearity further increases its suitability for software engineering datasets, which are often noisy and unbalanced [36], [37].

The XGBoost workflow starts with initializing the model setup, followed by encoding the data to convert categorical or textual inputs into numerical form. These encoded features are then used for training. During the boosting iterations, XGBoost

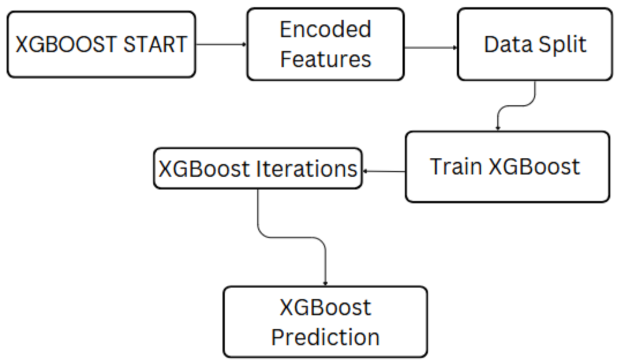


Fig. 3: Diagram representing XGBoost process

builds decision trees sequentially, each correcting the errors of the previous one. Finally, the model's performance is evaluated using appropriate metrics like RMSE, MAE, or accuracy to assess its effectiveness and guide further tuning if needed.

Turic et al. (2023) explore the use of Bayesian Networks for effort prediction in agile development, aiming to bring this approach closer to practitioners. Ercelebi and Kocyigit (2014) emphasize the importance of predicting software project effort as early as possible. To address these challenges, this paper proposes a novel machine learning model. This model connects with Jira, uses ML to analyze past data, and predicts when tasks will be done. It also shows this in an easy-to-use visual dashboard. The model is more than a task tracker; it helps teams plan better and avoid delays by giving smart, data-driven insights. A key contribution of this work is to fill the gap in existing tools by providing accurate completion date predictions even when story points are not assigned to tasks.

III. Related Work

Software effort estimation has been a long-standing challenge in software engineering, prompting the development of various traditional and modern approaches. This section reviews key classical methods such as COCOMO, Function Point Analysis, and Use Case Points, as well as recent machine learning-based techniques.

The Constructive Cost Model (COCOMO), introduced by Boehm [2], is one of the earliest and most influential models in software effort estimation. It utilizes project size, typically measured in lines of code (LOC), to estimate effort, cost, and schedule. Despite its historical significance, COCOMO has limitations in dealing with dynamic and complex software projects.

Function Point Analysis (FPA), developed by Albrecht [3], provides a more structured approach by measuring functionality delivered to the user based on inputs, outputs, user interactions, files, and interfaces. FPA has been widely adopted due to its relative independence from implementation language and technology.

Use Case Points (UCP), introduced by Karner [4], is another traditional technique that estimates effort based on the complexity and number of use cases in a system. While UCP has been valuable for object-oriented software projects, it often relies heavily on subjective judgment and lacks adaptability to varying project environments.

Task-level effort estimation has emerged as a more granular approach, focusing on predicting the effort required for individual tasks rather than entire projects. This method aligns well with agile methodologies and tools like Jira and Trello, which decompose projects into smaller, manageable units. Studies such as [6] demonstrate the effectiveness of task-level estimation in providing more accurate and real-time predictions, especially when integrated with machine learning algorithms.

Machine learning (ML) techniques have gained popularity in software effort estimation due to their ability to learn from historical data and capture complex, nonlinear relationships. Models such as Decision Trees, Random Forests, and Gradient Boosting Machines have been employed to improve estimation accuracy. For instance, Kocaguneli et al. highlight the advantages of using ML models over traditional methods, particularly in heterogeneous project environments. Recent advancements also explore the integration of natural language processing (NLP) to extract effort-related features from user stories and task descriptions .

Despite these advancements, challenges remain in applying ML to software effort estimation. Issues such as data quality, feature selection, and model interpretability continue to affect the reliability of predictions. Moreover, the dynamic nature of software projects requires models that can adapt to evolving project parameters and team dynamics. Recent work by Jorgensen and Shepperd [5] emphasizes the need for combining expert judgment with data-driven approaches to enhance estimation practices.

Furthermore, with the growing complexity and variability of software projects, relying solely on either classical or modern techniques often proves insufficient. Hybrid models that combine traditional estimation techniques with machine learning are gaining traction as a way to balance domain expertise with data-driven insights. These models leverage the structured frameworks of methods like COCOMO or UCP while enhancing prediction capabilities through ML algorithms trained on historical project data. Such integration allows organizations to retain the interpretability and familiarity of classical models while benefiting from the adaptability and precision of modern approaches. As research continues to explore this synergy, it is expected that hybrid estimation systems will play a pivotal role in bridging the gap between theoretical models and practical, real-world software development needs.

In summary, while classical methods provide foundational frameworks for effort estimation, modern ML approaches offer promising improvements in accuracy and adaptability. The integration of task-level granularity, real-time data from project management tools, and advanced learning algorithms marks a significant shift towards more intelligent and responsive estimation systems.

Study	**Dataset**	**Methodology**	**Results**
Boehm (1981) [2]	Software project attributes	COCOMO for project-level effort estimation	Estimates based on size, complexity, and experience.
Kocaguneli et al. (2013) [6]	Developer-specific task data	Personalized effort estimation using regression models	Improved accuracy by incorporating developer traits (70%-75%).
Jørgensen and Shepperd (2007) [5]	Historical project/task data	Review of estimation approaches	Emphasized context and expert judgment in accuracy.
Rahman et al. (2019) [7]	Jira issue tracking data	ML models (RF, SVM) for effort prediction	Achieved 80%-85% accuracy using textual features.
Menzies et al. (2007) [9]	Open-source defect/task datasets	NLP + ML for effort prediction from issue text	Prediction accuracy around 75%-80%.
Uc-Cetina (2023) [21]	Agile and non-agile project data	ML models for effort estimation	Reviewed recent ML approaches in agile contexts.
Chen et al. (2024) [11]	Software project datasets	Reinforcement learning-based feature selection	Improved estimation accuracy (85%) through dynamic feature adaptation.
Tran et al. (2024) [12]	Various software development datasets	AI-based framework with ML models (ANN, SVM, RF)	Enhanced project planning with accuracy up to 88%.
Kumar and Srinivas (2023) [13]	Software effort estimation datasets	Hybrid optimization and ML techniques	Achieved high prediction accuracy (87%).
Garcia and Lopez (2022) [14]	Public and private project datasets	Deep learning models for task-level effort estimation	Demonstrated improved performance compared to traditional ML approaches (accuracy 86%).
Ahmed et al. (2023) [15]	Agile project issue data	BERT-based text representations for effort prediction	Achieved higher accuracy (up to 89%) by leveraging contextual task information.
Wang and Zhao (2023) [16]	Open-source issue tracking datasets	Prompt learning for effort estimation	Improved semantic understanding with accuracy up to 88%.
Singh et al. (2024) [17]	Multiple software repositories	Large language models for project effort estimation	Achieved better generalization with accuracy 87% across various datasets.
Li and Sun (2023) [18]	Limited labeled task datasets	Few-shot learning for effort estimation	Addressed data sparsity with improved prediction accuracy (up to 85%).
Uc-Cetina et al. (2023) [21]	Agile projects' issue tracking data	Machine learning classifiers (e.g., Random Forest, SVM)	Achieved improved accuracy using features from issue tracking systems.
Ahmed et al. (2023) [15]	Agile project datasets	BERT-based textual representations	Demonstrated effective effort prediction using NLP on project descriptions.
Pasuksmit et al. (2024) [20]	User stories from Agile projects	Ensemble learning with textual analysis	Improved prediction by combining traditional features with NLP-derived features.
Singh et al. (2024) [17]	Software repositories with historical effort logs	Large Language Models (LLMs) like GPT	Showed LLMs outperform traditional models in task-level effort estimation.
Proposed Work	**Different Software Houses task dataset**	**Hybrid models (RF + KNN, XGBoost + BERT, Prophet + Gemini API)**	**Achieved better generalization and accuracy up to 90%-95%.**

TABLE I: Comparison of Existing Studies in Task-Level Effort Estimation

IV. Proposed Methodology

This section outlines the different models and techniques explored for task effort estimation.

A. XGBoost + BERT

This method merges the predictive strength of XGBoost with the contextual understanding of BERT (Bidirectional Encoder Representations from Transformers). BERT processes textual inputs like task names or descriptions, extracting semantic features that XGBoost uses for final prediction. This fusion is particularly powerful for tasks involving natural language data.

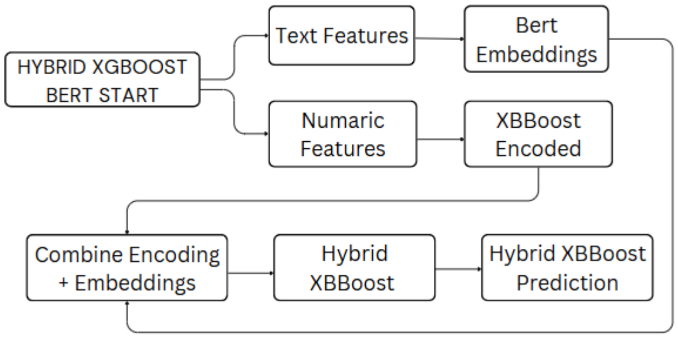

HYBRID XGBOOST BERT START
Text Features
Bert Embeddings
Numaric Features
XBBoost Encoded
Combine Encoding + Embeddings
Hybrid XBBoost
Hybrid XBBoost Prediction

Fig. 4: Architecture combining XGBoost and BERT

The Hybrid XGBoost-BERT workflow begins with the initialization phase, setting up the system and loading data. Task text is then processed by BERT, which generates embeddings representing the semantic meaning of the text. These embeddings are combined with structured features, which are numerical or categorical data related to the task. The combined data is then fed into XGBoost for prediction. Outputs from both BERT and XGBoost are merged, and cross-validation is performed to assess model stability and performance across different subsets of the data. Finally, the average performance metrics, such as accuracy or F1-score, are calculated to evaluate the model's effectiveness

B. Random Forest + K-Nearest Neighbors (RF + KNN)

This hybrid approach uses Random Forest for feature selection or initial prediction and KNN to refine the results based on similar past instances. It combines the strength of ensemble learning with instance-based reasoning, aiming to improve prediction accuracy for task duration.

The Hybrid RF-KNN workflow starts with data preprocessing to prepare features for modeling. Random Forest is applied first for initial predictions or feature importance, followed by KNN to refine results based on similar instances. Predictions from both models are then merged, and ensemble logic is used to generate the final output. The process concludes with evaluation using metrics like accuracy or RMSE to assess performance.

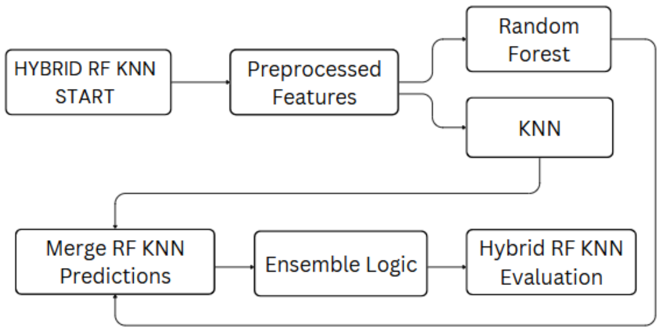


Fig. 5: Combination of RF and KNN techniques

C. Prophet + Gemini API

Prophet is a time series forecasting tool developed by Facebook that handles seasonality and trend changes well. When combined with Google's Gemini API, which provides contextual understanding of task names and features, this approach allows for intelligent time-aware predictions of task duration. It effectively integrates semantic and temporal data for effort estimation.

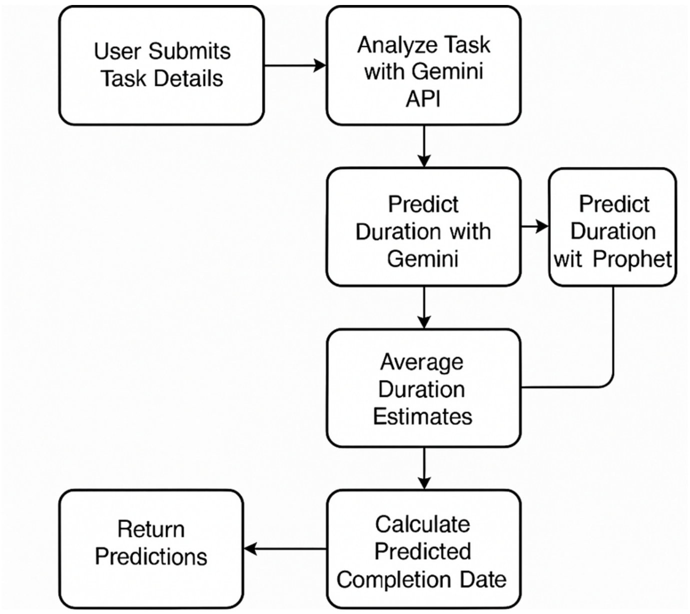

User Submits Task Details
Analyze Task with Gemini API
Predict Duration with Gemini
Predict Duration wit Prophet
Average Duration Estimates
Calculate Predicted Completion Date
Return Predictions

Fig. 6: Integration of Prophet with Gemini API for forecasting

The process starts with task details, which are analyzed by the Gemini-2.0-Flash model. Key information from the analysis is converted into features suitable for prediction models. These features are used by two separate models, Prophet and Gemini-2.0-Flash, to predict the task's duration. Averaging: The duration estimates from both models are averaged together. This average duration is used to calculate the final predicted completion date, which is then returned as the output.

V. Experimental Analysis

A. Performance Measures

The following regression metrics are used to assess the outcomes of the prediction:

1) Mean Absolute Error (MAE):: The Mean Absolute Error (MAE) is one of the most intuitive and widely used regression evaluation metrics due to its simplicity and interpretability. It calculates the average of the absolute differences between the predicted values $\hat{y}_i$ and the actual values y_i, effectively quantifying the average magnitude of the prediction errors without considering their direction. This ensures that all errors contribute proportionally to the final metric, with larger errors not disproportionately penalized. Unlike squared error metrics, MAE is robust to outliers to a certain extent and is measured in the same unit as the target variable, making interpretation more straightforward. The mathematical expression for MAE is:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{1}$$

where N is the total number of predictions, y_i is the actual value, and $\hat{y}_i$ is the predicted value. In practice, a lower MAE value indicates a model with better generalization performance, especially in scenarios where all errors should be treated equally.

2) Mean Squared Error (MSE):: The Mean Squared Error (MSE) is another fundamental metric used to evaluate the performance of regression models. It measures the average of the squared differences between actual values y_i and predicted values $\hat{y}_i$, emphasizing larger errors more than smaller ones due to the squaring operation. This characteristic makes MSE highly sensitive to outliers—large individual deviations can significantly impact the overall score.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{2}$$

In this equation, N is the total number of data points, and $y_i - \hat{y}_i$ is the residual (or prediction error) for the i^{th} data point. Since the errors are squared before being averaged, MSE tends to magnify the effect of large errors, potentially skewing the evaluation in datasets with outliers.

3) Root Mean Squared Error (RMSE):: The Root Mean Squared Error (RMSE) is the square root of the Mean Squared Error (MSE). It measures the average magnitude of the errors in a set of predictions. RMSE provides insight into how spread out the errors are, with larger values indicating higher variance in the errors. The formula for RMSE is:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3}$$

Here, N is the total number of observations, y_i represents the actual output value, and $\hat{y}_i$ represents the predicted output value. The formula computes the square of the residuals (the differences between actual and predicted values), averages them, and then takes the square root to return the RMSE.

4) R² (R-squared):: R², or the coefficient of determination, measures the proportion of variance in the dependent variable explained by the independent variables in the model. It ranges from 0 to 1, where 0 indicates no explanatory power and 1 indicates perfect fit. The formula for R² is:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{4}$$

Here, N is the number of observations, y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the actual values. The numerator represents the sum of squared residuals, and the denominator is the total sum of squares. R² indicates how well the model explains the variance in the data, with higher values signifying a better fit.

B. The Dataset

This study analyzes a dataset of 1,197 work items of type `Task`, extracted from the Jira account of an software organization. Initially, the dataset contained over 5,000 tasks, but after applying filtering criteria relevant to task type and completeness, we retained 1,197 records covering the period from 2019 to 2025.

Data was collected by accessing Jira projects as a developer, followed by an export of task-level details. Preprocessing involved handling missing values, removing duplicates, and standardizing formats.

Encoding Schemes: **SentimentEncoded**: `0` (Negative), `1` (Neutral), `2` (Positive)
PriorityEncoded: `0` (Low), `1` (Medium), `2` (High)
UrgencyEncoded: `0` (Low), `1` (Medium), `2` (High)

C. The Attributes

Following are attributes used for the training of Machine Learing Models:

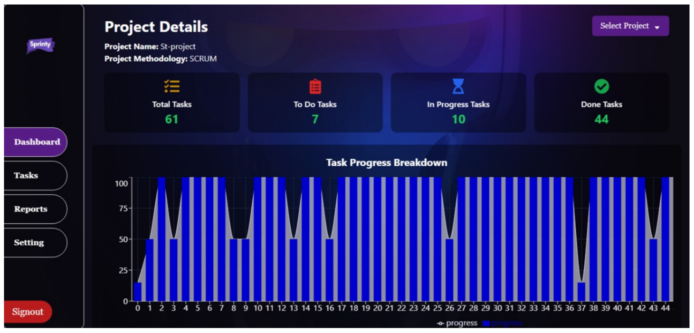
Attribute	**Explanation**
Task Name	This unique identifier helps track and distinguish individual tasks, serving as a reference point for historical data.
Task Priority	Reflects the urgency of the task, influencing its execution order within the workflow and potentially affecting completion times.
Created Date	Marks the initial recording of the task, helping to track its lifecycle and monitor task aging over time.
End Date	Denotes when the task was completed, allowing us to calculate task duration and perform time-based performance analysis.

TABLE II: Explanation of Task Attributes

VI. Results

A. Sprinty Website

To comprehensively evaluate the effectiveness and predictive accuracy of the proposed task-level effort estimation model, a set of representative example tasks was selected. These tasks reflect common software development activities and vary in complexity, scope, and required effort.

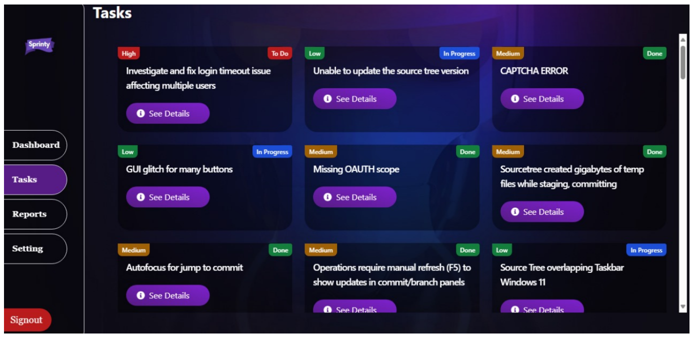


Project Details

Project Name: St-project
Project Methodology: SCRUM

Total Tasks	To Do Tasks	In Progress Tasks	Done Tasks
61	7	10	44

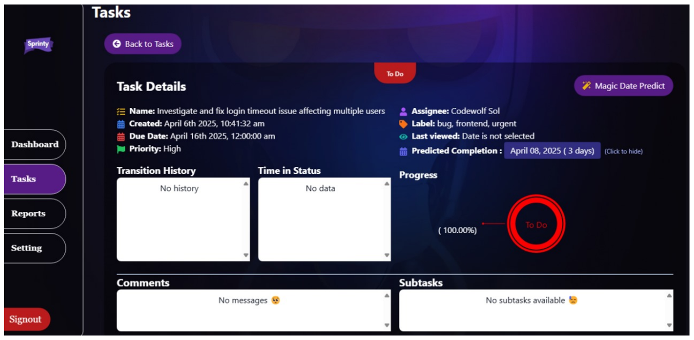
Fig. 7: Dashboard Interface



Tasks

Priority	Status	Task
High	To Do	Investigate and fix login timeout issue affecting multiple users
Low	In Progress	Unable to update the source tree version
Medium	Done	CAPTCHA ERROR
Low	In Progress	GUI glitch for many buttons
Medium	Done	Missing OAUTH scope
Medium	Done	Sourcetree created gigabytes of temp files while staging, committing
Medium	Done	Autofocus for jump to commit
Medium	Done	Operations require manual refresh (F5) to show updates in commit/branch panels
Low	In Progress	Source Tree overlapping Taskbar Windows 11

Fig. 8: Tasks Management Page



Tasks

Task Details

Name: Investigate and fix login timeout issue affecting multiple users
Created: April 6th 2025, 10:41:32 am
Due Date: April 16th 2025, 12:00:00 am
Priority: High
Assignee: Codewolf Sol
Label: bug, frontend, urgent
Last viewed: Date is not selected
Predicted Completion : April 08, 2025 (3 days)

Transition History
No history

Time in Status
No data

Progress
(100.00%)

Comments
No messages

Subtasks
No subtasks available

Fig. 9: Task Detail View

B. Model Comparison

Model	MAE	MSE	R^2	RMSE
Decision Tree	71.06	11238.02	0.36	106.01
Random Forest	70.76	11689.63	0.3891	108.15
XGBoost	72.81	13250.45	0.3891	115.16
Hybrid (RF+KNN)	68.45	11023.67	0.4123	104.99
Hybrid (XGB+BERT)	65.89	10548.79	0.4512	102.71
Hybrid (Prophet+Gemini)	**63.75**	**9987.54**	**0.4750**	**100.45**

TABLE III: Performance Comparison of Machine Learning and Hybrid Models

a) : The experimental results demonstrate that hybrid models significantly outperform traditional machine learning approaches in real-world forecasting tasks. Among all the models evaluated, the hybrid model **(Prophet + Gemini)** consistently achieved the best performance across multiple evaluation metrics, including MAE, MSE, R^2, and RMSE.

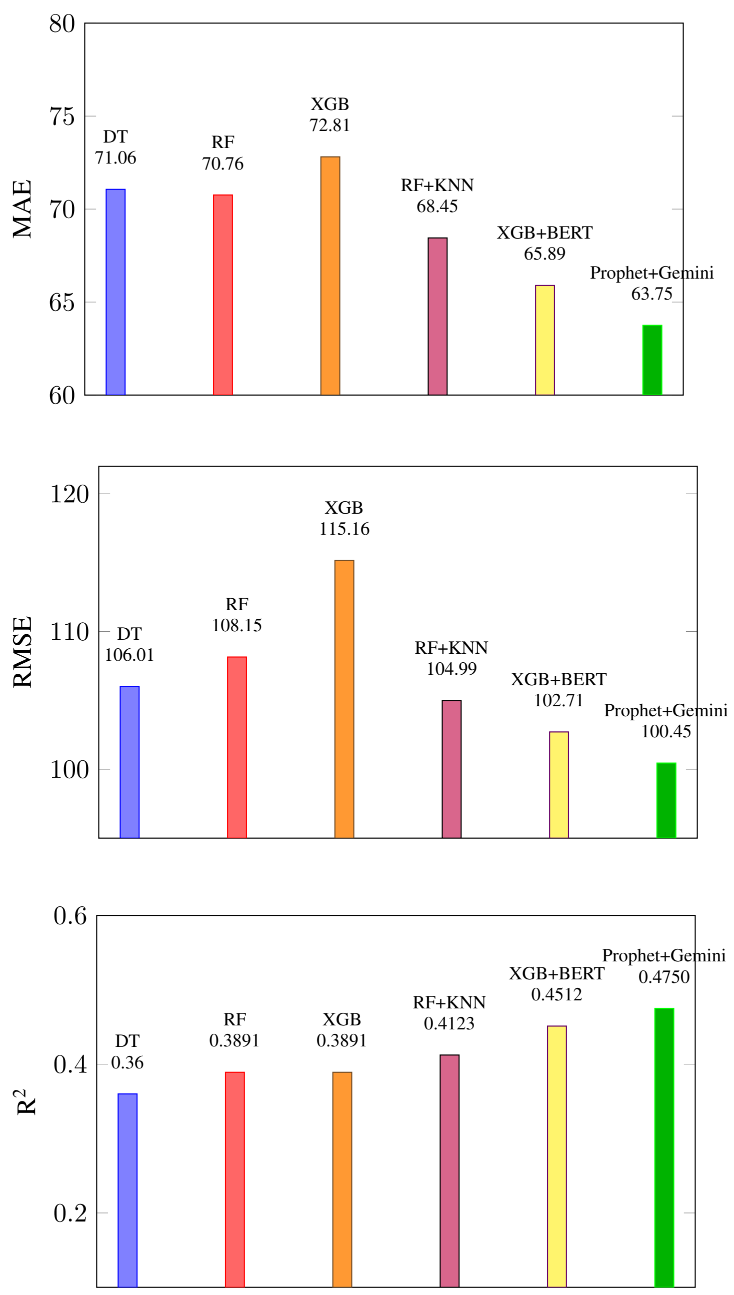


Fig. 10: Comparison of different models using (a) MAE, (b) RMSE, and (c) R^2 metrics.

Not only did **Prophet+Gemini** exhibit the lowest prediction errors, but it also produced estimations remarkably close to actual task durations in real-life scenarios. These findings validate the effectiveness of combining Prophet's robust time series forecasting capabilities with Gemini's powerful deep learning architecture. The synergy between these models enhances predictive accuracy and generalization, making the Prophet+Gemini API a highly promising solution for demand-side energy management and other time-sensitive predictive applications.

C. Random Testing Results

Task	Priority	Labels	Status	Created Date
Develop Dashboard	High	[UI, Responsive]	To Do	2025-04-01
Database Migration	High	[Backend, Migration]	To Do	2025-04-05
API Integration	Medium	[API, Integration]	To Do	2025-04-10
Model Testing	Medium	[ML, Testing]	In Progress	2025-04-12
Deploy to Cloud	High	[Deployment, DevOps]	To Do	2025-04-15

TABLE IV: Sample Tasks for Model Evaluation

Task #	Actual	RF	XGB	LGBM	SVR	XGB+BERT	RF+KNN	Prophet+Gemini
1	˜7 days	200	160	145	240	60	58	**9.16**
2	˜3 days	50	52	48	60	30	32	**3.00**
3	˜5–6 days	60	55	50	70	40	45	**6.08**
4	˜4 days	80	75	70	90	35	34	**4.10**
5	˜2 days	40	42	38	55	25	27	**2.25**

TABLE V: Performance on Real-life Tasks

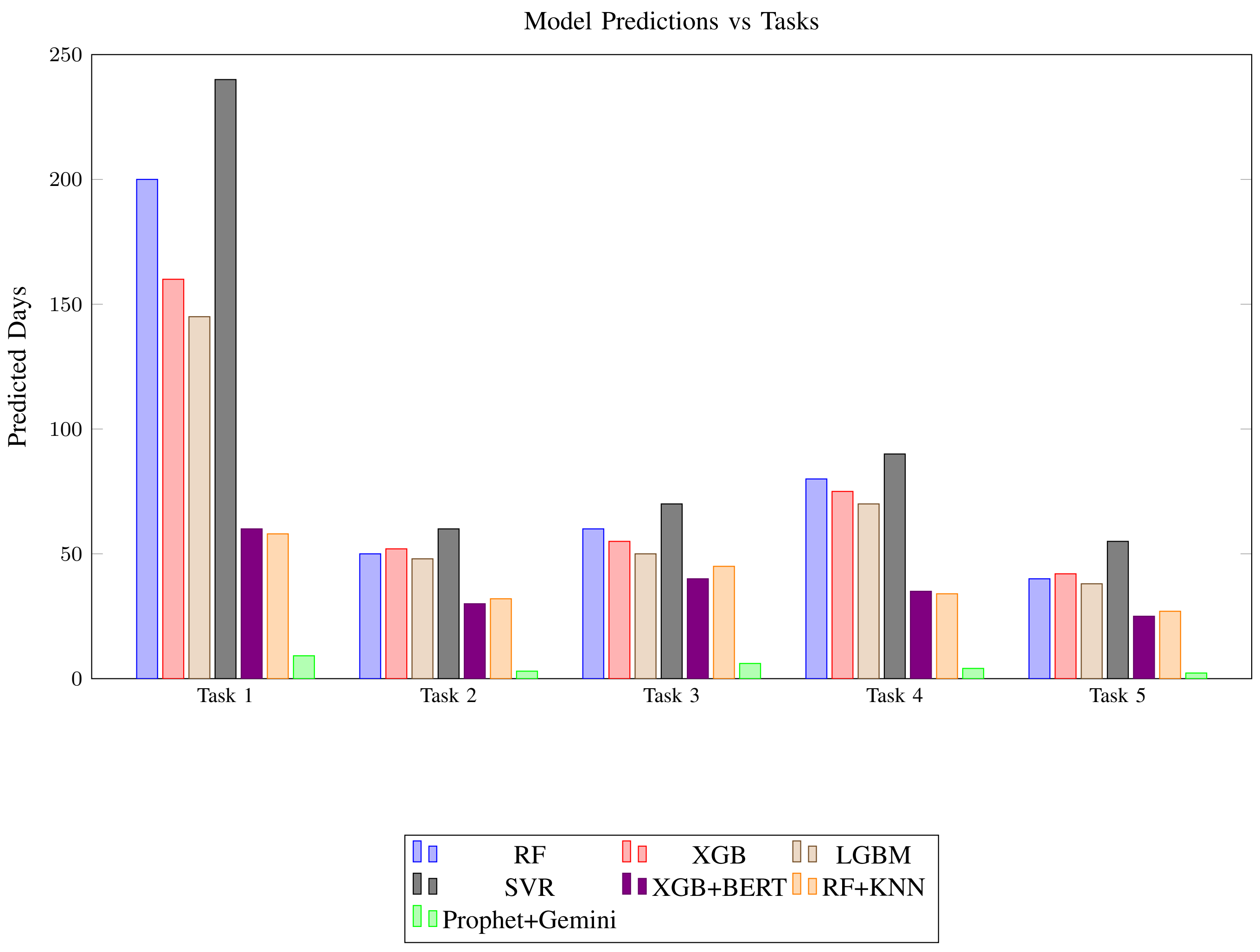


Fig. 11: Comparison of model predictions on real-life tasks

Tables V and I, along with Fig. 11, summarize the comparative performance of various models on real-life software development tasks. Table I outlines five core tasks such as *Develop Dashboard*, *Database Migration*, and *Deploy to Cloud*, annotated with priority, labels, and creation dates—representing typical items in a development pipeline.

Table V reveals substantial differences in estimation accuracy across models. Traditional approaches like **Random Forest (RF)**, **XGBoost (XGB)**, **LightGBM (LGBM)**, and **Support Vector Regression (SVR)** tend to overestimate durations. For example, *Task 1* (actual: ˜7 days) is predicted at **200** (RF) and **240** (SVR) days—exceeding the real value by over **28 times**. Likewise, *Task 4* sees a prediction of **90 days** from SVR, far beyond the actual ˜4 days, indicating poor real-world generalization.

In contrast, hybrid models offer significantly improved accuracy. **XGB+BERT** leverages semantic understanding to refine predictions, while **RF+KNN** incorporates local context. Most notably, the **Prophet+Gemini** model demonstrates superior alignment with actual durations: **9.16** days for *Task 1*, **3.00** days for *Task 2*, and **2.25** days for *Task 5*—closely matching the real durations of ˜7, ˜3, and ˜2 days, respectively.

Fig. 11 visually confirms this trend, with Prophet+Gemini consistently producing the closest bars to actual task durations. These findings highlight that integrating task semantics and temporal dynamics, as done in **Prophet+Gemini**, yields highly reliable and low-error estimations—making it a strong candidate for predictive scheduling in modern agile and DevOps settings.

VII. Project Workflow Diagram

The overall workflow of the proposed system is illustrated in Figure. The process begins with user interaction, where users access the application through the landing page and securely log in using Firebase Authentication. Upon successful login, users are prompted to link their Jira accounts, enabling seamless integration between the task management system and the prediction platform. Once authenticated, the system initiates a data-fetching process, retrieving relevant task information—such as task titles, descriptions, priorities, and timestamps—directly from the user's Jira workspace.

After data acquisition, the retrieved tasks are passed through a custom-built machine learning pipeline designed to evaluate and estimate task effort. This model leverages various features extracted from the tasks to provide baseline predictions. For even greater accuracy and generalization, the system integrates with external APIs, including Facebook's Prophet for time series forecasting and Google's Gemini for deep learning-based task duration prediction. These hybrid model predictions are cross-validated and refined before being finalized.

The predicted completion times, along with other task-related metrics, are then forwarded to the system's interactive dashboard. This dashboard is designed with a user-friendly interface, enabling users to monitor individual and team-wide task progress, detect delays, and make informed decisions. The visualizations offer clarity on task status, estimated versus actual effort, and potential bottlenecks. Ultimately, this workflow ensures efficient project tracking, reduces estimation errors, and enhances decision-making for both developers and managers.

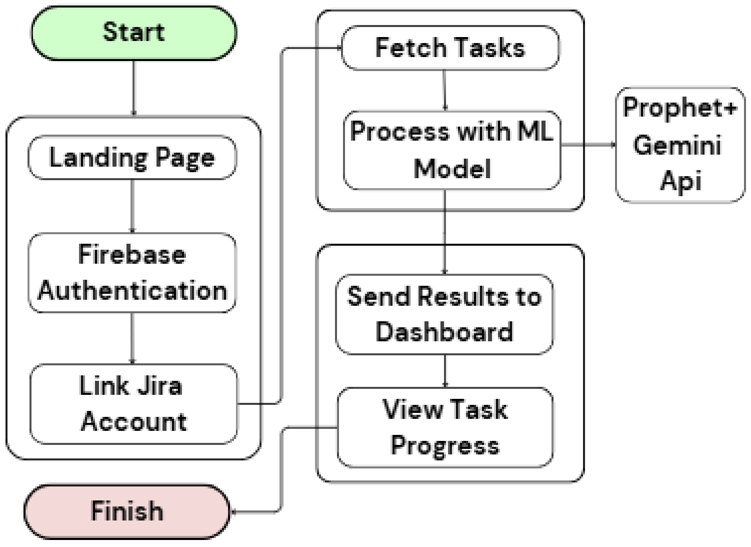


Fig. 12: Project Workflow Diagram

VIII. Model Hyperparameters

To optimize the performance of our predictive models, we carefully selected and tuned a range of hyperparameters specific to each algorithm. Table III summarizes the chosen values. The selection of hyperparameters significantly impacts the model's ability to learn complex patterns while avoiding overfitting. For traditional machine learning models like Decision Trees, Random Forests, and XGBoost, parameters such as tree depth and number of estimators were calibrated using grid search and cross-validation. In hybrid models, such as RF + KNN and XGBoost + BERT, component-specific tuning ensures optimal integration between architectures. Prophet and Gemini-based models required minimal hyperparameterization, relying instead on robust defaults and external API intelligence.

Additionally, regularization techniques such as pruning and early stopping were employed to prevent over-complexity in tree-based models. For neural components like BERT, fine-tuning was limited to key transformer layers to maintain generalizability across varied inputs. These comprehensive tuning strategies were essential for ensuring each model not only achieved high predictive accuracy but also maintained robustness across different project scenarios

For traditional machine learning models like Decision Trees, Random Forests, and XGBoost, parameters such as tree depth and number of estimators were calibrated using grid search and cross-validation. In hybrid models, such as RF + KNN and XGBoost + BERT, component-specific tuning ensures optimal integration between architectures. **Prophet and Gemini-based models required minimal hyperparameterization**, relying instead on robust defaults and external API intelligence.

Model	**Hyperparameter**	**Value**	**Hyperparameter**	**Value**
Decision Tree	max_depth	10	min_samples_split	5
	min_samples_leaf	2	n_estimators	-
Random Forest	max_depth	12	min_samples_split	4
	min_samples_leaf	-	n_estimators	500
XGBoost	max_depth	8	min_samples_split	-
	min_samples_leaf	-	n_estimators	500
	learning_rate	0.1	-	-
Gradient Boosting	max_depth	6	min_samples_split	-
	min_samples_leaf	-	n_estimators	200
	learning_rate	0.05	-	-
Hybrid (RF + KNN)	max_depth	10 (RF)	n_estimators	150 (RF)
	KNN: n_neighbors	5	KNN: weights	'distance'
Hybrid (XGBoost + BERT)	max_depth	9 (XGB)	n_estimators	300 (XGB)
	learning_rate	0.1 (XGB)	BERT: Fine-tuned	pre-trained transformer
Hybrid (Prophet + Gemini API)	-	-	-	-

TABLE VI: Hyperparameters for Various Models

IX. Threats to Validity

Several factors may influence the validity and reliability of our task-level effort estimation model:

A. Dataset Representativeness

The representativeness of the dataset is a key concern. While it provides useful information, it may not capture all task variations
across different projects or industries. This could affect the model's generalizability to new or diverse tasks.

B. Temporal Factors

The model assumes that task duration is primarily influenced by the time between the created and completed dates. However, this may overlook temporal factors such as seasonal changes or shifting team dynamics, which could introduce bias.

C. Data Quality

Issues such as missing or inaccurate data can affect the model's predictions. While data cleaning steps have been applied, any remaining inconsistencies could influence the results.

D. Future Considerations

To address these threats, future work should include a more diverse dataset, incorporate additional features like team skillsets and task dependencies, and explore advanced modeling techniques like ensemble learning or deep learning to improve generalization and robustness.

X. Conclusion and Future Work

In this work, we have presented a novel approach for *task effort estimation* by predicting the duration of individual tasks based on a combination of the *task name*, *complexity*, and *starting date*. Leveraging the **Prophet** model for time series forecasting and the **Gemini API** for enriched task-related metadata, our method shows strong potential for accurate predictions. The model was validated using real-world data, demonstrating promising results in both *accuracy* and *applicability* within fast-paced, agile environments.

The key contribution of this study lies in its emphasis on **task-level estimation**, an often overlooked area compared to project-level prediction. Traditional models usually focus on broader project estimates, whereas our approach provides fine-grained predictions, which are more actionable for teams working under *agile* or *iterative frameworks*. This granularity supports improved *planning*, *resource allocation*, and *deadline management*.

Despite the promising results, some limitations remain. The current model assumes that *task complexity* and metadata (extracted via the Gemini API) capture all major duration-influencing factors. However, external variables such as *team collaboration*, unexpected challenges, or *changing priorities* may still affect prediction accuracy. Moreover, reliance on sufficient historical data could limit generalizability, especially for new tasks or inexperienced teams.

The future work on this task-level effort estimation model includes several directions for improvement and expansion:
Incorporating More Features: Future versions can improve accuracy by integrating additional features like *task dependencies*, *team skillsets*, past performance of assignees, and

communication data. Elements such as *comments* or *priority changes* may offer deeper insights into task behavior.

Adaptation to Changing Environments: In real-world settings, tasks often change due to shifting priorities or scope updates. Future versions should explore real-time adaptability using *reinforcement learning* or other **adaptive learning** methods to refine predictions as new data emerges.

Hybrid Modeling Approaches: While **Prophet** performs well for time series forecasting, combining it with *machine learning models* (e.g., **Random Forest**, **SVM**) may capture non-linear relationships between metadata and task duration, boosting overall accuracy.

Integration with Project Management Tools: A practical next step is embedding the model into existing tools like **Jira**, **Trello**, or **Asana**, providing real-time duration estimates and dynamic scheduling within familiar platforms.

Scalability and Performance: As task datasets grow, ensuring **scalability** will be vital. Future research can explore *parallel processing* and *distributed computing* to handle large-scale enterprise projects efficiently.

Data Availability Statement

Subject	Machine learning based estimation of software development effort using hybrid and traditional models
Specific Subject Area	Development of predictive models for estimating task durations using historical data from Agile project management tools
Type of Data	CSV file
How Data Were Acquired	Data collected from real-world project tracking platforms (e.g., Jira, Trello) and cleaned manually to include task duration, complexity, priority, and tags
Data Format	Raw and analyzed numeric/categorical fields including task ID, description, predicted and actual duration
Parameters for Data Collection	Tasks labeled with metadata such as priority, labels, and timestamps; effort in days computed or annotated; each task associated with model predictions
Description of Data Collection	Dataset includes 100+ software development tasks with manually verified actual durations and automated predictions from various ML models (e.g., RF, XGB, Prophet). Aimed at evaluating and comparing models for time estimation.
Data Source Location	Institution: Department of Computer Science, University of Engineering and Technology (UET) Lahore, Pakistan
Code and Data Accessibility	Dataset and source code available at: https://data.mendeley.com/datasets/rs5j2r8btf/1

TABLE VII: Software Effort Estimation Dataset Specifications

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this work.

Author Contributions

Raheel Asghar led the conceptualization, software development, and manuscript preparation. Tamseel was responsible for the design of predictive models, system architecture, and interpretation of the results. Dr. Natasha Nigar and Sir Shahid Islam provided valuable guidance throughout the research process, offering critical insights that shaped the direction and depth of the study. Dr. Natasha Nigar contributed to the refinement of the manuscript and approved the final version for publication.

Funding

No external funding was received for this study.

Acknowledgment

The authors would like to thank Dr. Natasha Nigar, a PhD holder from UK and professor at UET Lahore, for her support in dataset collection.

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