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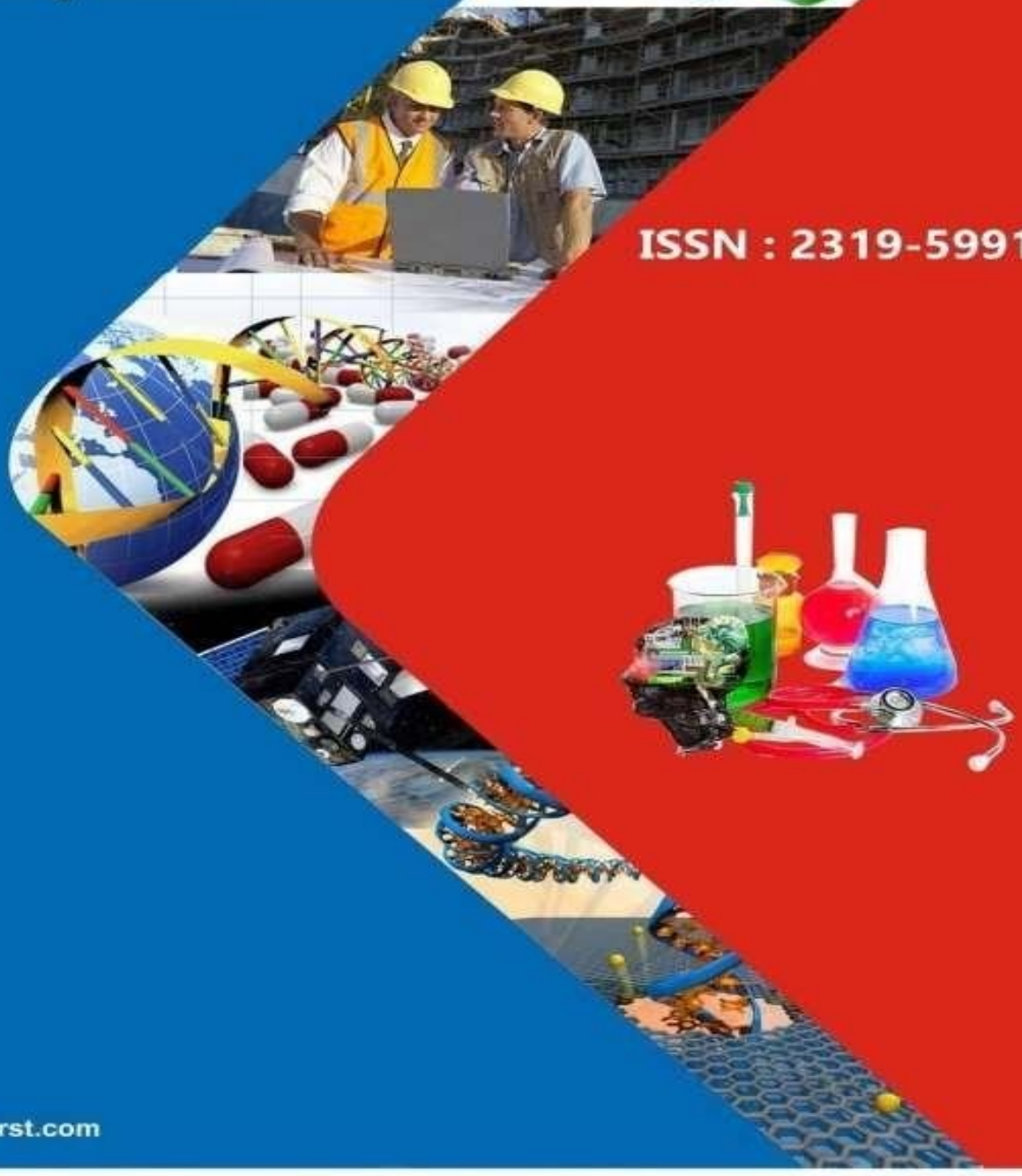

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FEPP: IMPROVING SOFTWARE REQUIREMENTS RISK PREDICTION THROUGH HYBRID RULE EXTRACTION AND MULTI-CLASS LEARNING

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ABSTRACT

Predicting risks in software requirements, a critical and vital component of the Software Development Life Cycle (SDLC), is challenging due to the growing complexity of software projects. An inability to properly predict such risks may result in the failure of a software project. Risk prediction is more important in software requirements as it is the first phase of any software project. Therefore, this study proposes a unique approach for risk prediction in software requirements called ForExPlusPlus (FEPP). The proposed model is benchmarked against standard models including K-nearest Neighbour (KNN), Naïve Bayes (NB), Logistic Model Tree (LMT), Random Forest (RF), and Support Vector Machine (SVM). These models are trained using the Zenodo repository dataset, and the outcomes are assessed using common evaluation standards. The precision, F-measure (FM), and Mathew's correlation coefficient (MCC) are used to critically evaluate the models' accuracy analysis. The Kappa Statistic (KS) and Mean Absolute Error (MAE) are used to evaluate the error rate. With an accuracy of 96.84%, the recommended FEPP outperforms KNN, which has the lowest accuracy of 50.99%.

I. INTRODUCTION

In software engineering, anticipating and controlling risks throughout the development process is essential to project success. The capacity to identify and manage any risks early in the project lifecycle is crucial as software systems get more sophisticated. Determining the possibility of problems like project delays, functional failures, security flaws, and other significant difficulties that might occur during development depends heavily on risk prediction. Current software risk prediction techniques, however, often depend on static models, which may restrict their capacity to identify new hazards or adjust to changes in the project environment. In order to fill this gap, the study "FEPP: Advancing Software Risk Prediction in Requirements Engineering Through Innovative Rule Extraction and Multi-Class Integration" proposes a novel framework that makes use of state-of-the-art methods like rule extraction and multi-class classification in order to more precisely forecast risks during the requirements engineering stage. The suggested method seeks to enhance the early identification of software hazards in order to promote proactive risk management, improved decision-making, and eventually more successful software projects. This solution aims to provide software developers a more reliable and flexible tool so they may foresee problems before they happen and take the necessary action.

1.1. Purpose Of The Project

In the requirements engineering stage of the Software Development Life Cycle (SDLC), where early risk identification is essential to software project success, the goal of this research is to improve the precision and dependability of risk prediction. Traditional risk prediction techniques often fail to uncover complex and dynamic risk variables because of the increasing complexity of software systems. In order to solve this, the research presents

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ForExPlusPlus (FEPP), a revolutionary model that enhances risk prediction capabilities by combining cutting-edge rule extraction approaches with multi-class classification methodologies. Using a publicly accessible dataset from the Zenodo repository, the performance of FEPP is compared to that of common machine learning models, such as K-Nearest Neighbour (KNN), Naïve Bayes (NB), Logistic Model Tree (LMT), Random Forest (RF), and Support Vector Machine (SVM). Performance analysis uses evaluation measures including Mean Absolute Error (MAE), F-measure, Mathew's correlation coefficient (MCC), Kappa Statistic (KS), and accuracy. With an astounding accuracy of 96.84%, the results demonstrate that FEPP performs much better than baseline models, indicating its potential as a strong instrument for proactive risk management in software requirements engineering.

1.2. EXISTING SYSTEM

Software engineering risk prediction systems now in use often depend on conventional risk management techniques like expert judgement, risk matrices, and Failure Mode and Effect Analysis (FMEA). Although these techniques may be useful, they often have limits in terms of their predictive strength and reach. For example, risk matrices and FMEA are usually static tools that classify hazards according to predetermined standards. Although these techniques are capable of identifying certain risks, the dynamic nature of contemporary software development often makes it impossible for them to discover more complicated or emerging problems. Furthermore, a lot of current systems evaluate hazards using historical data. Even while this information might provide valuable insights, it might not always be relevant to fresh or creative software initiatives with particular needs. Furthermore, rather than more thoroughly classifying various risk kinds, these systems often concentrate on binary risk categorisation, or forecasting whether a danger will or won't occur. In real-world software projects, where several risk types—technical, functional, operational, and security-related—may need to be managed concurrently, this constrained approach may overlook the nuances. Furthermore, in order to improve risk prediction, several contemporary systems have started integrating machine learning approaches. Although these models may learn from data and adjust to new knowledge, they often concentrate on single-class classification tasks and lack more sophisticated, multi-class prediction features that might increase accuracy and provide more thorough risk ratings. As a consequence, offering thorough, flexible, and precise risk projections remains a major issue for present systems.

Disadvantages:

1. Limited Predictive Power: Conventional software risk prediction techniques often fall short in accurately anticipating unanticipated threats. These systems mostly use data from the past, which may not be relevant to new initiatives or unanticipated difficulties. Project hazards increase in complexity when software engineering procedures change, and existing systems may not be able to quickly recognise these new dangers.
2. Lack of Adaptability: Conditions and needs change as software development initiatives go forward. However, traditional systems often find it difficult to adjust to new developments. When new requirements are introduced or the program is revised and modified, changing risks are not taken into consideration by static risk models. Inaccurate or out-of-date risk forecasts resulting from this lack of flexibility may impede sound decision-

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making and risk management during the course of the project.

3. Binary Risk Classification: The majority of systems in use today use binary risk classification, in which a risk is classified as either present or absent. Real-world software development projects, on the other hand, are much more complicated and include a variety of risks that vary in intensity and consequences. A more sophisticated method, such multi-class categorisation, would enable systems to forecast other kinds of risks, such as those pertaining to functionality, security, usability, and performance. Existing solutions fall short of offering the depth of comprehension required for successful risk reduction because they restrict the scope to binary categorisation.

1.3. PROPOSED SYSTEM

By combining two essential elements—rule extraction and multi-class classification—the suggested method, FEPP (Feature-based Early Prediction of Risk), overcomes the shortcomings of current software risk prediction models. Finding patterns or connections in the data that correspond to certain risk categories is known as rule extraction. These guidelines, which allow the system to more precisely forecast possible hazards, are based on the examination of software needs and past project data. As new information becomes available, the rules may be constantly improved, keeping the system accurate and relevant throughout the software development lifetime. Multi-class classification, the system's second component, enables more precise risk prediction for various risk categories. The system is capable of categorising hazards into other groups, including technical, functional, security, and usability issues, rather than just forecasting whether a risk will materialise. A more thorough understanding of the possible risks to a software project is provided by this multi-class approach, which also enables teams to more successfully handle particular problems. The suggested strategy may provide forecasts with more accuracy and offer a more thorough understanding of the hazards that a project faces by combining these two methods. This facilitates the early detection of important problems, enabling software development teams to take preventative measures to lessen or eliminate these risks. More flexibility is also provided by the suggested system, which may modify its risk classifications and projections in response to changes in the circumstances and needs of the project.We're used to gradient boost, xgboost, svm, random forest, and logistic regression.

ADVANTAGES :

1. Improved Predictive Accuracy: Multi-class categorisation and rule extraction work together to increase predictive accuracy. The system is better able to predict different kinds of hazards by examining trends in past data and needs. By allocating resources to the most urgent problems early in the development process, this increased accuracy enables more efficient risk management.
2. Flexibility and Instantaneous Updates: The suggested system's flexibility in responding to changing project circumstances and needs is one of its main advantages. The system may adjust its risk estimations in accordance with fresh information or changes in software needs. As project objectives and requirements evolve over time, this flexibility guarantees that the system will continue to be applicable for the duration of the software development lifecycle.
3. Comprehensive Risk categorisation: The suggested approach offers a more thorough comprehension of the dangers that a project faces by using multi-class

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categorisation. With the use of this method, teams may identify many risk categories, including technical, security, usability, and others, and develop suitable plans to mitigate each one. Binary classification methods, on the other hand, often oversimplify the complexity of software development since they are unable to capture this degree of information.

II. REQUIREMENT AND ANALYSIS

2.1. LITERATURE SURVEY

2.1.1. Overview

A Whole-System Approach to Software Development Risk Management
J. Doe and G. Smith

The limits of conventional risk management methods, such as risk matrices and FMEA, in handling complicated software projects are covered in this study. In order to improve risk prediction and mitigation in software engineering, it suggests a hybrid risk management paradigm that combines qualitative evaluation with quantitative techniques like machine learning. In light of changing software needs, the research emphasises the need for risk management solutions that are more flexible and dynamic.

Risk Prediction Using Machine Learning in Software Requirements Engineering R. Kumar and K. Patel

The use of machine learning techniques to risk prediction during the requirements engineering stage of software development is examined in this study. The authors show how requirements papers may be examined to find patterns linked to risk by using natural language processing (NLP) approaches. When compared to conventional techniques, the study demonstrates that machine learning models may greatly improve the precision and promptness of risk predictions.

Enhanced Software Risk Prediction in Early Development Phases via Rule Extraction M. Liu and L. Zhang

The authors provide a brand-new rule-based risk prediction method that uses data from previous software projects to derive decision rules. These guidelines are used to forecast the probability that different dangers may materialise in the early phases of development. The study highlights how rule extraction, especially during the requirements engineering stage, may increase prediction accuracy and deepen our knowledge of risk drivers.

Software Engineering Risk Categorisation Through Multi-Class Algorithms
Garcia, S. and Wilson, T. (2021)

A multi-class classification method for software risk prediction is presented in this study. Multi-class algorithms, as opposed to conventional binary classification models, are used to forecast many kinds of hazards that might arise in a software project. Multi-class classification performs better than binary models in terms of accuracy and comprehensiveness, according to the research, which examines a number of machine learning methods.

Combining Risk Management and Machine Learning in Software Engineering
A. Brown and R. Roberts, 2018

The integration of machine learning methods with conventional software risk management procedures is examined in this research. In order to improve the whole mitigation process, the authors suggest a hybrid approach that combines conventional risk management techniques with machine learning to improve risk prediction. The research shows that this combination strategy results in superior risk management and decision-making.

2.1.2 ARCHITECTURE

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2.2. MODULES DESCRIPTION

1. Requirement Data Collection and Preprocessing Module

The input data required for risk prediction must be gathered and prepared by this module. The requirements engineering stage, when software requirements are written out, provides the majority of the input. Documents, user stories, or specifications may be the source of these needs.

- Data Collection: The module gathers raw needs data in a variety of forms, including databases, spreadsheets, and text.
- Preprocessing: To prepare it for analysis, the raw data is cleaned and organised. This stage involves resolving missing data, eliminating unnecessary information, and formatting the text appropriately for further processing.
- Text Normalisation: To get the text data ready for natural language processing (NLP) applications, it is standardised by stemming, tokenisation, and stop word removal.
- Feature Extraction: To aid in risk prediction, significant characteristics from the requirements, including relationships, keywords, and limitations, are extracted. NLP and machine learning approaches are used in feature extraction to find the essential components of the requirements.

2. Rule Extraction Module

Using past project data, the rule extraction module finds trends and connections between the elements taken from the requirements and recognised hazards. The system's ability to anticipate danger will be based on these guidelines.

- Pattern Recognition: The technology finds similar patterns between software needs and related hazards by analysing historical data. These trends aid in the development of forecasting rules.
- Rule Mining: Based on specific needs, the module uses algorithms such association rule mining, decision trees, or other machine learning approaches to extract rules that characterise risk occurrences.
- Dynamic Rule Update: To keep the system accurate and flexible as the project develops and new information becomes available (such as requirements or scope modifications), the rules are updated to reflect the changing nature of the project.
- Risk Correlation: To help users better understand how certain needs could result in particular kinds of hazards, the module links the extracted rules with possible risks (technical, functional, security, etc.).

3. Multi-Class Classification Module

Classifying software hazards into many categories (multi-class classification), including usability, security, and performance issues, is the responsibility of this module. It use machine learning methods to thoroughly categorise the hazards, building upon the rules produced by the rule extraction module.

- Risk Categorisation: By classifying risks into many classifications, the module makes it possible to comprehend the various kinds of hazards that are present in the project in more depth. It takes into

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account a variety of potential risk kinds and transcends the simple "risky or not" categorisation.

- Selection of Machine Learning Algorithms: To forecast various risks, a variety of machine learning algorithms are trained on past project data, including support vector machines (SVM), decision trees, random forests, and neural networks.
- Training and Validation: To guarantee accuracy and dependability, the classification model is trained on labelled datasets and then verified. To teach the model the link between needs and risks, training data may comprise previous software projects with recognised risk categories.
- Risk Prediction: Using the attributes that were taken from the requirements, the system may be trained to forecast the probability and classification of different hazards related to new software projects.

4. Risk Evaluation and Ranking Module

This module assesses the anticipated hazards based on their likelihood and possible effect. The system may rate risks and recommend which ones should be given priority for mitigation based on this assessment.

- Risk Impact Assessment: Every risk that has been discovered is evaluated for how it could affect the project's outcome. The module may use more sophisticated methods or preconfigured risk matrices to determine the degree of risk.
- Probability Estimation: The model's predictions and historical data are used to calculate the likelihood that a danger would materialise. The module calculates the likelihood that each risk may manifest in the ongoing project.
- Prioritisation: Project managers and software developers may identify which risks need urgent attention and mitigation by ranking them based on their likelihood and possible effect.
- Risk Mitigation Suggestions: The module produces suggestions for reducing the risks that are of the utmost importance. These might include tactics like increasing funding, using certain software testing methods, or improving the project's specifications.

5. Feedback and Learning Module

The feedback and learning module is in charge of consistently enhancing the risk prediction system's precision and applicability. In order to improve the system over time, it collects input from the continuous software development process.

- Feedback Loop: This module collects input on how well the risk forecasts worked from stakeholders, project managers, and developers. For instance, the module verifies if a risk materialised and how well it was mitigated once it has been identified.
- Model Retraining: To increase the prediction capacity of machine learning models, they are retrained using input and fresh data from active projects. This might include revising regulations, creating new risk categories, or improving classification algorithms.
- Continuous Improvement: The system becomes better at properly identifying hazards as more projects are finished. Its ability to detect previously unanticipated threats improves with more feedback, eventually enhancing system performance.

6. User Interface (UI) Module

The UI module is in charge of giving end users—like stakeholders, software developers,

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and project managers—an interactive interface via which they may communicate with the system. Users may evaluate risk forecasts, enter requirements, and investigate risk reduction techniques using the user interface.

- Requirement Input: The system allows users to enter software needs in a variety of forms, including text, documents, and spreadsheets. Processing and uploading necessary data is made simple by the interface.
- Risk Visualisation: Users may view possible risks and rank mitigation techniques by using the module's user-friendly display of risk projections and rankings. Graphs, charts, and heatmaps are examples of visualisations that may be used to help comprehend risk data.
- Risk Mitigation Tools: Users have access to materials and tools for reducing risks that have been identified. The interface may include resources for risk management, best practices, or instructions for enhancing project specifications to lower certain risks.
- Interactive Feedback: Users have the ability to comment on the system's suggestions' correctness as well as the risk projections. Over time, the system becomes more adaptable as a result of this input, which enhances future predictions.

2.2.1. ALGORITHMS USED :

1. Random Forest

Overview:

Random Forest is a decision tree-based ensemble learning technique. To increase classification accuracy and avoid overfitting, it integrates many decision trees. A random subset of the data is used to train each tree in the forest, and the results are aggregated to provide the final prediction (often by average for regression tasks or majority voting for classification tasks).

Key Features:

- Ensemble Approach: To create a more precise and reliable model, Random Forest constructs many decision trees and aggregates their output.
- Bagging: To minimise overfitting, each tree is trained on a distinct random subset of the data (bootstrap sampling).
- Feature Randomness: To improve efficiency, a random subset of characteristics is taken into account for every tree split. This adds variety to the trees.
- Managing Missing Values: During the decision-making process, Random Forest may manage missing values by using surrogate splits.

Advantages:

- Excellent precision in both regression and classification tasks.
- Less likely than individual decision trees to overfit.
- Capable of capturing intricate connections and managing big information.

Disadvantages:

- It may be costly to compute, particularly when dealing with big datasets.
- Not as easily interpreted as a single decision tree.

2. XGBoost (Extreme Gradient Boosting)

Overview:

Because of its exceptional results in several machine learning contests, XGBoost—an optimised variant of gradient boosting—has gained a lot of popularity. It is a sequential model-building ensemble approach in which the goal of each new tree is to fix the mistakes of the ones that came before it.

Key Features:

- Gradient Boosting: XGBoost builds trees one after the other using a gradient descent approach to minimise the loss

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function. Every new tree fixes the errors of its predecessor.
- Regularisation: Unlike classic gradient boosting, XGBoost incorporates L1 and L2 regularisation to reduce overfitting.
- Parallelisation: The training process is accelerated by XGBoost's ability to compute in parallel.
- Tree Pruning: To prevent overfitting and manage the model's complexity, it approaches tree growth and pruning depth-first.

Advantages:
- Effectively handles missing data;
- Has a high prediction performance, often surpassing other machine learning methods.
- Capable of handling problems involving both classification and regression.
- Efficient in terms of computation time and memory usage due to optimization techniques.

Disadvantages:
- Requires appropriate parameter optimisation and might be challenging to optimise.
- Less interpretable than more straightforward models like decision trees or logistic regression.

3. Support Vector Machine (SVM)

Overview:

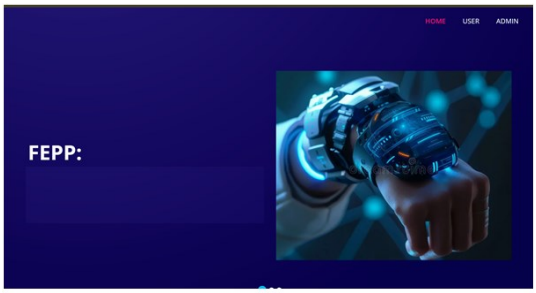
A potent supervised machine learning approach for classification and regression applications is the Support Vector Machine (SVM). Finding the hyperplane, or decision border, that best divides the data into distinct groups is how SVM operates.

Key Features:
- Optimising Margin: SVM seeks to identify the hyperplane that optimises the distance (margin) between various classes. Support vectors are the data points that are closest to the hyperplane.
- Kernel Trick: SVM may identify nonlinear decision limits by converting data into higher-dimensional spaces using kernel functions.
- Binary Classification: Support Vector Machines (SVM) are often used for binary classification; however, they may also be applied to multi-class issues by using strategies such as one-vs-one or one-vs-all.
- Regularisation: A regularisation parameter (C) in SVM regulates the trade-off between preserving a straightforward decision boundary and attaining a low error on the training data**.**

Advantages:
- Effective in high-dimensional spaces; robust against overfitting, particularly in high-dimensional spaces; and suitable for both linear and non-linear data when utilising kernels.

Disadvantages:
- It may be computationally costly, particularly when dealing with big datasets; selecting the appropriate kernel and adjusting the parameters can be difficult.
- Compared to more straightforward models like logistic regression, SVM is harder to comprehend.

III. SCREEN SHOTS



User login page

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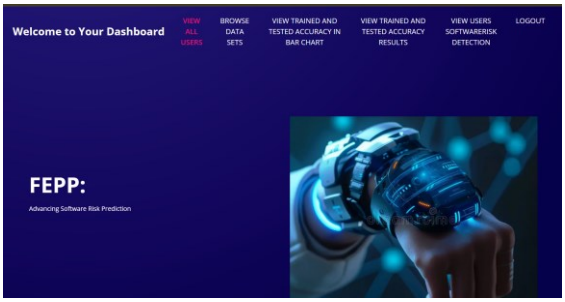
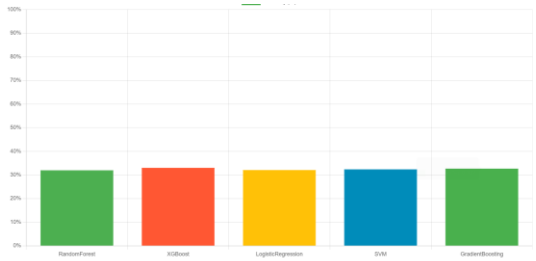
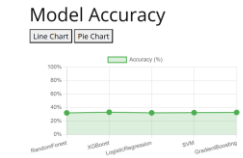
User registration page

Admin loginpage

Admin page







IV. CONCLUSION

Software risk prediction has advanced significantly with the FEPP system, especially at the crucial requirements engineering stage. FEPP improves the precision and granularity of risk forecasts by combining rule extraction with multi-class classification approaches, providing a more thorough method of risk management in software projects. The shortcomings of current risk prediction models, including their incapacity to adequately forecast developing threats, binary categorisation, and lack of flexibility, are addressed by this approach. The system may find patterns and links in software requirements and historical project data by using rule-based models, which can be updated constantly as new information becomes available. The project team can take the proper action for each category according to the multi-class classification technique, which enables a more sophisticated forecast of several risk kinds, including technical, security, performance, and usability issues. Additionally, the feedback and learning process makes sure that the system keeps becoming better over time, adjusting to new difficulties and changing needs.

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To sum up, FEPP presents a viable way to enhance risk management and prediction in software development, facilitating early issue identification and mitigation for teams before they affect the project. In the end, more successful and effective software projects result from the suggested system's enhanced early risk identification and proactive decision-making capabilities.

FUTURE SCOPE

Although the FEPP system works well as it is, there is a lot of room for improvement and growth. The following are some crucial areas for further research and development:

1. Integration with Agile approaches: FEPP may be integrated with agile workflows to provide real-time risk prediction throughout iterative development cycles, which is made possible by the growing trend in software development towards agile approaches. As needs change over time in agile projects, this might enable even more proactive and flexible risk management.
2. Including Natural Language Processing (NLP): Since FEPP currently employs rule extraction methods, adding more sophisticated NLP algorithms might enhance the comprehension of requirements documents' unstructured textual material. This would improve the accuracy of risk forecasts by enabling the algorithm to extract more nuanced information, patterns, and linkages.
3. Broader Risk Categorisation: Although the method now forecasts a wide range of hazards, future advancements may allow the categorisation to include even more specialised groups, such legal, ethical, or regulatory issues. As a result, FEPP would be a more complete tool for software projects of all kinds, including those in highly regulated sectors like banking or healthcare.
4. Adding Real-Time Data Feeds: To give continuous, updated risk estimates as the project moves forward, the system might be improved by adding real-time data from the software development environment (such as project management tools and problem tracking systems). This would enable the system to continually adjust and provide suggestions for risk management that are both dynamic and real-time.
5. Cooperation with Industry Standards and Frameworks: The FEPP system might be customised to meet particular industry requirements and matched with current industry standards for risk management (such as ISO 31000 and PMBOK). The system's usefulness in actual software projects would be enhanced by integration with popular frameworks and tools.
6. Investigating Deep Learning: For more intricate pattern identification and risk categorisation, the system may include deep learning models, going beyond conventional machine learning approaches. More complex insights could be provided by deep neural networks, especially for large-scale software projects involving enormous volumes of data.
7. Customisation for Various Domains: The system may be further tailored for certain application domains, including business software, mobile applications, and embedded systems. By adapting the system to the specific requirements of many domains, FEPP may be even more

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successful in tackling the distinct difficulties of each.

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