
EFFECTIVE SOFTWARE EFFORT ESTIMATION LEVERAGING MACHINE LEARNING FOR DIGITAL TRANSFORMATION

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ABSTRACT

Today, digital reviews play a pivotal role in enhancing global communications among consumers and influencing consumer buying patterns. E-commerce giants like Amazon, Flipkart, etc. provide a platform to consumers to share their experience and provide real insights about the performance of the product to future buyers. In order to extract valuable insights from a large set of reviews, classification of reviews into positive and negative sentiment is required. Sentiment Analysis is a computational study to extract subjective information from the text. In the proposed work, over 4,000,00 reviews have been classified into positive and negative sentiments using Sentiment Analysis. Out of the various classification models, Naïve Bayes, Support Vector Machine (SVM) and Decision Tree have been employed for classification of reviews. The evaluation of models is done using 10 Fold Cross Validation.

1. INTRODUCTION

1.1. ABOUT THE PROJECT

The implementation of digital transformation [1] in industries is made possible, in large part, by the use of industrial software systems. The term “digital transformation” refers to the practice of adopting and integrating digital technology [2] into many elements of corporate operations, processes, and models in order to promote innovation, enhance efficiency, improve business performance and development and obtain a competitive edge. Industrial software systems are specialized software programs that have been built for industrial and manufacturing environments. These applications offer the foundation for digitizing and automating essential activities in a variety of industries [3], including but not limited to corporate [4], manufacturing, logistics, energy, and transportation.

The following are some of the ways that industrial software systems make digital transformation possible [5]: Automation of processes; Industrial software systems make it possible to automate a wide variety of business processes, including production planning and scheduling, inventory management, quality control, and supply chain management. Data Management and Analytics; it makes it easier to integrate and connect a variety of different devices, systems, and procedures inside an industrial setting. They make it possible for the many components of an industrial ecosystem, such as sensors, machines, control systems, and enterprise resource planning (ERP) systems, to communicate with one another and share data and information with one another [6].

Remote Monitoring and Control, as well as Predictive Maintenance, are a couple of the ways that equipment failures and downtime can be anticipated and avoided. These systems are able to spot trends and abnormalities that suggest probable failures by analyzing historical data and monitoring real-time data from industrial assets. This enables proactive maintenance and minimizes unplanned downtime. The production of digital twins, which are digital replicas of physical assets, processes, or systems, is made possible by industrial software systems. The ability to simulate, model, and conduct analysis on real-world scenarios is made possible by digital twins. This assists in the optimization of design, as well as predictive maintenance and performance optimization.

OBJECTIVE

- The project identifies the importance and impact of software effort estimation in the process of digital transformation.

- The project explored the datasets in the field of SEE which are associated with the digitization of the industrial software system.
- The machine learning and ensemble learning models are applied on the dataset, in order to obtain higher accuracy in terms of effort estimates.
- Later, the project explains the impact of effective effort estimation in product engineering and industrial software systems.

Architecture Diagram

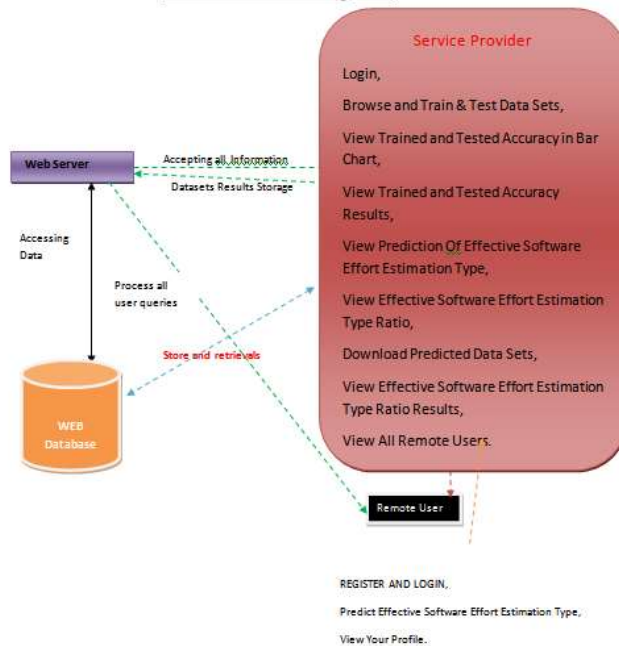


Fig.1.1: System Architecture

1.2 MODULES

1.2.1 Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as

- Login,
- Browse and Train & Test Data Sets,
- View Trained and Tested Accuracy in Bar Chart,
- View Trained and Tested Accuracy Results,
- View Effort Prediction,
- View Effort Prediction Type Ratio,
- Download Predicted Data Sets,
- View All Remote Users,

1.2.2. Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like

- Register and login
- Browse and Train & Test Data Sets,
- View Trained and Tested Accuracy in Bar Chart,
- View Trained and Tested Accuracy Results,

- View Effort Prediction,
- View Effort Prediction Type Ratio,
- Download Predicted Data Sets

2. LITERATURE SURVEY

A literature survey or literature review is the study of references and old algorithms that we have read for designing the proposed methods. It also helps in reporting summarization of all the old references papers, and their drawbacks. The detailed literature survey for the project helps in comparing and contrasting various methods, algorithms in various ways that have implemented in the research.

"Enhancing Software Effort Estimation through Reinforcement Learning-based Project Management-Oriented Feature Selection"

Authors: Haoyang Chen, Botong Xu, Kaiyang Zhong

Summary: This study investigates the application of reinforcement learning algorithms for feature selection to improve the accuracy of software effort estimation. The authors propose a solution that leverages the data element market and reinforcement learning-based algorithms to enhance estimation precision, addressing challenges faced by traditional methods.

arXiv

"Enhancing Software Effort Estimation Through Stacked Deep Learning Models"

Authors: Beesetti Kiran Kumar, Saurabh Bilgaiyan, Bhabani Shankar Prasad Mishra

Summary: This research explores the use of stacked deep learning models for software effort estimation. The authors employ ensemble learning techniques to combine multiple base models, aiming to mitigate individual weaknesses and improve overall prediction accuracy. The study demonstrates the effectiveness of this approach in enhancing forecast precision and resilience in software project management.

IJISAE

"Automated Software Effort Estimation for Agile Development System by Heuristically Improved Hybrid Learning"

Authors: Neha Gupta, Rajendra Prasad Mahapatra

Summary: This article introduces a novel framework for software effort estimation in agile development using a heuristically improved hybrid learning model. The proposed method integrates deep belief networks and artificial neural networks, with weight optimization performed through a combination of forest optimization and moth-flame optimization algorithms. The approach aims to enhance estimation accuracy by addressing the limitations of traditional forecasting measures.

Wiley Online Library

"Incorporating Statistical and Machine Learning Techniques into the Optimization of Correction Factors for Software Development Effort Estimation"

Authors: Nguyen Thi Nhung, Pham Thi Thu Hien, Nguyen Thi Thu Thuy

Summary: This study explores the integration of statistical and machine learning techniques to optimize correction factors in software development effort estimation. The authors analyze various models, including multilayer perceptron, support vector regression, decision tree, and random forest, to model the relationship between effort and software variables, particularly in non-linear contexts. The research highlights the effectiveness of these techniques in improving estimation accuracy.

Wiley Online Library

"An Effective Approach for Software Project Effort and Duration Estimation with Machine Learning Algorithms"

Authors: Piotr Pospieszny, Bożena Czarnačka-Chrobot, Andrzej Kobylinski

Summary: This project presents an approach to software project effort and duration estimation utilizing machine learning algorithms. The authors focus on improving the accuracy of predictions by applying various machine learning techniques, demonstrating their effectiveness in estimating both effort and project duration

3. ANALYSIS

3.1. EXISTING SYSTEM

Uses traditional machine learning models for software effort estimation. Relies on single or basic ensemble models for predictions. Limited adaptability to different datasets and project environments. Often lacks optimization techniques to enhance prediction accuracy.

3.1.1 Limitations in Existing System

- Low accuracy and reliability in effort estimation.
- Struggles with generalization across different datasets.
- Cannot dynamically adjust the model selection process.
- Limited improvement in evaluation metrics due to static approaches.

3.2. PROPOSED SYSTEM

Introduces an Omni-Ensemble Learning (OEL) approach. Combines static ensemble selection with a genetic algorithm and dynamic ensemble selection. Enhances model selection and prediction robustness. Evaluates the proposed approach using Finnish and Maxwell datasets. Outperforms traditional machine learning models in software effort estimation.

3.2.1. Features of the Proposed System

- Provides higher accuracy in effort estimation.
- Adaptable to different datasets and project requirements.
- Dynamic ensemble selection improves prediction performance.
- Utilizes genetic algorithms for better optimization.
- Outperforms existing machine learning models in evaluation metrics.

4. SAMPLE SCREENS

ID	Name	Duration	Budget	Effort	Cost	Category	Effort	Cost	Effort	Cost					
1	1.72.227.5. P&C Admin	1,214+00	25,782	20	4	4.3	0.55	00	Harmon	10	5	10	1	1004	0
2	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Shadokh	10	5	10	1	100	0
3	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Weather	10	5	10	1	10	0
4	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Shipping	10	5	10	1	10	0
5	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
6	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
7	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
8	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
9	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
10	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
11	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
12	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
13	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
14	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
15	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
16	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
17	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
18	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
19	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
20	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
21	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
22	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
23	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
24	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
25	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
26	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0
27	1.72.227.5. P&C Admin	1,214+00	10,000	20	4	5.5	0.2	00	Reference	10	5	10	1	10	0

Screen : Home Page of Project



Screen: ML Accuracy using various ML classifiers



Screen : Pie Graph Showing MI Accuracy

ID	Item Name	Actual Effort	Predicted Effort	Accuracy	Confidence	Category		
172.217.10.42-10.42.8.42-443-34889-8	oRay- Best App to Get Soft. Soutel Shopping	128512008	352241	94.8	4	4.5	5.10.8 12+	Shopping
183.171.83.222-10.42.8.751-80-48812-8	PGate- The Best Calculator	48258304	1117	4	4.5	5	3.6.8 4+	Utilities
10.42.8.151-78.135.27.188-3793-9229-8	Ms. PRO-MAN	78023168	7885	40	4	4	4.8.4 4+	Games
216.58.218.202-10.42.8.751-442-30582-8	WeatherPro	88670640	1572	34	4	4.5	4.8.2 4+	Weather
SORABBIT		777547136	1059343	100	3.5	3.5		

Screen : List of Preidctions

Screen : Profile Ratio

Username	IP Address	Country	Profile
user	10.42.8.151	USA	Profile
admin	10.42.8.151	USA	Profile
root	10.42.8.151	USA	Profile

Screen : List of User Profiles



Screen : User Prediction Page

5. CONCLUSION AND FUTURE SCOPE

Software effort estimation is required for software development projects associated with industrial software systems and initiatives for digital transformation. Digital transformation is the process of incorporating digital technology into various aspects of a business or organization in order to enhance operations, procedures, consumer experiences, and overall performance. Industrial software systems are software programs that have been instructed for use in industrial and manufacturing processes. The software development industry continues to face difficulties with software effort estimation. Planning, allocating resources, and finishing a project successfully are all affected by how effectively one can estimate how much effort is required. Researchers are looking for ways to incorporate AI and automation technologies into software effort estimation as the software business develops. The purpose of this project is to develop an effective and robust model for predicting effort based on machine learning

FUTURE SCOPE

In future, we intend to apply same model on some other datasets with more impacted features towards digital transformation. Also we will implement an hybrid model for estimating effort, in order to reduce the challenges faced by decision makers in software companies. This project provides an example of how the technology can be used to automate industrial software systems and society. This project is an effort to enhance and digitize society, a step towards digital transformation, establish the concept of intelligent software systems, and contribute to developing these technologies

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