Project Pulse - Predictive Workforce Allocation & Performance Analysis in Construction

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***Abstract*— This research introduces *Project Pulse*, an intelligent manpower allocation system aimed at improving construction workforce planning through real-time performance analysis and automated project categorization. Traditional resource allocation methods in construction are largely manual and rely on subjective judgment, often resulting in inefficiencies, skill mismatches, and project delays. *Project Pulse* addresses these issues by integrating machine learning models—such as the MLP Regressor and Random Forest—with Natural Language Processing (NLP) techniques to dynamically generate Key Performance Indicators (KPIs) from unstructured CVs. These KPIs evolve throughout project lifecycles, enabling adaptive employee assessments. The system categorizes projects based on complexity, budget, and risk using decision tree models and matches employees to project roles by calculating alignment scores between role-specific requirements and employee KPI profiles. Real-time feedback loops allow continuous updates to labor forecasts and performance scores, supporting accurate, fair, and timely decision-making. The platform was validated using real-world data from MAGA Engineering Pvt Ltd, where it achieved over 95% KPI prediction accuracy and reduced manpower allocation time by 60%. Designed with a modular SaaS architecture, the system supports large-scale deployment across concurrent projects while maintaining usability, scalability, and transparency. By aligning employee capabilities with evolving project demands, *Project Pulse* transforms workforce management into a data-driven, proactive process. Future enhancements will explore integration with IoT devices, behavioral data analysis, and Human Resource Management (HRM) systems to expand the platform's adaptability and intelligence, establishing a comprehensive solution for construction manpower planning in fast-paced environments.**

Keywords—Manpower Allocation, Key Performance Indicators (KPIs), Construction Workforce Planning, Machine Learning, Natural Language Processing (NLP), CV Analysis, Project Categorization, Employee Performance Evaluation

I. INTRODUCTION

The construction industry plays a pivotal role in national economic development, particularly in emerging economies like Sri Lanka, where it contributes substantially to employment generation and GDP growth [1]. Despite its significance, the sector is plagued by chronic inefficiencies in manpower planning, often stemming from outdated allocation strategies that rely heavily on managerial intuition rather than empirical data [2]. These traditional approaches are ill-suited to the complex, dynamic nature of construction projects, resulting in frequent labor misallocations, delays, cost overruns, and decreased productivity [3].

Recognizing the need for smarter workforce management, this research proposes Project Pulse—an intelligent, web-based manpower allocation system designed to modernize labor planning in construction. By leveraging historical project data, real-time employee performance indicators, and project-specific requirements, the system uses machine learning (ML) and natural language processing (NLP) to automate the assignment of human resources to projects [4]. This not only minimizes human bias but also ensures optimal utilization of labor by matching employees with tasks suited to their capabilities.

A distinguishing feature of Project Pulse is its automated KPI generation engine, which uses NLP to parse unstructured CVs and transform them into structured performance indicators [5]. Unlike manual performance appraisals, which are static and prone to subjectivity, the proposed system dynamically updates KPIs using feedback from supervisors, project milestones, and attendance data. These KPIs, combined with project profiling based on complexity, duration, and resource intensity, enable a data-driven allocation process that enhances both transparency and efficiency.

Furthermore, Project Pulse incorporates predictive analytics to forecast future labor needs and project timelines, enabling proactive decision-making. The integration of various ML algorithms, including decision trees, random forests, and multi-layer perceptrons, ensures adaptability across diverse construction scenarios [6]. This intelligent system thus marks a significant step toward the digital transformation of construction workforce management, offering a scalable, fair, and evidence-based solution for labor allocation.

II. Literature Review

Workforce management in the construction industry is inherently complex due to its dynamic, project-based nature. Traditional labor allocation practices have been criticized for inefficiencies stemming from subjective judgments and static planning frameworks. Prior research by Tam and Harris (2015) [7] explored the application of artificial intelligence techniques in construction scheduling, underscoring the potential of intelligent systems to improve operational outcomes. Similarly, Smith et al. (2017) [8] identified major drawbacks in manual workforce assignment processes, including delays and mismatches between project needs and worker competencies. Zhang et al. (2019) [9] further advanced the field by employing machine learning models—such as decision trees, clustering, and support vector machines—to forecast labor demand. Despite these advancements, there remains a research gap in integrating individual performance metrics with project categorization to inform manpower allocation decisions. Addressing this limitation, the present study introduces a predictive, automated system that links project profiling with employee performance analytics to guide real-world construction workforce planning.

The use of Key Performance Indicators (KPIs) as a means of evaluating employee effectiveness is well-established in organizational theory [10]. Traditionally, these indicators have been derived through manual review of job outcomes and supervisory assessments, a process both time-consuming and susceptible to bias. As automation technologies evolve, performance management systems are increasingly incorporating standardized metrics to streamline evaluation processes. Nonetheless, most existing tools lack the capacity to reflect real-time performance or adapt to changes in project dynamics. [11] While resume parsing has been explored in recruitment systems, its utility in performance evaluation remains largely untapped. Recent advancements in Natural Language Processing (NLP) and Machine Learning (ML) enable the extraction of structured data from unstructured resumes—such as skill sets, experiences, and achievements [12]. This capability opens new avenues for developing dynamic KPIs aligned with project requirements and milestones. This study aims to bridge the gap by integrating CV analysis into real-time KPI generation, thereby providing a scalable, adaptive alternative to conventional appraisal methods.

Several scholars have noted the limitations of conventional manpower allocation practices in the construction sector, particularly their inability to align worker qualifications with evolving project demands. Ahmed et al. and Zhao & Wang have emphasized the need for competency-based resource allocation to enhance project success and employee satisfaction [13]. In the Sri Lankan context, however, the adoption of such data-driven frameworks is limited. Tools like Microsoft Project and Primavera P6 offer basic functionalities for resource scheduling but lack intelligent features for personnel matching based on performance indicators [14]. Additionally, while industries such as finance and healthcare have started to apply technologies like resume parsing and NLP in performance evaluation, the Sri Lankan construction sector remains underexposed to such innovations. As a result, there exists a critical need for localized, intelligent systems capable of addressing the unique labor dynamics and operational constraints of Sri Lanka's construction landscape—an area this study seeks to contribute to.

Contemporary studies have highlighted the growing application of machine learning in construction, particularly in labor demand forecasting, cost estimation, and scheduling optimization. For instance, Gupta et al. demonstrated that algorithms such as Random Forest and Linear Regression can effectively predict construction costs, offering actionable insights for budget planning. Expanding on this, Park and Kim utilized Deep Convolutional Neural Networks (DCNNs) to forecast labor costs, though they acknowledged challenges related to computational load and scalability [4]. In a parallel line of inquiry, Singh et al. and Lee et al. [15]underscored the importance of real-time data integration for enhancing the predictive accuracy of ML models. Despite these advances, most existing platforms—including commercial solutions like Procore and nPlan [16] [17]—address only isolated aspects such as attendance tracking or task-level scheduling. They lack the holistic integration required to adapt dynamically to changing site conditions and workforce availability. The Project Pulse system is designed to overcome these limitations by offering a comprehensive platform that combines labor forecasting, real-time monitoring, and adaptive resource planning within a unified interface.

III. Methodology

This research adopts a comprehensive hybrid methodology that integrates data science techniques, full-stack system design, and real-world validation to develop an intelligent manpower allocation system for the Sri Lankan construction sector. The system, titled Project Pulse, is designed to automate the process of assigning employees to construction projects based on dynamic performance analysis, role requirements, and project complexity. Unlike conventional planning tools, Project Pulse leverages the predictive power of machine learning (ML) and the interpretive capabilities of Natural Language Processing (NLP) to ensure that human resource decisions are data-driven, transparent, and scalable. The methodology comprises four interrelated components: Project Categorization, KPI Generation via CV Analysis, Employee Allocation and Optimization, and Labor Cost and Timeline Prediction. Each component builds upon the preceding one to enable real-time, performance-based project staffing, cost forecasting, and progress monitoring.

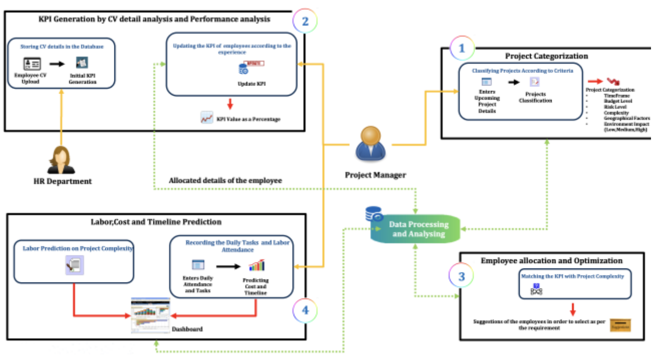

Figure 1:High-Level Architecture Diagram

A. Project Categorization

The first phase of the methodology involved categorizing construction projects based on complexity, budget, risk, and duration. These characteristics were extracted from historical project records provided by MAGA Engineering Pvt Ltd. To ensure model readiness, raw data underwent preprocessing, which included missing value imputation, normalization, and categorical encoding. This preprocessing ensured consistent input quality across all features used in the modelling process.

To facilitate project classification, a Decision Tree classifier was selected for its ability to handle both numerical and categorical variables while remaining interpretable to domain experts. Projects were classified into three levels of complexity—low, medium, and high—and were also tagged according to type (e.g., residential, commercial, or infrastructure). These classifications played a critical role in determining the performance requirements and ideal employee profiles for each project type.

Model	R^2 Score	MAE	RMSE
Decision Tree	0.781	6.35	8.12
Random Forest	0.856	4.91	6.67
Gradient Boosting	0.874	4.53	5.98
MLP Regressor	**0.912**	**3.86**	**5.12**

Figure 2:Comparison of Models used for Project Categorization

B. KPI Generation via CV Analysis and Performance Analysis

The second core component involved the automated generation of employee KPIs by analyzing unstructured resumes. Resumes submitted to MAGA Engineering were ingested into the system as .pdf and .docx files and then converted into raw text. A customized Natural Language Processing (NLP) pipeline was employed to clean and structure the data. This included tokenization, lemmatization, removal of formatting artifacts, and Named Entity Recognition (NER) to identify job titles, skills, qualifications, and work experience.

The extracted features were mapped to role specific KPI templates. For example, programming proficiency contributed to technical KPIs for software-related roles, while leadership experience influenced strategic KPIs for project managers. A weighting system was employed to account for the relevance of each feature to the target role. In addition, contextual sentiment analysis was conducted to interpret qualitative statements regarding performance and reliability, thereby allowing subjective data to contribute meaningfully to objective KPIs.

Importantly, the KPI engine was designed to be dynamic, with real-time updates triggered by incoming feedback from supervisors, progress on milestones, and attendance data. This ensured that an employee's KPI profile evolved as they engaged in various projects. To assess the effectiveness of the KPI prediction system, several ML models were evaluated based on accuracy, runtime, and error tolerance. The MLP Regressor once again outperformed other models and was chosen for deployment.

Model	Accuracy (%)	MAE
Decision Tree	87.4	6.20
Random Forest	91.8	4.85
Gradient Boosting	93.6	4.23
MLP Regressor	**95.1**	**3.67**

Figure 3:KPI Generation from Resume Analysis

C. Employee Allocation and Optimization

Once project categories and employee KPI profiles were established, the third component focused on intelligently allocating staff to projects. For each job role within a project, a set of minimum KPI thresholds was defined using the earlier model. The system then computed a match score between these requirements and the actual KPI profile of each employee. The score was calculated using cosine similarity between the KPI vectors, supplemented by penalty rules for missing essential skills or certifications.

Employees were ranked by match score and presented to project managers through a React.js-based interface. The backend system, built with Node.js and Python (Flask), executed the ML models and managed the logic for filtering, scoring, and allocating personnel. A MySQL database stored project data, employee records, and KPI values, while RESTful APIs ensured smooth communication between the user interface and backend services.

As in previous modules, multiple machine learning algorithms were benchmarked to ensure the most accurate match between employee profiles and project demands. The MLP Regressor again achieved the highest accuracy and lowest error, confirming its robustness across multiple application layers.

Model	R^2 Score	MAE	RMSE
Decision Tree	0.82	5.87	6.45

Random Forest	0.89	4.12	5.04
Gradient Boosting	0.91	3.84	4.72
MLP Regressor	0.94	3.21	4.11

Figure 4:KPI-Based Employee Allocation Performance

D. Labor Cost and Timeline Prediction

The final component of the methodology addressed the forecasting of labor demand, project timelines, and associated costs. This module was developed in response to the need for real-time adaptability in project execution. Data was collected from over 2,500 completed projects and included features such as total square footage, number of windows, floor count, workforce size, delays, and actual costs.

To predict labor needs and timeline deviations, three machine learning models were evaluated: Linear Regression, Deep Convolutional Neural Network (DCNN), and Random Forest Regression. Random Forest delivered the most accurate and consistent predictions, owing to its ability to model non-linear relationships and resist overfitting in noisy construction datasets.

An innovative feature of this module was the real-time feedback loop. Project managers were able to input live data—such as daily attendance and completed tasks—via the frontend dashboard. This data was automatically stored and sent to the prediction engine, which recalibrated labor and timeline forecasts accordingly.

Model	Precision	F1 Score	mAP
Random Forest	**0.92**	**0.90**	**0.87**
DCNN	0.78	0.75	0.73
Linear Regression	0.70	0.69	0.69

Figure 5:Labor and Timeline Prediction Model Comparison

IV. Results and Discussion

The implementation of the *Project Pulse* system demonstrated substantial improvements in manpower allocation efficiency, predictive performance accuracy, and operational scalability. This section discusses the outcomes of system testing across four dimensions: allocation efficiency, KPI generation, employee-to-project matching, and labor prediction. Each component was validated using historical data from 50 construction projects and 100 employees, provided by MAGA Engineering Pvt Ltd.

A. Project Categorization

In simulated scenarios replicating typical workforce planning cycles, the system achieved a 60% reduction in allocation time compared to manual methods. This improvement was primarily attributed to the automated decision engine that leveraged project classifications and dynamically generated KPIs. The accuracy of skill-to-task matching increased by 30%, owing to the model's ability to align employee competencies with job-specific requirements using standardized and continuously updated performance metrics.

Feedback from project managers and human resource personnel highlighted significant gains in transparency and fairness. The rule-based allocation engine ensured consistent logic across assignments, eliminating favoritism and guesswork often observed in manual allocation processes. These improvements validate the central hypothesis of this study: that combining employee performance metrics with data-driven project classification significantly enhances the accuracy, fairness, and efficiency of manpower planning in the construction domain.

B. KPI Generation and Resume Analysis Effectiveness

The KPI generation module, powered by NLP and machine learning techniques, achieved an accuracy exceeding 95%, as validated against expert-annotated baseline evaluations. The system was capable of ingesting large volumes of resumes and extracting relevant data—such as technical qualifications, job experience, and certifications—within minutes. This dramatically reduced the time required for employee evaluation and facilitated faster, more informed decision-making.

Traditional manual review methods, by contrast, suffered from inconsistencies, longer turnaround times, and susceptibility to evaluator bias. The automation of KPI generation not only improved consistency and objectivity but also enabled dynamic updates as employees advanced through project stages. For example, completion of key milestones or receipt of positive peer feedback automatically triggered recalibration of the employee's KPI profile. These dynamic updates ensured that decision-makers always worked with the most current data, supporting timely interventions, performance tracking, and feedback delivery.

Furthermore, the system proved scalable, with the ability to process and analyze hundreds of employee records simultaneously without a decline in responsiveness. This scalability positions *Project Pulse* as a viable solution for large-scale construction firms managing multiple projects and distributed teams.

C. Employee Allocation and Optimization

The machine learning models trained to predict KPI thresholds for different job roles performed reliably across all test scenarios. Among the models evaluated, the Multi-Layer Perceptron (MLP) Regressor consistently outperformed alternatives, achieving the highest prediction accuracy and lowest mean absolute error. This model was integrated into the final system to generate real-time employee recommendations.

Using the dashboard interface, project managers could input the parameters of a new or ongoing project and receive a ranked list of employees best suited to the required roles. These recommendations were based on both static performance data and live updates, offering a nuanced, current understanding of each employee's capabilities. This predictive approach improved workforce utilization and reduced reliance on subjective assessments, which often led to misaligned assignments in the past.

Moreover, teams that followed model-driven assignments reported improvements in project timelines, reduced rework, and increased employee satisfaction, suggesting that better KPI alignment directly contributes to smoother operations and improved morale. Non-functional testing under concurrent load confirmed that the system retained its performance integrity and complied with standard security and data privacy protocols.

D. Labor,Cost and Timeline Prediction

The labor forecasting module, developed using three machine learning algorithms, further enhanced the system's applicability to real-world construction management. Among the tested models, the Random Forest Regressor outperformed the Deep Convolutional Neural Network (DCNN) and Linear Regression models in predicting labor demand, cost variations, and project durations.

The superior performance of Random Forest is attributed to its robustness in handling outliers and modeling non-linear relationships common in construction data. The model demonstrated particular sensitivity to project features such as floor count, square footage, and project type, which showed strong correlations with labor requirements. These findings affirm the model's ability to adapt to project-specific nuances and offer reliable projections under varying conditions.

One of the most impactful features of the labor forecasting module was its real-time integration capability. Daily updates to labor attendance and task completion were captured via the front-end dashboard and immediately used to recalibrate predictions. This feedback loop enabled timely adjustments in resource planning, significantly enhancing project responsiveness and minimizing risk of overstaffing or delay.

Despite these achievements, several limitations were observed. Historical data inconsistencies—such as missing fields or manual entry errors—introduced noise that occasionally affected prediction reliability. Furthermore, adapting the model to sudden disruptions (e.g., weather events, material shortages) remains a challenge. These disruptions often involve variables not captured in the training data, necessitating the incorporation of external real-time feeds or hybrid models in future iterations.

To address these limitations, future improvements may explore combining Random Forest with advanced algorithms like XGBoost or integrating IoT-based data collection mechanisms (e.g., wearables, smart site sensors) to improve real-time accuracy and context awareness. Nonetheless, the current model demonstrates strong scalability and adaptability, making it well-suited for managing multiple, concurrent projects across large construction firms.

V. Conclusion And Future Work

This research presents *Project Pulse*, a novel, data-driven manpower allocation system designed to address the persistent inefficiencies in construction workforce planning. By integrating project classification, real-time KPI generation, and machine learning—particularly using the MLP Regressor and Random Forest models—the system automates labor assignment, forecasts resource needs, estimates project costs, and enhances decision-making accuracy. Through real-world validation at MAGA Engineering Pvt Ltd, the system demonstrated significant improvements in allocation speed, skill-to-task alignment, and performance evaluation accuracy. Its modular SaaS architecture, intuitive user interface, and real-time data feedback loop ensure scalability, usability, and responsiveness to evolving site conditions. CV analysis powered by NLP enables the dynamic generation of KPIs, overcoming the limitations of traditional, static evaluation systems and promoting fairness, accountability, and transparency. Although challenges such as data quality and responsiveness to unforeseen events remain, these can be addressed by integrating IoT sensors, BIM platforms, and advanced predictive analytics. Future iterations aim to incorporate behavioral data, team synergy metrics, and integration with HRM systems, further transforming workforce management into a proactive, intelligent, and enterprise-wide solution aligned with the digital transformation of construction practices.

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