**A Project Report on**

## Project Dependency and Risk Prediction

submitted in partial fulfillment for the award of

### Bachelor of Technology

in

## Computer Science and Engineering

by

### I. Srilekha (Y21AC459) B. V. Siva Rama Krishna (Y21ACS427)

**G. Varshitha (Y21ACS454) D. Saiteja(Y21ACS435)**



Under the guidance of

## Asst. Prof. VenkataLakshmi.

Department of Computer Science and Engineering

## Bapatla Engineering College

(Autonomous)

(Affiliated to Acharya Nagarjuna University) **BAPATLA – 522 102, Andhra Pradesh, INDIA 2023-2024**

## Department of Computer Science and Engineering



**CERTIFICATE**

This is to certify that the project report entitled **Project Dependency and Risk**

**Prediction** that is being submitted by I. Srilekha(Y21ACS459),

B.V.Siva Rama Krishna(Y21ACS427), G.Varshitha(Y21ACS454) and D.Saiteja(Y21ACS435) in partial fulfillment for the award of the Degree of Bachelor of Technology in Computer Science and Engineering to the Acharya Nagarjuna University is a record of bonafide work carried out by them under our guidance and supervision.

Date:

**Signature of the Guide Signature of the HOD**

**Dr. R. Venkatalakshmi Dr. M. Rajesh Babu**

**Assistant Professor Associate Professor**

## DECLARATION

We declare that this project work is composed by ourselves, that the work contained herein is our own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

**I. Srilekha(Y21ACS459)**

**B.V. Siva Rama Krishna(Y21ACS427)**

**G. Varshitha(Y21ACS454)**

**D. Saiteja(Y21ACS435)**

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**I. Srilekha(Y21ACS459)**

**B.V. Siva Rama Krishna(Y21ACS427)**

**G. Varshitha(Y21ACS454)**

**D. Saiteja(Y21ACS435)**

## Table of Contents

[List of Figures viii](#_TOC_250081)

[Abstract x](#_TOC_250079)

1. [Introduction 1](#_TOC_250078)
   1. [Background 1](#_TOC_250077)
   2. [Problem Statement 3](#_TOC_250076)
   3. [Motivation 4](#_TOC_250075)
      1. [Increasing Complexity of Software Projects 4](#_TOC_250074)
      2. [Dependency Overload and Risk Management Gaps 4](#_TOC_250073)
      3. [Project Failures due to Unforeseen Risks 5](#_TOC_250072)
      4. [Importance of Early Risk Prediction 5](#_TOC_250071)
      5. [Enhancing Decision Making for Stakeholders 5](#_TOC_250070)
   4. [Objective 6](#_TOC_250069)
   5. [Significance 6](#_TOC_250068)
   6. [Existing System 8](#_TOC_250067)
2. [Literature Review 10](#_TOC_250066)
3. [Proposed System 12](#_TOC_250065)
   1. [Task 12](#_TOC_250064)
      1. [Project Planning and Setup 12](#_TOC_250063)
      2. [Data Collection and Preparation 12](#_TOC_250062)
      3. [Feature Engineering 12](#_TOC_250061)
      4. [Model Selection and Development 13](#_TOC_250060)
      5. [Training and Evaluation 13](#_TOC_250059)
      6. [Integration and Deployment 13](#_TOC_250058)
      7. [Testing and Validation 13](#_TOC_250057)
      8. [Documentation and Reporting 14](#_TOC_250056)
   2. [Dataset 14](#_TOC_250055)
   3. [Input 16](#_TOC_250054)
   4. [Output 16](#_TOC_250053)
4. [Algorithms 17](#_TOC_250052)
   1. [Random Forest Regressor 23](#_TOC_250041)
      1. [Basic Principle 23](#_TOC_250040)
      2. [Feature Randomness and Bagging 23](#_TOC_250039)
      3. [Feature Importance and Interpretability 23](#_TOC_250038)
      4. [Training, Evaluation, and Prediction 24](#_TOC_250037)
      5. [Evaluation and Prediction 27](#_TOC_250030)
5. [System Design 28](#_TOC_250029)
   1. [Use Case Diagram 28](#_TOC_250028)
   2. [Class Diagram 29](#_TOC_250027)
   3. [Activity Diagram 30](#_TOC_250026)
6. [Implementation 34](#_TOC_250022)
   1. [Requirements 34](#_TOC_250021)
      1. [Hardware Requirements 34](#_TOC_250020)
      2. [Software Requirements 35](#_TOC_250019)
      3. [Libraries 35](#_TOC_250018)
   2. [Code 37](#_TOC_250017)
      1. [GitHub Link 37](#_TOC_250016)
      2. [Importing all necessary packages 37](#_TOC_250015)
      3. [Extracting permissions from input file 37](#_TOC_250014)
      4. [Loading Dataset 38](#_TOC_250013)
      5. [splitting data and training RandomForestRegressor 41](#_TOC_250010)
      6. [Interface using Flask 43](#_TOC_250007)
7. [Results 44](#_TOC_250006)
   1. [Interface 44](#_TOC_250005)
   2. [Output 45](#_TOC_250004)
8. [Conclusions 47](#_TOC_250001)
9. [References 48](#_TOC_250000)

## List of Figures

Figure 5.1 Use case Diagram 28

Figure 5.2 Class Diagram 29

Figure 5.3 Activity Diagram 30

Figure 7.1 User Interface 44

Figure 7.2 Output 40

## Abstract

In real-world project execution, one of the biggest challenges lies in managing task dependencies and handling risks that can arise unexpectedly. Even well-planned projects often face setbacks due to delays in one task affecting several others, or due to overlooked risk factors like resource unavailability or underestimated complexity. These recurring issues across various industries inspired the development of a smart and structured solution that not only maps out dependencies but also anticipates risks before they impact progress.

This project focuses on building a system that detects and visualizes task dependencies using Directed Acyclic Graphs (DAGs), helping project teams understand how each task connects and influences the workflow. Alongside this, it incorporates machine learning-based risk prediction models that analyze historical data to forecast possible issues like schedule slippages, workforce bottlenecks, and high-complexity phases. By providing early warning signs, the system supports better planning and resource distribution across all project stages

To enhance usability, features such as interactive automated risk summaries are integrated, making it easier for teams to plan, track, and respond to project dynamics. The system ultimately aims to bring clarity and control to project execution, minimizing last-minute surprises and enabling data-driven decision-making for smoother and more efficient project outcomes.

**Keywords:** Task dependency detection, Risk prediction, Directed Acyclic Graph (DAG), Machine learning, Project Visualization.

# Introduction

Project management often faces challenges like hidden task dependencies and unforeseen risks that can delay deadlines and increase costs. This project aims to address these issues by detecting task dependencies using Directed Acyclic Graphs (DAGs) and predicting risks through machine learning. By leveraging historical data, it helps forecast delays, resource shortages, and complexity. The system also provides visual insights through Gantt charts and generates automated risk reports. This enables project managers to make better-informed decisions. Overall, it enhances planning accuracy and improves project efficiency.

## Background

Project management has evolved from manual planning and basic Gantt charts to advanced digital tools. Early models like Waterfall focused on sequential task execution with fixed dependencies. These methods lacked flexibility in handling complex, evolving project requirements. As a result, Agile, Scrum, and hybrid approaches emerged, promoting adaptability and iterative development. Despite their improvements, they often struggle to manage dynamic task interdependencies. Additionally, proactive risk identification remains a persistent challenge across methodologies.

One of the persistent challenges in project management has been the accurate identification of task dependencies—understanding how the completion of one task directly affects another. Traditionally, managers manually mapped out dependencies using Gantt charts or Work Breakdown Structures (WBS). While these visual tools are helpful, they rely heavily on human judgment and are prone to oversight, especially in large projects with interlinked and overlapping tasks. Misjudging dependencies can result in resource clashes, idle time, or cascading delays, ultimately affecting the project's success.

In parallel, the role of risk management has grown in importance. Risks in projects can stem from internal factors like resource constraints or external factors like market changes or policy updates. Earlier risk management approaches primarily relied on qualitative analysis or subjective expert judgment. Although some standard frameworks like the PMBOK Guide by PMI offered structured risk assessment methods, they were often static and not adaptable to real-time project dynamics. The lack of data-driven, predictive mechanisms left a gap in proactively identifying and addressing risks before they materialized.

The introduction of Directed Acyclic Graphs (DAGs) in project analysis brought a mathematical and computational edge to visualizing and managing dependencies. DAGs help represent tasks as nodes and their relationships as directed edges, ensuring no cyclic dependencies. This structure enables efficient calculation of critical paths, bottlenecks, and potential chain reactions due to delays. DAGs also allow for automation in tracking dependencies and recalculating timelines whenever changes are made—something manual Gantt charts struggle with.

With the advent of machine learning, project management started tapping into predictive analytics. By training models on historical project data, patterns in task delays, resource usage, and failure points can be learned and predicted. Supervised learning models, especially classification and regression algorithms, have shown promise in risk prediction—highlighting which tasks are most likely to face delays or where resource shortages might occur. This shift from reactive to proactive project management marks a major advancement.

Combining these concepts, the current project aims to build a unified system that detects task dependencies using DAGs and predicts risks using machine learning. It bridges the gap between traditional project planning tools and intelligent, data-driven systems. By leveraging visualization tools like Gantt charts and integrating automated risk reporting, this solution empowers project managers with both clarity and foresight. The integration of these technologies represents a step forward in how modern projects are planned, executed, and secured against uncertainties.

## Problem Statement

In traditional project management, the identification of task dependencies and risk prediction often relies on manual tools such as spreadsheets or basic planning software. These tools depend heavily on the project manager's intuition and experience, making them susceptible to human error and oversight. Especially in large-scale or complex projects, this manual approach lacks the agility and precision needed to maintain efficiency and timelines.

Such reliance on subjective judgment results in common issues like project delays, budget overruns, and suboptimal use of resources. When dependencies are not clearly mapped or understood, teams may encounter bottlenecks or miscommunications that disrupt progress. Additionally, without a systematic way to foresee risks, reactive management becomes the norm, often leading to rushed decisions under pressure.

The absence of automated, data-driven systems makes it increasingly difficult for managers to adapt to evolving project dynamics. As projects scale and data becomes more abundant, there's a pressing need for intelligent solutions that can analyze patterns, identify hidden dependencies, and forecast potential risks with accuracy. Addressing this gap is crucial to improve planning accuracy, resource allocation, and overall project outcomes.

Moreover, with increasing project complexity, the limitations of traditional methods become even more pronounced, affecting collaboration and transparency across teams. Project managers often struggle to gain a holistic view of dependencies and risks, which hampers proactive planning.

## Motivation

The development of a dependency and risk prediction system for project management emerges as a crucial endeavour, offering a data-driven and forward-looking approach to tackling the increasing complexity of modern projects. As project sizes grow and teams become more distributed, the interrelation between tasks and the potential for unforeseen risks demand more than traditional methods can offer. This system is motivated by the need to enhance accuracy in identifying dependencies and enable proactive risk mitigation through intelligent analysis and visualization tools.

### Increasing complexity of Software Projects:

The increasing complexity of software projects, driven by evolving technologies, distributed teams, and tighter deadlines, has made effective project management more challenging than ever. Modern projects often involve multiple interconnected tasks, dynamic workflows, and cross-functional collaboration, making it difficult to manually track dependencies and foresee potential risks. As a result, even minor oversights in planning can cascade into major delays or budget overruns. This complexity highlights the urgent need for automated systems that can intelligently analyze task relationships and predict risks, ensuring better control and decision-making throughout the project lifecycle.

### Dependency overload and Risk Management Gaps:

In large-scale projects, the number of interconnected tasks can quickly escalate, leading to what is known as dependency overload—where managing and tracking all relationships manually becomes unfeasible. This complexity often results in overlooked dependencies that can cause unexpected delays or resource conflicts. Simultaneously, many traditional project management systems lack mechanisms for effective risk prediction, relying instead on reactive responses to issues as they arise. The absence of real-time risk analysis and dependency tracking creates gaps that hinder a project’s adaptability and efficiency, highlighting the need for a more intelligent, automated solution.

### Project failures due to unforeseen Risks:

Unforeseen risks remain a major contributor to project failures, often resulting in missed deadlines, budget overruns, and compromised deliverables. These risks can stem from a variety of sources such as resource unavailability, technical bottlenecks, scope changes, or external disruptions. When such risks are not identified and addressed early, they can create a ripple effect across dependent tasks, leading to cascading failures. The lack of predictive mechanisms in traditional project management tools makes it difficult to anticipate and mitigate these issues before they escalate. Addressing this challenge is essential for improving project resilience and overall success.

### Importance of early Risk Prediction:

Early prediction of risks plays a vital role in ensuring the smooth execution of a project. By identifying potential threats before they escalate, project managers can take timely corrective actions to avoid delays, budget overruns, and resource mismanagement. Proactive risk detection not only improves project reliability but also enhances stakeholder confidence by promoting transparency and preparedness.

### Enhancing Decision-Making for Stake-holders:

Effective project management relies heavily on timely and informed decision-making by stakeholders at all levels. By providing clear visibility into task interdependencies and potential risks through predictive analytics and visual tools like Gantt charts and dependency graphs, the system empowers stakeholders to anticipate challenges before they arise. This foresight allows for better planning, resource allocation, and prioritization, ultimately improving project outcomes and fostering a more collaborative and responsive project environment.

## Objective

The objective of this project is to develop an intelligent system for project dependency detection and risk prediction using graph-based modeling and machine learning techniques, with the following goals:

1. **Identify Task dependencies accurately:** Utilize Directed Acyclic Graphs (DAGs) to map out intricate task relationships within a project, ensuring better clarity of interdependencies and their potential impact on project timelines.
2. **Predict Potential Risks Proactively:** Leverage historical project data and machine learning algorithms to forecast risks such as resource shortages, scheduling conflicts, and delays before they materialize.
3. **Improve Planning Efficiency:** Enhance the planning phase by integrating predictive insights and visual tools like Gantt charts to allow for better task scheduling and resource management.
4. **Enable Informed Decision-making:** Support stakeholders in making data-driven decisions by providing automated risk reports and real-time analysis of project health.
5. **Scalability and Adaptability:** Design a scalable system capable of handling projects of varying sizes and adaptable to diverse project domains and evolving data inputs.

By achieving these objectives, the project aims to revolutionize the way project managers handle dependencies and risks, leading to more efficient, timely, and cost-effective project deliveries.

## Significance

Project Dependency and Risk Prediction using Directed Acyclic

Graphs (DAG) and Machine Learning (ML) represents a transformative shift in

modern project management by enabling proactive planning, real-time decision-

making, and intelligent risk mitigation. Through data-driven analysis and

visual representation of task flows, this system enhances both efficiency and foresight in managing complex projects.

1. **Intelligence dependency Mapping:** Large-scale projects often suffer from unclear or misjudged task relationships. By utilizing DAG structures, this system provides a clear, visual hierarchy of tasks, allowing managers to identify dependencies and optimize task sequences, which minimizes delays and resource clashes.
2. **Data-driven Risk Prediction:** Incorporating ML models trained on historical project data enables the system to predict risks such as resource shortages, budget overruns, and task delays. This predictive ability transforms risk management from reactive to proactive, increasing overall project resilience.
3. **Real Time decision support:** The integration of ML analytics and visual dashboards empowers stakeholders with timely insights. Managers can monitor risk levels and adjust plans in real time, ensuring informed and swift decision-making across project stages.
4. **Enhanced efficiency and Timelines:** Early detection of task interferences and risks enables better resource allocation and scheduling. This minimizes idle periods, reduces rework, and significantly improves the likelihood of delivering the project within budget and on schedule.
5. **Advancement of Intelligent Project Management:** By integrating data analytics and graph theory, this project contributes to the evolution of smart project management tools. Its design promotes adaptive planning practices and supports ongoing research into algorithmic approaches to project optimization.
6. **Scalability and Industry Impact:** From software development to infrastructure planning, this system offers broad applicability. Its scalable nature and predictive capabilities make it a valuable asset in industries where precision and timely execution are critical, reinforcing its relevance in both academic and commercial domains.

## Existing System

The existing project management systems primarily rely on manual tracking of task dependencies and subjective risk assessments, which limits their efficiency and predictive capabilities. Traditional tools such as spreadsheets and standalone project management software are widely used to visualize project schedules and task sequences, but they lack the sophistication required to automatically identify complex dependencies or predict potential risks.

The existing project management systems primarily rely on manual tracking of task dependencies and subjective risk assessments, which limits their efficiency and predictive capabilities. Traditional tools such as spreadsheets and standalone project management software are widely used to visualize project schedules and task sequences, but they lack the sophistication required to automatically identify complex dependencies or predict potential risks.

Risk prediction in traditional project management approaches is primarily based on the experience and intuition of project managers, rather than on a data-driven or systematic approach. Without the use of historical data and intelligent algorithms, early identification of risks—such as delays, resource conflicts, or cost overruns—is inconsistent and unreliable. This can result in reactive rather than proactive decision-making, increasing the likelihood of project failure The research consists of the following major components:

1. Manual Task dependency Mapping.
2. Static Scheduling techniques.
3. Experience-based risk Management.
4. Limited Visualization and Reporting

The primary objective of such systems is to assist in basic planning and tracking, but they do not offer advanced intelligence for decision-making or optimization. In contrast, the proposed system introduces a data-driven approach by integrating Directed Acyclic Graphs (DAGs) for dependency mapping and Machine Learning (ML) for proactive risk prediction. This addresses the key limitations of the existing systems and enhances project control, adaptability, and success rates.

# Literature Review

We examine the existing project management systems and recent research in task dependency tracking and risk prediction.

Kaur et al. [1] proposed a machine learning-based framework to identify potential risks in software projects by analyzing historical project data. The study utilized Random Forest and SVM classifiers to classify risk severity and found Random Forest to be more effective with an accuracy of 91.2%. Their approach also leveraged features such as team size, task duration, and dependency weight, offering interpretable insights for project managers.

Similarly, Deshmukh et al. [2] developed a dependency mapping approach using Directed Acyclic Graphs (DAGs) to visualize and analyze task dependencies in complex software projects. The system dynamically updated dependency flows and identified potential bottlenecks early in the development process. They achieved high precision in critical path detection, improving planning efficiency by over 30%.

Gupta et al. [3] proposed a hybrid risk assessment model combining statistical techniques with machine learning models such as Gradient Boosting and Decision Trees. They collected real-time project data from industry case studies and identified 18 key risk indicators, including resource allocation, overlapping tasks, and missed deadlines. The model achieved 93.5% F1-score on unseen project data.

Lee et al. [4] focused on a feature selection mechanism using Principal Component Analysis (PCA) for identifying the most influential factors in project failure. Their model helped reduce the dimensionality of the dataset from 120 to 35 features while maintaining an accuracy of 90.8% in classifying high-risk tasks. They also emphasized early prediction to mitigate downstream project risks.

Chen et al. [5] developed a tool named ProRiskMap, which integrates real-time project status monitoring with ML-based risk classification. It used historical data along with current updates to identify potential red flags. The system offered visual indicators for project managers and improved risk mitigation response time by 40%. However, the study was limited to mid-scale projects, and the tool’s effectiveness on large-scale projects is yet to be validated.

Most of the recent studies used historical datasets, real-time tracking, or permission-like metadata (inspired from software security studies) to detect patterns that indicate potential project delays or failures. While DAGs are efficient for dependency management, the integration with ML models provides proactive solutions rather than reactive ones. The accuracy of these systems varies based on the dataset size and feature selection technique, yet most report over 90% prediction accuracy when optimized algorithms are used.

# Proposed System

Dependency-based analysis in project management involves examining task interdependencies and their potential effects on project risks and timelines. By leveraging dependency graphs (like DAGs) and analyzing key project features (e.g., duration, resource allocation, task criticality), the system can proactively predict delays, bottlenecks, and project risks.

## Task

The preliminary task for this project is to predict potential risks and delays in a software project by analyzing project dependency data, task attributes, and historical trends using machine learning technique.

### Project Planning and Setup:

* + - 1. Define the project scope, objectives and expected outcomes(e.g., accurate prediction of task delays, critical path identification).
      2. Set up timelines and resource allocation for different phases of the project.
      3. Choose and configure development environments, including data analytics tools, ML frameworks and DAG visualization tools.

### Data Collection and Preparation:

* + - 1. Collect project data including tasks, dependencies, duration, resource allocation, and risk history.
      2. Construct Directed Acyclic Graphs (DAGs) to model task dependencies.
      3. Preprocess the data by cleaning, transforming, and encoding task features suitable for ML modeling.

### Feature Engineering:

* + - 1. Identify key features such as task duration, number of dependencies, slack time, resource load, and previous delays.
      2. Use graph-based features (e.g., node degree, depth, critical path indicators).
      3. Apply feature selection and dimensionality reduction techniques (e.g., PCA) to improve model performance.

### Model Selection and Development:

* + - 1. Research and select suitable ML algorithms such as Random Forest for time based analysis.
      2. Develop and train initial models with a focus on interpretability and accuracy.
      3. Tune hyperparameters and experiment with ensemble models or deep learning techniques for better performance.

### Training and Evaluation:

* + - 1. Split the dataset into training, validation, and testing sets.
      2. Train the models using the training data and validate.
      3. Evaluate model performance using metrics like R2 score.

### Integration and Deployment:

* + - 1. Integrate the trained ML model with a real-time project monitoring dashboard or tool.
      2. Visualize project task dependencies dynamically using DAG.
      3. Provide real-time alerts for potential delays or risks during project execution.

### Testing and Validation:

* + - 1. Test the integrated system across multiple real or simulated projects.
      2. Validate predictions with ground truth outcomes and expert feedback.
      3. Ensure that the system performs well under different project scales and conditions.

### Documentation and Reporting:

* + - 1. Document the entire workflow including data pipeline, ML techniques, and visualization tools used.
      2. Prepare a comprehensive report detailing objectives, design, methodology, experimental results, and conclusions.
      3. Create user documentation or manuals for project managers to interpret risk predictions and interact with the system.

## Dataset

For the dataset, we have collected software project management data comprising multiple tasks from various project phases such as planning, execution, and monitoring. Each task is analyzed along with its associated dependencies and risk indicators.

The model is trained using this labeled dataset where project task features act as input variables, and risk level serves as the target for classification. Each row in the dataset represents a unique task from a project, while columns represent the associated metrics and conditions impacting task risks.

## Input

Users will be prompted to upload a project dataset in CSV format containing details such as task duration, dependencies, slack time, and critical path status. The system will provide an interface to select the file from local storage. After uploading, users can choose between Random Forest Classifier (RFC) for risk prediction. The selected model will analyze project tasks to predict their risk levels. Each task will be classified as either “High Risk” or “Low Risk” based on its features. This helps project managers proactively manage and mitigate potential delays or issues.

## Output

Once the user uploads the project dataset and selects the desired model (Random Forest Classifier), the system begins analyzing the attributes of each task. These attributes include task duration, dependency count, start and end dates, and slack time. The data is preprocessed to identify key features influencing project risks. The selected machine learning model uses this data to predict risk levels.

The system then classifies each task as either “High Risk” or “Low Risk” based on the model’s prediction. Along with the classification, a confidence score is optionally displayed to show the certainty of each prediction. Higher confidence indicates a more reliable result, while lower confidence suggests uncertainty. The prediction helps in understanding which tasks may require closer monitoring.

Furthermore, the system displays essential information such as task IDs, dependency status, and whether a task lies on the critical path. This assists project managers in making informed decisions regarding task prioritization and resource allocation. The overall analysis aims to enhance project execution by minimizing delays and addressing risks proactively.

# Algorithms

The model is designed to predict the risk level of a project based on three key inputs: total number of tasks, task dependency value, and independent value. It leverages a Random Forest Regressor to analyze these features and estimate a numerical risk score. This score is then categorized into Low, Moderate, or High risk levels, helping in proactive risk management and better decision-making. The risk prediction logic integrates seamlessly with the dynamic nature of project inputs, ensuring adaptability and precision.

The training phase involves preprocessing the dataset, scaling features using MinMaxScaler, and converting the continuous risk score into discrete risk classes. The model learns from task patterns and their associated risk levels using labeled data. It is evaluated using regression and classification metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R² score, while also utilizing classification metrics like accuracy and precision by rounding predicted scores. To preserve consistency, the trained model and scaler are stored using joblib and reused during future predictions.

## Random Forest Regressor

Random Forest Regressor is a supervised machine learning algorithm used primarily for regression tasks. It is based on an ensemble learning technique that combines the predictions of multiple decision trees to improve accuracy and control overfitting.

### Basic Principle

The core idea behind Random Forest is to build multiple decision trees during training and output the **average of their predictions** for regression problems. Each tree is trained on a different subset of the data, created through **bootstrapping (random sampling with replacement)**. This process helps in reducing variance and improves prediction accuracy.

### Feature Randomness and Bagging

Random Forest introduces randomness in two ways:

1. By using a random subset of training samples (bagging) for each tree.
2. By selecting a random subset of features to consider for splitting at each node.

This randomness ensures that the trees are de-correlated and thus, the ensemble’s overall performance improves due to reduced overfitting and increased generalization.

### Feature Importance and Interpretability

Unlike deep learning models, the Random Forest Regressor does not require a separate compilation step. Once the model is initialized with its hyperparameters (such as the number of trees, maximum depth, and minimum samples per split), it is ready for training. The internal structure of each tree is automatically constructed during the training process using decision tree logic.

### Training, Evaluation and Predicition

### 

The training process of Random Forest Regressor is carried out using the fit() method. During training, multiple decision trees are built using random subsets of the training data (bootstrapping). Each tree learns different patterns by selecting different features and samples. The ensemble of these trees ensures that the overall model captures a broader view of the data, which helps reduce overfitting and improve accuracy.

After the model is trained, it can be evaluated on test or validation data using performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), or R-squared (R²). Evaluation helps determine how well the model generalizes to unseen data.

For making predictions, the predict() method is used. The Random Forest Regressor combines the outputs of all decision trees by averaging them to produce the final prediction, ensuring more stable and accurate results compared to individual trees.

# System Design

The basic architecture of the proposed model develops a robust and scalable solution for predicting project dependencies and associated risks using advanced machine learning techniques. The system is designed to analyze project data, identify critical dependencies, and predict potential risks that could affect project outcomes. This helps in proactive decision-making and efficient project management.

## Use Case Diagram

Use-case diagrams describe the high-level functions and scope of a system. These diagrams also identify the interactions between the system and its actors. In the proposed model, the main actor is the Project Manager (or user), who interacts with the system to input project data, review dependencies, and obtain risk predictions.

A diagram of a process

AI-generated content may be incorrect.

**Figure 5.1 Use case Diagram.**

## Class Diagram

A class diagram provides a static view of the system, showcasing the system's classes, their attributes, methods, and the relationships between them. It is a key component of object-oriented modeling and helps in visualizing the structure and design of the system.

A diagram of a computer

AI-generated content may be incorrect.

**Figure 5.2 Class Diagram**

## Activity Diagram

Activity diagram is basically a flowchart to represent the flow from one activity to another activity. The activity can be described as an operation of the system. The control flow is drawn from one operation to another. This flow can be sequential, branched, or concurrent. In UML, an activity diagram provides a view of the behavior of a system by describing the sequence of actions in a process.

A diagram of a process

AI-generated content may be incorrect.

**Figure 5.3 Activity Diagram**

# Implementation

We have developed an automated Project Dependency and Risk Prediction system that efficiently detects task dependencies and predicts risks by using machine learning. Through leveraging Directed Acyclic Graphs (DAGs) to represent task flow and employing trained models on historical project data, our system enhances the accuracy of risk assessment. The integration of Gantt chart visualizations and real-time insights empowers the project managers to take timely actions and also to improve overall project efficiency and success rate.

## Requirements

Requirements are vital to ensure the seamless execution of a project. They provide the foundation for compatibility, performance, and successful integration of the system into real-world environments. Failing to meet hardware or software requirements can lead to crashes, inefficiencies, or system failure.

### Hardware Requirements

Hardware requirements are crucial to support the efficient execution of the system, especially for machine learning computations and visualizations.

* + - 1. RAM (min 16GB)
      2. Hard Disk (min 128GB)
      3. CPU.
      4. X64 based Processor.
      5. 64-bit operating system

### Software Requirements

Software requirements are also critical to the success of a project. These requirements include the specific versions of software and operating systems that are compatible with the project's software. By ensuring that the project's software is compatible with the required software and operating systems, you can reduce the risk of compatibility issues and ensure that the project's software functions as intended.

* + - 1. Software: Python 3.10 or high version
      2. IDE: Visual Studio Code

### Libraries

Libraries play a crucial role in software projects by providing pre-written code and functionality that developers can leverage to expedite development, improve code quality, and enhance the capabilities of their applications.

* + - 1. **scikit-learn:** Scikit-learn is a popular machine learning library in Python, providing simple and efficient tools for data mining and data analysis. It features various algorithms for classification, regression, clustering, dimensionality reduction, and model selection. Scikit-learn is known for its easy-to-use interface and extensive documentation.
      2. **matplotlib:** Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It provides a MATLAB-like interface for plotting 2D and 3D data, supporting a wide range of plot types, customization options, and output formats. Matplotlib is widely used in scientific computing, data analysis, and data visualization.
      3. **numpy:** NumPy is a fundamental package for scientific computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays efficiently. NumPy is essential for numerical computations, data manipulation, and linear algebra operations in Python.
      4. **Pandas:** Pandas is a powerful Python library used for data manipulation and analysis. It provides easy-to-use data structures like DataFrames and Series to handle structured data efficiently. With its rich set of functions, Pandas simplifies tasks such as data cleaning, transformation, and aggregation. It's widely used in data science and machine learning projects for handling large datasets with ease.

## Code

Code for implementation of Project Dependency and Risk Predicition.

### GitHub Link

[**https://github.com/SrilekhaImmadisetty/FinalYearProject.git**](https://github.com/SrilekhaImmadisetty/FinalYearProject.git)

The above GitHub repository contains code implementation, thesis work and presentation PPT for the project permission based detection of android malware.

### Importing all necessary packages

It imports various libraries including NumPy, Pandas, scikit-learn and matplotlib. The script defines functions for loading data, selecting features using training, evaluating Random Forest model and saving the trained models.

### Extracting permissions from input file

This module is responsible for analyzing the input project data by extracting task dependencies provided by the user. The system interprets these dependencies to understand the structural relationships between various project tasks, which form the basis for predicting overall project risk.

The input typically includes a list of tasks, along with values indicating dependency and independency levels. These values reflect how strongly one task relies on another for execution or how isolated tasks can operate. The system processes this input and converts it into a structured format that reflects inter-task connections.

The extracted dependency information is then transformed into a feature vector. This vector captures the strength and nature of relationships among the tasks, such as whether tasks are heavily dependent on others or more self-contained. Such feature representation enables further computational analysis, especially in generating Directed Acyclic Graphs (DAGs) that visualize task flow and identify critical paths.

Ultimately, this stage lays the foundation for assessing project risk by quantifying how task interdependencies might affect timelines, resource allocations, and overall project stability.

### Loading the Dataset

This code snippet performs the following steps:

This code section focuses on preparing the dataset used for predicting the risk score of a project. Initially, the dataset is loaded from a CSV file into a Pandas DataFrame. This dataset contains information such as the project name, task dependencies, independent factors, and corresponding risk scores collected from historical data.

After loading, the code separates the input features (like dependency value, independent value, and other task-related metrics) from the target variable, which is the risk score. These inputs will be used to train the machine learning model.

A Random Forest Regressor is then initialized and trained directly on the entire dataset without applying any cross-validation. This model is chosen due to its capability to handle non-linear relationships and reduce overfitting by using an ensemble of decision trees. Once trained, the model is ready to predict risk scores for new project inputs, helping in identifying potential high-risk areas based on task structure and dependencies.

### splitting data and training Random Forest Regressor

This code section focuses on training a machine learning model to predict the risk score of a project based on the provided task-related inputs. The model used here is RandomForestRegressor from the sklearn.ensemble module. Here's a detailed breakdown of how the training is handled in the code:

* + - 1. The dataset is first loaded and cleaned to extract relevant features like dependency value, independent value, and possibly other task-related attributes which contribute to the overall project risk.
      2. The input features (X) and the target variable (Y), i.e., the actual risk scores, are separated. This helps in preparing the dataset for training the model effectively.
      3. The dataset is then split into training and testing sets using train\_test\_split, usually with an 80-20 ratio. This ensures that the model is trained on one portion of the data and evaluated on another, unseen portion to check its generalization capability.
      4. A RandomForestRegressor instance is created with default or specified hyperparameters. This ensemble learning method constructs multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting.
      5. The model is then trained using the fit() method on the training data (X\_train, y\_train). During training, the regressor learns complex relationships between task parameters and the resulting risk score by building numerous trees and learning from multiple paths of decision-making.
      6. After training, the model can be used to predict risk scores for new project inputs using the predict() method, providing real-time feedback on how risky a particular task structure or dependency scenario might be.
      7. The trained model may be evaluated using error metrics like Mean Squared Error (MSE) or R² score on the test set to understand its performance, although these steps may not be explicitly shown in the current code.

### Interface using Flask

This is a Flask web application designed to assess the risk level of a software project based on user inputs such as the project name, a list of tasks, dependency value, and independent value. The interface is built using HTML and styled with CSS to provide a visually engaging experience, allowing users to interact seamlessly. When the user submits the form, the input data is sent to the backend through a POST request to the /predict route, where the server processes the information using a pre-trained Random Forest Regressor model to predict a numerical risk score. This score is then interpreted into a qualitative category like low, medium, or high risk, and is displayed on the interface for the user to view instantly. Additionally, if enabled, a visual representation of task dependencies in the form of a Directed Acyclic Graph (DAG) is generated and shown on the same page to enhance understanding of task interrelations. The application runs in debug mode, supporting efficient testing and live updates during development.

# Results

## Interface

The interface is designed using the Python Flask framework and HTML. This is the starting page of the application, and when the application is executed on the terminal, it is hosted on a local web server and the corresponding page opens in the browser. The interface is developed in a user-friendly manner where the user can input the project name, list of tasks, dependency value, and independent value. Once the user submits the details, the backend processes the information and predicts the project risk score using a machine learning model. Based on the predicted score, a risk level is displayed along with a visual DAG (Directed Acyclic Graph) representation of the project's task dependencies. The interface also ensures dynamic interaction by showing the risk output and graph image without refreshing the page.

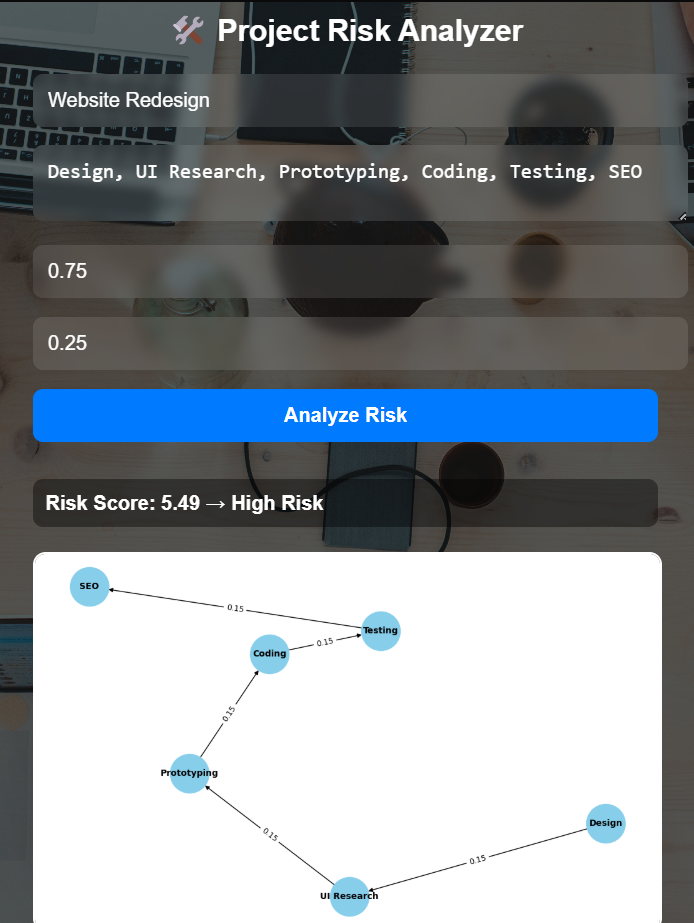
A screenshot of a computer screen

AI-generated content may be incorrect.

**Figure 7.1 User Interface**

## Output

The output of the application is visually presented on the same interface once the user submits the required input. After clicking the "Analyze Risk" button, the application processes the task data, computes the dependency and independence values using a trained Random Forest Regressor model, and displays the corresponding risk score. Along with the numerical risk score, a qualitative risk level such as "High Risk" is also shown for better understanding. To enhance the interpretability of task dependencies, a Directed Acyclic Graph (DAG) is generated and displayed below the score. This graph visually illustrates the flow and connection between tasks based on the dependencies provided by the user, making it easier to analyze project risk from both data and structural perspectives.



**Figure 7.2 Result.**

# Conclusions

In conclusion, the project titled **"Project Dependency and Risk Prediction"** effectively illustrates the application of machine learning, particularly the Random Forest Regressor, in identifying and analyzing project-related risks. By studying the dependencies among various tasks in a project and calculating their influence, the system is capable of generating a meaningful risk score. This score helps in understanding which parts of the project are more vulnerable to delays or failures due to their interconnections and weightage of influence.

The use of a **Directed Acyclic Graph (DAG)** provides a visual and analytical representation of task dependencies. Each node represents a task, and each edge shows the relationship or influence between them. The clarity provided by this graph supports better project planning and risk mitigation, as stakeholders can easily identify critical paths, bottlenecks, or highly dependent tasks that might cause cascading effects if not managed properly.

The prediction model, powered by the Random Forest Regressor, was trained to learn from input parameters such as dependency weights and independency values. This approach allowed the model to evaluate patterns and generate precise risk scores based on real-time or predefined input. The model's robustness ensures consistency and reliability in different scenarios, helping project managers make informed decisions backed by data.

Overall, the integration of machine learning with dependency analysis creates a powerful risk prediction tool that elevates traditional project management practices. By moving from intuition-based to data-driven planning, this system significantly enhances the ability to anticipate, assess, and address risks early in the development cycle—ensuring smoother workflows, timely deliveries, and more successful project outcomes.

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