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Machine Learning and Deep Learning Analytical Approaches to Assist Software Project Managers: Dashboard

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Abstract -***Companies frequently turn to project management systems for advice with the ongoing data growth caused by stakeholders throughout a product life cycle. The team will be able to communicate more effectively, plan their next moves, have an overview of the current project state, and act before the projections are delivered with project-oriented business intelligence approaches. These technologies are becoming even more beneficial as agile working mindsets proliferate. It establishes a fundamental concept of how the project should function so that the implementation is simple to use and follow. Teams and the potential for economic generation are held back by the high project failure rates brought on by inadequate project planning. The advancement of Machine Learning (ML) and Deep Learning (DL) methodologies has greatly benefited business and project management. To assist project managers in planning their projects and evaluating risks, we have examined techniques that help them anticipate potential hazards when planning their project milestones based on their prior experiences. The system's three components are the database, the web-based platform, and the machine learning core. To do this, we applied a variety of artificial intelligence techniques. Our system must be able to do risk analysis as quickly as is practical and provide project managers with recommendations using the least amount of data necessary. This article thoroughly analyses much research that has addressed the use of machine learning in software project management. This study thoroughly analyses the literature on three critical subjects: software project management, machine learning, and methods from Web Science, Science Directs, and IEEE Explore. There are 111 papers divided into four categories in these three archives. Our contribution also offers context and a broader viewpoint, essential for potential project risk management initiatives.***

Keywords: Business Intelligence, project planning, project management, Machine Learning (ML), and Deep Learning (DL).

1. INTRODUCTION

Every organisation has information which might be simple or complicated. It may or may not be in an arranged format. Such information has to be transformed into a form that is easier for the machine to process. Information converted to binary digital form for contemporary communication is known as such data. A Repository consists of a vast amount of data regarding the organisation. The amount of data on all websites is growing, making it particularly challenging for businesses or organisations to manage. What promotes the idea that it is necessary to discover methods, instruments, or models to aid or support those who deal with these data in organisations? Because so many people will interact with a business, the company must maintain data on each of its clients. For example, in e-commerce, businesses have clients worldwide, rather than just in the same locality. However, there is a need to handle this massive data collection because it is essential for the organisation. The management of this extensive data collection is necessary. Then, Analytics enters. This is the procedure for locating and disseminating essential data trends. It is beneficial in fields with a plethora of recorded knowledge. Analytics usually prefers data visualisation to communicate insight.

The same thing should be done in software development from the standpoint of businesses discovering ways and means to handle the vast amounts of data in their repositories. Some companies have centred their whole business model on their ability to collect, analyze, and take action on data (Thomas, 2006). The work that these businesses do is beneficial for all businesses. Project performance activities highly value project management planning and assessment. With a rational and realistic plan, managing a project efficiently is easier. The high project failure rates caused by inadequate project planning hinder teams and potential revenue production. Numerous methods enable project managers to foresee potential risks when planning their project milestones based on their own prior experiences. These methods aid project managers in planning their projects and assessing risks. The system's three components are the database, the web-based platform, and the machine learning core. To do this, we applied a variety of artificial intelligence techniques. Our system must be able to do risk analysis as quickly as is practical and provide project managers with recommendations using the least amount of data necessary. Successful project management possesses many essential characteristics. Understanding the fundamental characteristics of a project, the fundamental characteristics of project management processes, how success is measured, the roles, responsibilities, and activities of a project manager, the expertise necessary, as well as the conceptual context in which projects are carried out, is necessary to comprehend the value of project management fully. This article provides a comprehensive analysis of research that has addressed the use of machine learning in software project management.

➢ CHALLENGE IDENTIFICATION AND RELATIVE MAKING

After studying the amassed papers, we determined the challenge themes from the perspectives of SE and ML, and we created a relational map between the challenges and Swebok KAs. Fig. 1 shows the relation map image. The difficulties with software requirements, design, and quality of ML applications are discussed in Paper A. Paper B examines difficulties with specific learning algorithms that affect the development of ML applications. These difficulties are connected to software construction and design. Some publications examine several machine learning application areas, including security, healthcare, and automated vehicles. However, other survey publications from the SE perspective describe the unique difficulties of the application area and machine learning. These papers were not mapped in any way.

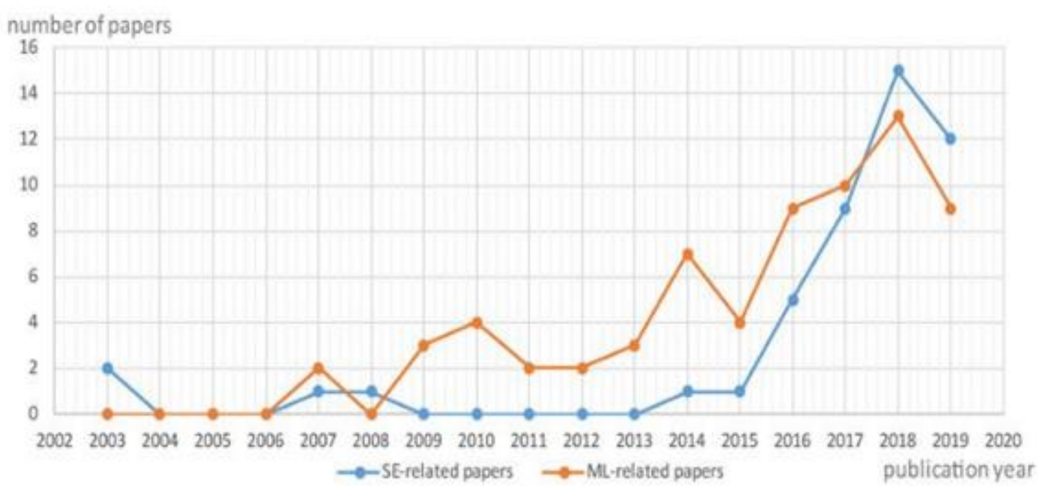

Figure 1: The number of chosen papers and their inter-annual variations from 2002 to 2020.

1.1. THE PURPOSE OF THE RESEARCH

This research aims to provide methods or a framework to help project managers do the following tasks.

1. To gather information efficiently from the team while they work on the software project.
2. To recognise group activity.

3. To determine each member's activities (barometer).
4. To forecast how the software will perform.
5. To offer a model application that may be used to develop the performance of project management methodology services using artificial intelligence.
6. To establish a beginning point (Gap) for researchers interested in using artificial intelligence (ANN) in project management services to improve performance using this study's proposed model application.

2. REVIEW - STUDIES CONDUCTED ON MACHINE LEARNING AND ITS USE IN SOFTWARE PROJECT MANAGEMENT (SPM)

The analysis and research documents summarised the most recent perceptions of ML technologies used in SPM development and evaluation and the use of ML methodologies. The ML procedures are covered and used in this section. There were several subjects and implementations covered in these publications. Large groups of specific studies that are concentrated on ML ways of manufacturing have been formed. There are three subcategories for each of the six publications in this group.

K-Nearest Neighbor Algorithm was used for this sub-cluster (KNN). [20] Analysed and evaluated the observations, metrics, data sets, and computation measurements; the maintenance prediction field uses ensemble models, various forecast models, and ML problems. As a result of KNN for managing missing data, another [21] has highlighted growing concern for ML technology.

There have been other categorisation studies on Regression. The methodologies and predictors for volatility forecasting and the categorisation criteria were identified in the paper [19]. It has been determined which characteristics were used as literary volatility parameter indicators and which forecasting strategies were used to increase the precision of the volatility of prevision needs. Software projects require volatile specifications since they directly affect costs and the length of overruns. The SLR was a formally structured approach for recurring results [22]. Like with other data sets, the study cannot infer a data set's specific application from its organisation. Another [18] covered estimating the program effort using ML approaches. The systematic analysis demonstrated the importance of ML methodologies, size scales, comparative data, evaluation methods, etc.

An article in Fuzzy Logic Studies [23] examined how to measure program effort using ML techniques. He also covered cost studies of system-functioning methodologies and many software projects. The primary conclusions were that process and model should prefer only one method.

Based on the production methodology's ML approaches, large groupings were formed by sorting the chosen articles. In the following category, there are seven subcategories made up of 27 publications.

The 26 papers in this section are utilised for SPM with various ML techniques. The current ML, Definition, Domain, and other crucial elements established empirically are contrasted in Table 1.

Table 1: Type of ML and their studies done by different authors.

Ref	Type of ML	Description	Domain	Feature Extraction	Limitation of Old System
Zhang, D. 2011	several types of ML	argued that computational technology is applied in information analytics.	a wide range of knowledge and experience in the subject	Non	Comprehensive machine analytics, software evaluation, machine learning, data processing, and knowledge visualisation
ManikReddy, 2018	Several types of ML	demonstrates a cutting-edge fusion of digitization and ML to approach this perennial problem innovatively.	Project evaluation, team pace and time estimation	Non	Creation of a waterfall concept about a decade ago

Moharreri, 2016	Several types of ML	Complementing Agile manual planning poker	Software development effort estimation	Token Extraction	There is no framework for agile growth, which is the most suitable.
Hosni, M.; 2016	Several types of ML	Many solo strategies to forecast the software development effort were suggested System	Software effort estimation	Dataset figures include the number of ventures and the number of characteristics	It is seen to be sufficient in any case.
Papatheocharous, 2012	DT, FL	It occasionally offers reasonably trustworthy data.	Cost calculation for software	Features from the ISBSG	Even while they provide IT stakeholders with significant financial rewards, built accurate and useful models are limited.
Hongming, 2013	SVM	One of the primary strategies for creating software with a high failure probability is the externalised development project. The timing of high-risk initiatives can be aided by intelligent risk prediction models.	Software project	25 chosen risk factors	Existing models are generally based on the idea that all costs of misclassification are equal, which is inconsistent with the existence of risk prediction in the context of software projects.
Twala 2014	SVM	Examines the effects of noisy domains on eight ML accuracy and statistical trend identification systems.	computer effort forecasting	Randomly selected feature	Solutions from a probabilistic perspective for the noisy domains issue in software effort prediction
Wu, J.H.; Keung, 2016	K-Means	Used a specific information engineering design approach to spot flawed software	worldwide development of software	Feature Subset Selection	to encourage data-driven decision-making for PM software and generate useful outcomes.
Rahman, M.T 2019	DT	Software effort estimation is the most crucial task in both software engineering and project management.	Calculating Software Work	Non	Calculate the effort required for various programme sizes based on a comparison of ML algorithms.
Li, Y.; Huang, Z[2017]	SVM and NB	Gave a thorough analysis of well-known data filters.	Cross-project defect prediction	Feature-based strategies	Cross-project defect prediction is substantially more effective with data filtering, and the suggested hierarchical technique also performs significantly better.
Lopez-Martin 2014	Neural\s network	For the efficiency forecast, and in-app practises, ML was dubbed the universal neural network regression.	Software practitioners	Non	The output of tech experts is referred to by developers and managers and is often calculated as the size/time ratio.

This section contains papers that heavily rely on SPM equations. The assignment is divided into large sections using the software development methodology and the ML methodologies. The documents [Karim, 2016] were primarily concerned with improving the predictability of estimating and allocating the proper amount of effort for resolving various customer, project management, and development challenges. It will be argued that reporting procedures, knowledge, and regular blind analysis are all issues that must be resolved to resolve the issue. Others [Abdellatif 2018] proposed a method for examining stakeholders' points of view, segmenting industry-specific problems, and developing profiles that encapsulate their preferences across all themes. Predictive regression techniques and software processing power were also contrasted.

The Bayesian Networks Algorithm is covered in the articles in this category. [Asif et al., 2020] provide a value estimate solution by combining qualitative and ML responses. This probabilistic model will be employed to predict the ultimate value of a certain product management and development decision. The authors created a model that automatically determines the association between risk factors and mitigation using an intelligent Decision Support System (DSS). The proposed approach considers the frequently noted current risk management limitations, including the lack of a standardized DSS and the connection between software risks and mitigation.

An automated machine-learning method for assessing software effort calculated from the task text was introduced in two articles [Ionescu et al., 2017]. Functions for estimating effort are made simpler using an ANN. The outcomes of a software firm's software evaluation SPM outperform those reported in the pertinent literature, and the system asserts to be a great deal easier to implement into any product. SPM Contrary to other tactics, technologies that keep textual task descriptions typically use them as they are frequently available.

The authors of [Tollin, 2017] reported the findings of an investigation of real-world data mining activities, including the production of test cases, calculations of effort, and social indicators. After being formalized, the findings of that informal research were divided into a dozen more recommendations and seven guiding principles. Although some of these concepts might also apply to academic data mining, the goal is to present ways to achieve good industrial data mining results. A new hybrid model has been created more precisely thanks to research. The concept is excellent since it can be used with just one database and a more comprehensive range of procedures. Our model is evaluated using ANN and SVM ML methods. The work provides a more trustworthy iteration of the SVM Model for predicting risk.

In [Kumar, Pospieszny 2018], the authors provided a methodology after analysing source code metrics. The best set of performance indicators for the model was chosen. The predictive failure models are tested using the cost estimation method. Others recommended using past software engineering data to help project managers choose the most appropriate development process model. Think of utilizing automated techniques, then sequentially describe the problem.

This section includes descriptions of the articles that employed Artificial Neural Networks (ANNs). Two publications [Baytar, 2019] on developing ML risk stimulator systems offer the optimum risk incentives for requirements, scenarios, and taxonomy tags for developing a software project. Each taxonomies should be considered separately from the study because they are independent of the danger sources. One of the critical objectives of [Desai, 2018] is to use the current ANN learning procedure to assist with SCE projections. The outcomes are the root average and the median proportionate magnitude of the mistake.

Research on support vector machines belongs to a different category (SVM). What project gating systems do and how they clean the building line, which is the primary usage for CI systems, are clarified in two studies [Volf, 2017]. We suggest and assess three submission handling heuristics for the Gating system. These findings demonstrate that successful screening and continuous monitoring with low attentiveness led to these outcomes. This result is reliable.

The use of ML to optimise selection is assessed in the third and final heuristic evaluation. Others created the Less Square project risk evaluation methodology [Lopez-Martin, 2017]. (LS-SVM). It can be seen from the simulation that the expected SVM result was obtained. LS-SVM methodology was used to investigate the project's risk assessment model. The created LS-SVM regression model is trained using the expert risk assessment data, which maps the link between hazard and characteristics. The results further demonstrate the LS-SVM model's accuracy and broad applicability. The most recent study [Dahab, 2017] suggests using runtime SVM learning algorithms for inspecting and grading stages.

Deep learning was the subject of one article. Long-range memory and highway networks were trustworthy deep-learning architectures [Choetkiertikul, 2018]. The prediction framework can forecast impacts without manual function engineering through end-to-end training with little input data.

There are numerous clustering method choices. In addition to suggestions for a better-organized updating mechanism for CC projects, additional clustering algorithms, and fundamental concepts, the following topics may be covered: project input features, clustering functionalities, parameter values, and tuning procedures [Zhang, 2019]. Dycom obtained the CC subgroups using additional clustering techniques. Hierarchical clustering, K-means, and preference maximization are the three clustering techniques. 2019 [Larsson]. The original Dycom and the Dycom Clustering use four CC sub-sets of four SEE tables of different sizes. For instance, the investigation includes a toilet arrangement. Using K-mean clustering, Dycom can be separated from CC programs with a delivery comparable to Dycom or with higher prediction capability.

3. METHODS

3.1. Estimation for Software Project Management based on ML

As shown in Fig. 2, the step-by-step procedure of software projects can be summarised as follows.

1. Data Collection
2. Preparation phase
3. Feature Extraction
4. Model Construction
5. Analysis

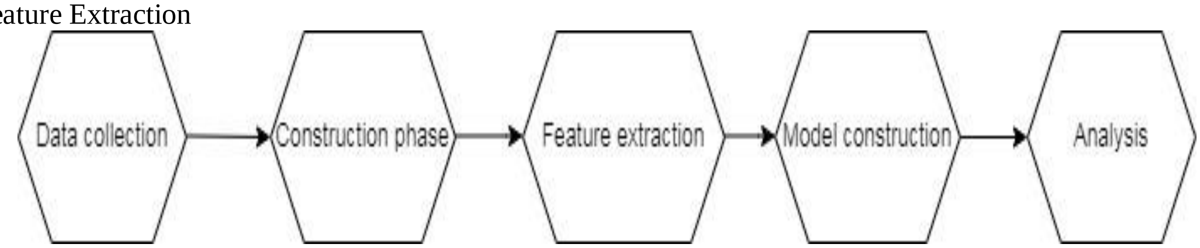

Figure. 2: Procedure for a software project

➢ DATA COLLECTION

Only interviews with people active in ML initiatives allowed for collecting such data. Conclusions have been reached using both primary data—audio recordings and transcriptions—and secondary data—interpretations of meetings and interviews.

➢ PREPARATORY PHASE IN MACHINE LEARNING

Managers need to comprehend how data influences machine learning application development differently than traditional development. Felix Wick, corporate VP of data science at supply chain management platform provider Blue Yonder, said that, unlike conventional rule-based programming, machine learning consists of two components that make up the final executable algorithm: The ML algorithm itself and the data to learn from. "However, it happens frequently that raw data are not ready for use in ML models. ML's fundamental component is thus data preparation." These operations ought to be prioritised when preparing data for machine learning applications. Data preparation is a multi-step procedure that takes longer than other stages of creating a machine learning programme. Data preparation takes up an average of 22% of a data scientist's work, according to a 2021 study by platform supplier Anaconda. This takes more time than tasks like model deployment, training, and data visualisation.

FEATURE EXTRACTION TECHNIQUES

Choosing the most relevant subset of traits to incorporate in a potent AI/machine learning model is a process known as feature selection. The feature selection process removes redundant and irrelevant data from the primary database, potentially enhancing the efficiency of the diagnostics model. The feature selection process will lighten the system's computing workload, increasing computational efficiency.

The four fundamental steps of future selection methods should generally be (1) subset generation; (2) subset assessment; (3) procedure-stopping criteria; and (4) validation.

In the first step, subsets are selected using the search methodology. The search methodology and search direction are frequently used to establish the strategy.

Step two depends on several evaluation variables, such as closeness, dependability, consistency, etc. The step three stopping criteria depends on many other variables (in step four, the chosen feature is evaluated using a range of cutting-edge AI/ML methodologies, based on the step three criteria) (such as if the error is less than necessary or chosen, whether the search is complete, etc.).

➢ MODEL CONSTRUCTION PHASE

A dataset representing real-world tunnel surface settlement is used to assess the suggested strategy's effectiveness. Overall, the work we detailed in this study makes the following three contributions to the scientific and industrial fields.

(1) using machine learning methods to forecast tunnel settling. Forecasting tunnel settlement is a practical problem in developing civilisation in the actual world. Properly utilising historical data in the tunnel construction process must be highlighted. Even though there have been few studies in this field, particularly considering how quickly AI-enhanced approaches have grown.

(2) Small data size univariate time series data forecasting. A Shanghai-based metro tunnel-building business compiled the tunnel settlement data used in this study. A time series dataset with a 100-point sample size is offered for each measured tunnel surface point. Additionally, the building company keeps track of the height of each measurement point. However, the tunnel settlement is impacted by many outside influences, including the environment and human activity. The forecasting challenge gets more complex as more data are univariate and small.

(3) Extended machine learning approaches are proposed. To make existing machine learning approaches like SVR, BPNN, and ELM more appropriate for forecasting tunnel settlement, the suggested forecasting method modifies them. A PSO process is added to find the best settings for several classifiers. A comparison analysis is done throughout the experiment phase to demonstrate the suggested strategy's effectiveness.

➢ DATA ANALYSIS

Coding was one method of data analysis. Data is divided into themes or components during the coding process, and each theme or component is given a name (Bryman and Bell, 2011). These themes, which were further divided into subcategories, were discovered through analysis of the interview data. Later interviews would address questions about any noteworthy pieces found in the data but absent from the literature. More categories were created with every interview, and the data inside the existing categories grew. These categories provided a foundation for comparing the interviews when the final interview was conducted. The concepts that didn't relate to addressing the study questions were disregarded. Fig. 2 shows. The estimation process for software projects

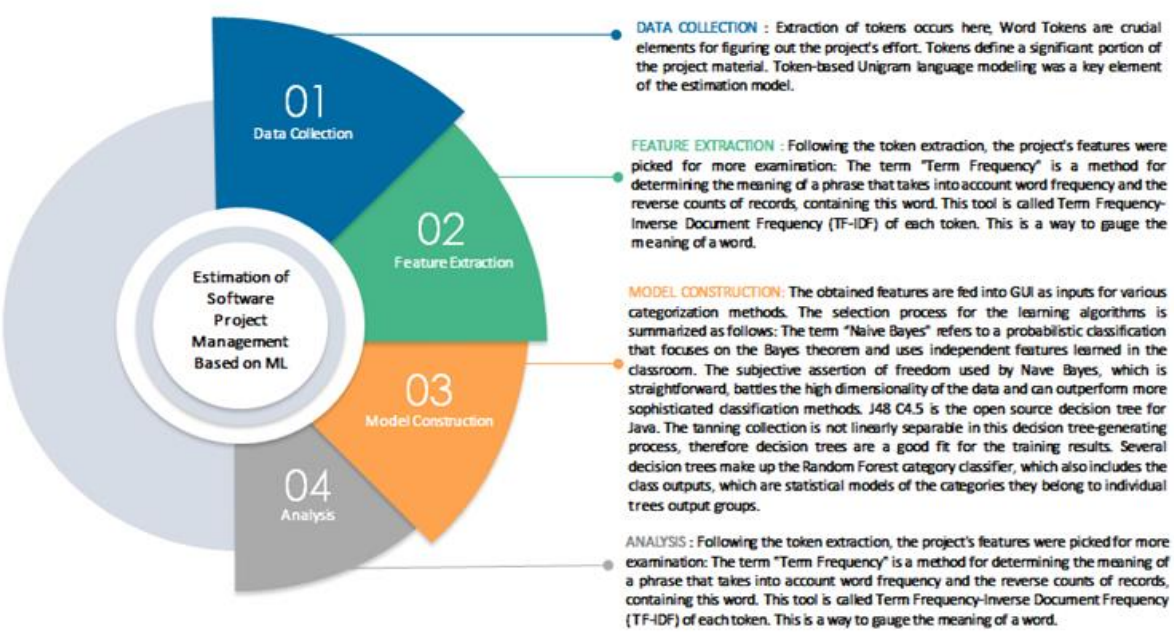

Figure 3: An illustration of a methodology for developing software estimation for project management.

On examining the advantages of utilising the Project Management ML platform, it was understood that the merits are transparent and appealing. Here we shall analyse the major advantages of using Project Assessment software as below:

1) Prediction Cost Evaluation Model advantages
2) Positive aspects of risk management
3) Advantages of Global Software Development
4) Points for Expert-Based Measures

Figure 4 illustrates the various factors leading to achieving benefits from the Project Management assessment software.

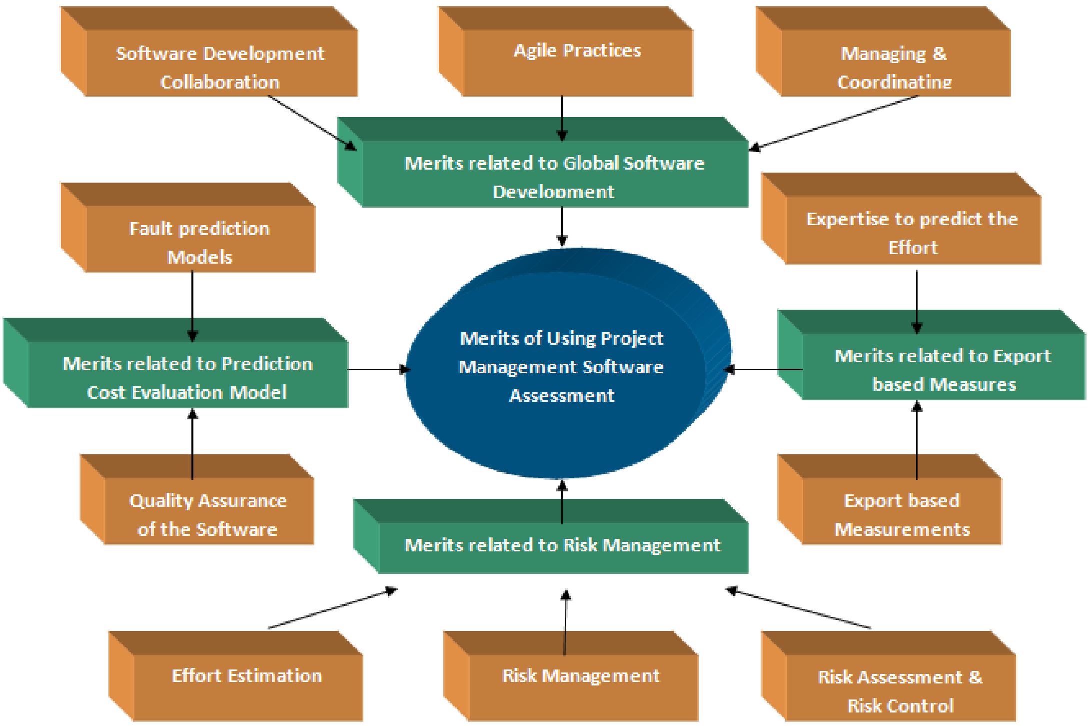

Figure 4: Merits of using Software Project Assessment

4. RESEARCH DESIGN

Given the nature and difficulty of the research, a combination of methodologies is the best course of action for us. When combining quantitative and qualitative research techniques, approaches, concepts, or language in a single study, a researcher utilises a mixed-method design (Johnson & Onwuegbuzie, 2004). Johnson and Onwuegbuzie suggest using "induction (or pattern discovery), deduction (the testing of ideas and hypotheses), and abduction (selecting and relying on the best of a selection of explanations for interpreting one's discoveries) (2004, p. 17), is also included in the logic of inquiry. Thus, a mixed-method approach offers a platform for bridging the gap between the qualitative and quantitative paradigms and has a logical and intuitive appeal. Because of this quality, more researchers are inclined to choose mixed-method designs for research ((Onwuegbuzie & Leech, 2005). As was already said, the advantages of quantitative and qualitative research approaches are combined in a mixed-method design. Although using quantitative and qualitative methodologies independently has benefits, doing it together produces much more benefits. According to Connelly (2009, p. 31), the goal of mixed methods research is to "draw on the strengths and minimise the defects of both types of study," which further emphasises this issue. Quantitative research typically improves the accuracy of research tools and provides a numerical dimension when analysing phenomena (Sun, 2009). The human experience can be quantitatively simplified by quantitative studies, which makes it easier to analyse study findings. Some research assignments aren't precise about whether a quantitative or qualitative technique is required because the study may need qualities from both qualitative and quantitative methods. There may be a case for utilising a mixed technique approach to maximise the effectiveness of both. However, Yin asserts that mixed-method research should not always combine quantitative and qualitative approaches (2006). In other words, a mixed-technique approach may still be used even when two quantitative methodologies have been used entirely.

5. FINDINGS

The input is the anticipated demand for complex project control models and IT solutions that use ML-based frameworks and information imprecision care, vagueness, or ambiguity by the major success indicators connected to all knowledge disciplines. Research on a subject related to the technical convergence of IT resources has been made possible by contemporary learning assessment libraries and open-source project management development frameworks. [Prakash] 2017.

The categorisation model predicts cost slippage using a data mining technique and then computes a cost slip in the project category using the budget and schedule from an ICT project's initial planning. Action is required in all falls, whether natural, medium-slip, or high [Badshah, 2020]. The objective is to clarify the construction of a classification model utilising data mining techniques to calculate cost losses. Depending on the input of a specific subset of project characteristics, such as the starting budget and timeline, the proposed model separates projects into three categories (regular, medium, and large).

6. LIMITATIONS

Previous methodologies had flaws due to poor scheduling algorithms, poor modelling techniques, and inadequate analytical tools. Our research has modelled how effective managers deal with large projects' size, complexity, and changes and how they encourage cooperation considering organisational heterogeneity and loose coupling.

7. CONCLUSION

The literary analysis discovered that ML methods for software project management have been thoroughly investigated. Over time, there has been a steady dispersion of positions. We found that ANN, fuzzy logic, and algorithms are essential to machine learning (ML) tools for autonomous effort estimates. One of the critical methods used in software development is the accurate measurement of effort. Time and problems specifically affected the software. Fundamental motifs in numerous ML works in software project management can be gleaned. We recognised that a mixed approach is preferable to the earlier ML methods and their limitations. We ultimately concluded that Oracle Project Analytics would be an excellent tool to help project managers manage their dashboards efficiently.

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