AI FOR PERSONALIZED TASK ASSIGNMENTS IN CIVIL ENGINEERING

A PROJECT REPORT

Submitted by

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to

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of

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in

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DECLARATION

I hereby declare that the project report ““AI FOR PERSONALIZED TASK ASSIGNMENTS IN CIVIL ENGINEERING,” submitted for partial fulfillment of the requirements for the award of the degree of Bachelor of Technology of APJ Abdul Kalam Technological University, Kerala, is my bonafide work done under the supervision of Ms. Fathima Shana E, Assistant Professor, Dept. of Artificial Intelligence and Data Science. This submission represents my ideas in my own words, and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to the ethics of academic honesty and integrity and have not misrepresented or fabricated any data, idea, fact, or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and the University and can also evoke penal action from the sources that have not been properly cited or from whom proper permission has not been obtained. This report has not previously formed the basis for the award of any degree, diploma, or similar title of any other University.

Place: Kuttippuram
Date: 30/10/2024

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CERTIFICATE

This is to certify that the report entitled **"AI FOR PERSONALIZED TASK ASSIGNMENTS IN CIVIL ENGINEERING"** submitted by **MOHAMMED FALAHI** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Artificial Intelligence and Data Science is a bonafide record of the project work carried out under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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MOHAMMED FALAHI

ABSTRACT

This project integrates Artificial Intelligence (AI) to enhance task assignments and workplace safety in the civil engineering sector. A **pretrained BERT model** is used to intelligently match workers with tasks based on their **skills, experience, and health conditions**, ensuring optimal workforce utilization. Additionally, a **YOLOv8-based PPE detection system** is implemented to monitor and enforce **safety compliance** by identifying the presence or absence of essential protective gear in real-time. The system is deployed as a **Django-based web application**, enabling **worker registration, task allocation, real-time communication, complaint management, and payment processing** for a seamless workflow. By combining AI-driven task optimization with automated safety monitoring, this project aims to **increase productivity, minimize costs, reduce accidents, and improve overall worker well-being**, ultimately fostering a more efficient and safer construction environment.

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CHAPTER 1

INTRODUCTION

The allocation of tasks in civil engineering projects is a critical factor that influences productivity, worker well-being, and overall project efficiency. Traditional task assignment methods rely heavily on human judgment, which can be subjective, time-consuming, and inefficient. Factors such as worker expertise, experience, and health conditions are often not systematically considered, leading to suboptimal task distribution [1, 3]. With advancements in artificial intelligence (AI), there is a growing interest in leveraging AI to automate and optimize task assignments in the civil engineering sector.

This work presents an AI-driven approach for personalized task assignments in civil engineering. The system utilizes machine learning techniques, including a pre-trained BERT model, to analyze worker profiles, skills, experience, and health status to allocate tasks optimally. By integrating AI into task distribution, the system enhances productivity, reduces errors, and improves worker satisfaction [7, 4]. The AI model processes input data such as worker details, project requirements, and safety conditions to recommend the most suitable worker for a given task, ensuring a more efficient and fair assignment process.

The dataset used for training and evaluation includes worker profiles, project details, and historical task assignments. This data is structured and preprocessed to improve the learning efficiency of the AI model. The training process enables the system to understand patterns in task assignments and develop a model that considers multiple factors, such as worker safety, past performance, and project constraints

[5, 6]. The AI-driven system not only improves efficiency but also reduces operational costs by minimizing rework and optimizing resource allocation [9, 10].

To enhance the reliability and fairness of task assignments, the system incorporates a feedback loop that refines the AI model based on worker performance and user ratings. The model continuously learns from real-world assignments, ensuring its recommendations remain accurate and effective over time. Additionally, a safety monitoring component is integrated, using a trained YOLOv8 model to detect the presence of personal protective equipment (PPE) on construction sites, further improving worker safety [2, 11].

The AI-powered task assignment system has wide-ranging applications in the construction industry, offering benefits such as improved worker utilization, reduced project delays, and enhanced safety measures. It can be deployed as a decision-support tool for project managers, automating the process of assigning tasks while considering worker well-being. Moreover, this approach fosters a more sustainable and data-driven work environment, making civil engineering projects more efficient and cost-effective [13, 14].

CHAPTER 2

LITERATURE SURVEY

2.1 Related Works

Cheng and Wu [1] explored the use of machine learning models to optimize role assignments within a workforce based on factors such as worker skills, experience, and workload. Their approach uses data-driven analysis to match workers with tasks that best align with their competencies, ultimately enhancing productivity and reducing mismatches. By leveraging predictive algorithms, this system dynamically adapts to changes in worker performance, ensuring optimal alignment between task requirements and worker abilities. The main benefit of this approach is its ability to improve workforce efficiency, as employees are assigned roles that suit their individual skill sets and experience. However, the study identifies significant limitations related to the reliance on accurate data. The system's effectiveness is contingent upon the quality of input data—any biases or inaccuracies in the data could result in poor task assignments and undermine overall productivity. Moreover, frequent retraining of the machine learning models is necessary to account for evolving worker capabilities and task requirements, which presents computational challenges.

O'Reilly and Thompson [2] developed a data-driven framework for optimizing workforce operations in smart factories. Their study focuses on the use of predictive analytics for real-time task allocation, aiming to improve individual performance and minimize downtime. By analyzing ongoing performance data, their system dynamically adjusts workload distribution, ensuring that tasks are allocated efficiently and bottlenecks are minimized. This real-time task allocation can lead to significant productivity gains in manufacturing and construction environments alike. While the methodology shows promise in enhancing productivity, the study highlights several challenges. A major limitation of this framework is its reliance on continuous data collection, which can be cost-prohibitive, especially for smaller factories or organizations with limited resources. Additionally, the system's effectiveness depends on the availability of a stable network infrastructure, as interruptions or delays in real-time data could hinder the system's ability to make timely adjustments. Implementing such a framework also requires substantial upfront investment in infrastructure and employee training, which could be a barrier for smaller organizations or those in the early stages of adopting AI-driven systems.

Patel and Singh [3] focused on the role of AI in reducing human error in civil infrastructure projects. Their study employed machine learning models to analyze historical error data and identify patterns that could predict future errors in construction activities. These models provide real-time feedback to project managers, suggesting preventive measures and helping to mitigate the risks associated with human error. This framework enhances decision-making by identifying high-risk activities and offering recommendations to improve task execution and prevent mistakes. It is particularly beneficial in projects that involve complex operations, where human error can significantly impact safety, quality, and efficiency. However, the effectiveness of the AI model is highly dependent on the availability of quality historical data. In projects with limited or inconsistent error records, the model may not be able to provide accurate predictions, which could hinder its implementation. This highlights the challenge of applying AI models in projects where sufficient historical data is not available.

Karakhan et al. [4] focused on workforce development and sustainability in the construction industry. They identified several strategies to improve workforce sustainability, which was defined as the extent to which a workforce is nurtured and retained. Through a survey of industry experts and field personnel, the study highlighted seven key workforce sustainability attributes: nurturing, diversity, equity, health and well-being, connectivity, value, and maturity. These attributes were seen as essential in developing and sustaining a skilled, motivated, and productive workforce. The research offers actionable strategies for construction organizations to not only attract but also retain skilled employees, fostering a sustainable workforce in the face of high turnover rates.

Nayeem [5] examined workforce management decisions in the construction industry within the UAE. The research aimed to develop a comprehensive framework that considers all factors influencing workforce management, including hiring, selection, and worker quality. This study emphasized the need for effective human resource management practices to boost productivity in construction firms, highlighting that decision-making in workforce management has a direct impact on organizational performance. The findings of this study were in alignment with previous research, underscoring the importance of day-to-day HR decisions in managing workforce efficiency and addressing turnover issues.

Wajidi [6] focused on Archies Construction Pvt. Ltd, exploring both internal and external factors contributing to workforce turnover. The study identified key internal drivers such as job satisfaction, promotions, management support, and career development opportunities. External pressures, including competition and regulatory demands, also played a significant role in increasing turnover rates. The research suggested strategies to address these issues, including improved communication, career progression plans, competitive rewards, and fostering a supportive work environment. These strategies aimed at reducing turnover can improve workforce stability and, in turn, increase organizational productivity and reduce operational costs.

CHAPTER 3

FEASIBILITY STUDY

Developing an AI-powered task assignment system in civil engineering requires a detailed feasibility analysis to assess its practicality, efficiency, and effectiveness in optimizing task distribution based on worker skills, experience, and health conditions. The primary objective is to automate and enhance task allocation while ensuring worker well-being, making it a viable solution for improving construction site efficiency and safety. This feasibility study examines the requirements, current methodologies, challenges, and system objectives.

3.1 Purpose

The proposed system utilizes artificial intelligence, specifically a pretrained BERT model, to analyze worker attributes and match them to tasks based on relevant factors. The purpose of this system is to provide an automated task assignment tool that considers worker expertise, past performance, and physical condition to allocate tasks optimally. By reducing the dependency on manual assignment processes, the system enhances project efficiency, minimizes errors, and ensures a safer working environment.

3.2 System Objectives

The objective of this system is to create an AI-driven task allocation model that can autonomously match workers to tasks based on their qualifications and real-time conditions. The key goals include:

1. Extracting meaningful worker attributes such as skills, experience, and health status using AI techniques
2. Training the AI model to optimize task assignments while considering project constraints
3. Improving overall project efficiency by minimizing rework and enhancing worker utilization
4. Enhancing safety compliance by integrating real-time PPE detection using a YOLOv8 model
5. Providing a framework that allows for adaptive task allocation based on dynamic site conditions

3.3 Issues

Despite advancements in AI-driven task allocation, there are challenges in ensuring accurate and effective worker-task matching. Some of the key issues include:

1. Variability in worker expertise levels, making it difficult for AI to generalize across all task types
2. Ensuring fairness in task distribution without bias in AI recommendations

3. Computational complexity involved in processing and analyzing large-scale worker and task data

4. Evaluating task performance in a way that aligns with project goals and worker satisfaction

3.4 Assumptions and Constraints

3.4.1 Assumptions

1. The worker dataset provides sufficient diversity in skills and experience for training the AI model

2. AI-driven task assignments can be evaluated based on predefined metrics such as efficiency and worker satisfaction

3. The system can generalize across multiple construction project types without requiring separate models for each

3.4.2 Constraints

1. The accuracy of task assignments depends on the availability of high-quality worker data

2. Training AI models for task allocation requires significant computational resources

3. Real-time adjustments in task assignments may be limited based on data processing speed

The feasibility analysis suggests that AI-powered task assignment is a practical and scalable solution for optimizing workforce management in civil engineering. While challenges exist in ensuring accurate task distribution, the integration of AI techniques such as BERT for worker profiling and YOLOv8 for safety compliance offers promising results. The system can be further improved by incorporating real-time worker feedback, refining task-matching algorithms, and enhancing computational efficiency.

This AI-driven approach has the potential to transform task allocation in the construction industry by making workforce management more efficient, data-driven, and safety-focused.

CHAPTER 4

PROPOSED METHODOLOGY AND FRAMEWORK DESIGN

The objective of the proposed system is to optimize task assignments in civil engineering using artificial intelligence. The system processes worker attributes such as skills, experience, and health conditions to assign tasks efficiently. A pretrained BERT model is utilized to analyze worker profiles and match them with suitable tasks based on project requirements. The system aims to enhance productivity, minimize errors, and improve worker safety through intelligent task distribution.

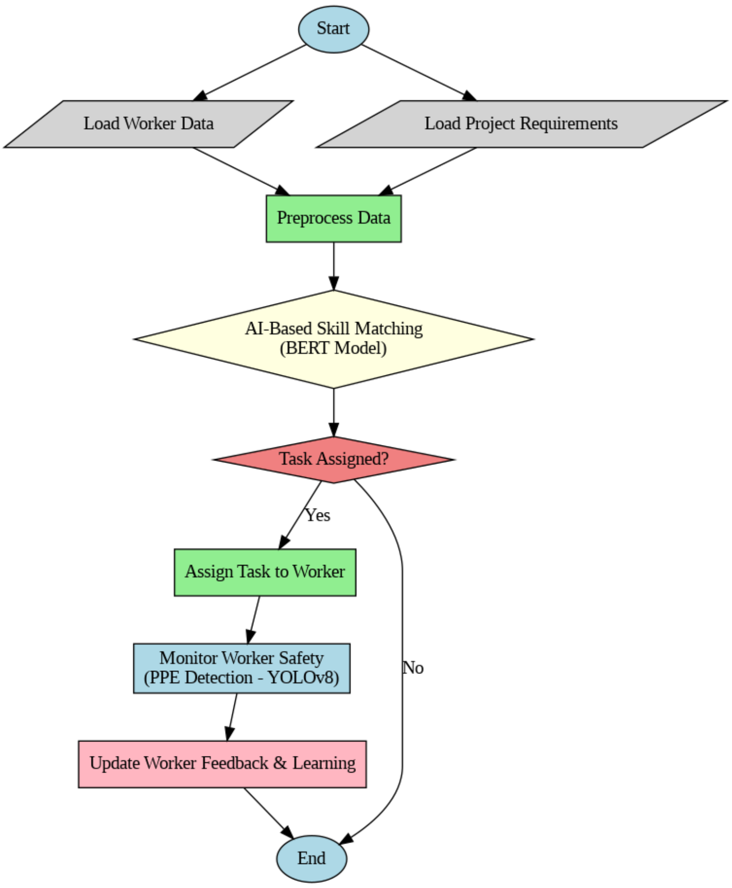


Figure 4.1: Overall System Architecture

The overall structure of the AI-powered task assignment system is illustrated in Fig. 4.1. The system consists of multiple stages, including data preprocessing, feature extraction, model training, and task optimization. The pipeline ensures that worker attributes are effectively transformed into meaningful task allocations.

The system is trained on a dataset that includes worker profiles, historical task records, and real-time health data. Key features such as skill level, past performance, and safety compliance are extracted using natural language processing (NLP) techniques. The model is trained to optimize task assignments by balancing project efficiency and worker well-being.

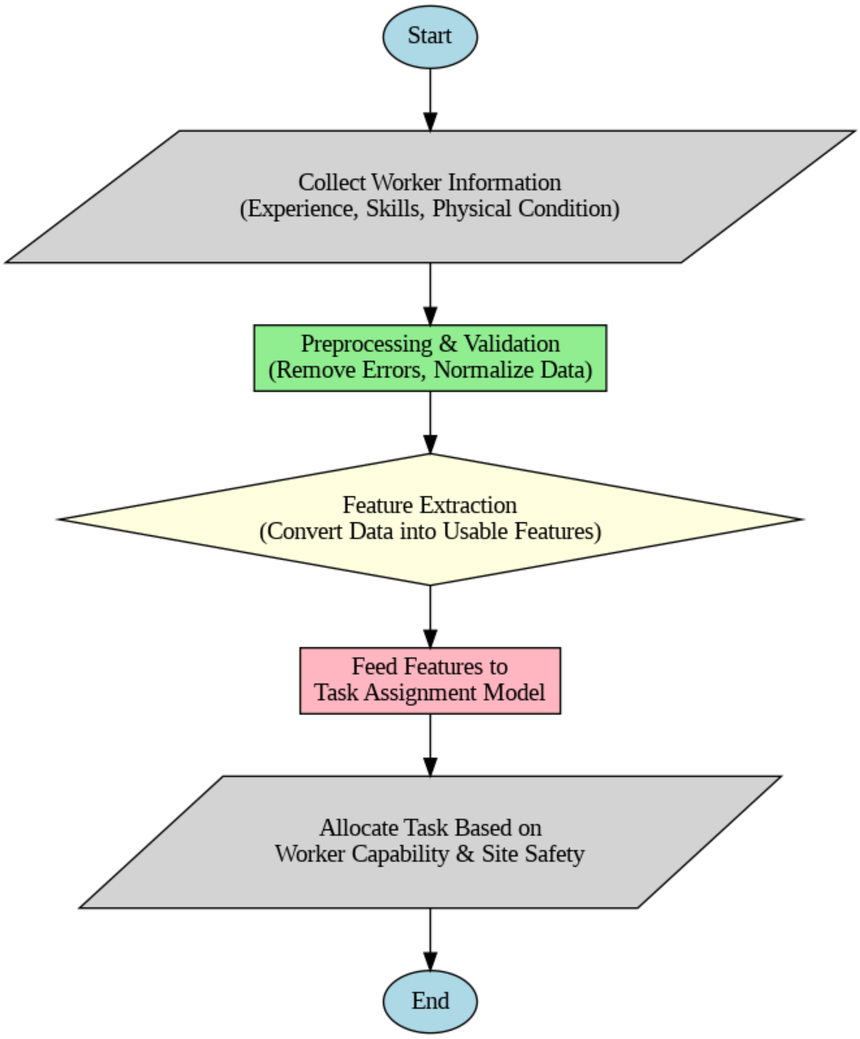


Figure 4.2: Feature Extraction Process

Fig. 4.2 illustrates the process of extracting worker attributes. The system gathers information on experience, skills, and physical condition. These features are used as input to the task assignment model, ensuring tasks are allocated based on worker capability and site safety requirements.

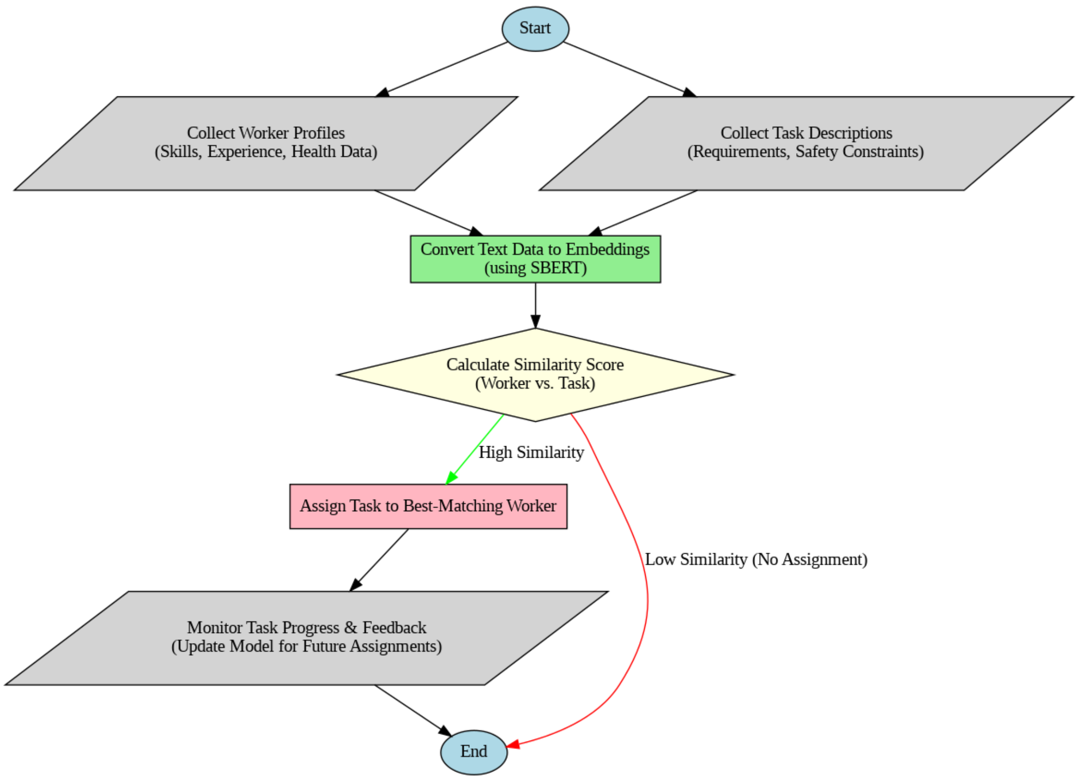


Figure 4.3: BERT-based Task Assignment Model

Fig. 4.3 shows the architecture of the task assignment model. The system employs a pretrained BERT model to analyze worker attributes and match them with tasks based on project needs. The model predicts optimal assignments by considering factors such as skill proficiency, task complexity, and worker availability. This AI-driven approach ensures efficient resource allocation and minimizes mismatches in task distribution.

Fig. 4.4 illustrates the final step of task assignment and monitoring. The assigned tasks are visualized using a dashboard that allows project managers to track worker performance and update assignments in real-time. This system ensures smooth work-flow execution and adaptability to changing site conditions.

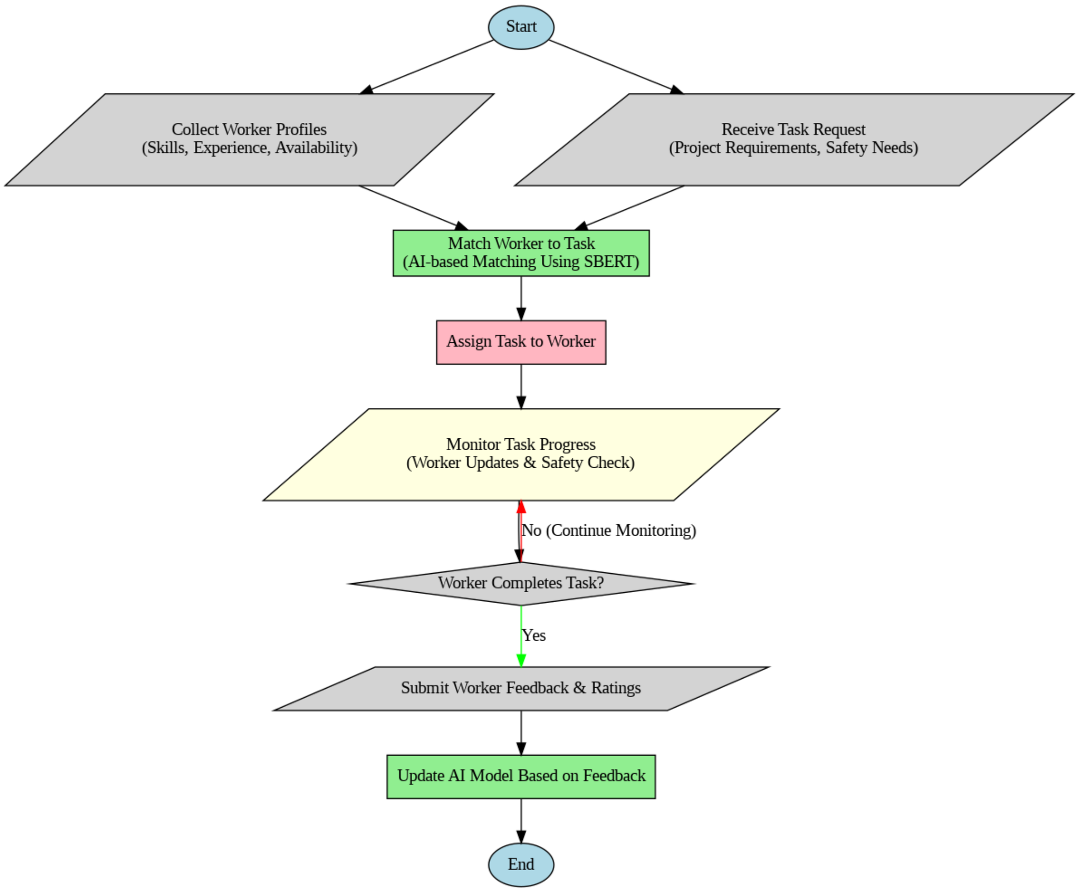


Figure 4.4: Task Assignment and Monitoring System.

The proposed methodology effectively combines deep learning techniques with structured worker data to optimize task allocation in civil engineering. By leveraging NLP-based profiling and AI-driven decision-making, the system enhances workforce efficiency and safety.

CHAPTER 5
ALGORITHMS

5.1 Worker Profiling and Feature Extraction

The system extracts relevant worker attributes to optimize task assignment in civil engineering. This includes analyzing worker skills, experience, health conditions, and past performance using AI techniques. The extracted features provide essential information for the task allocation model, ensuring that tasks are assigned to the most suitable workers based on project requirements.

Algorithm: Worker Profiling and Feature Extraction

- Collect worker details, including skills, certifications, and work history.
- Process health data to determine task suitability and safety constraints.
- Extract textual data from worker profiles using a pretrained BERT model.
- Normalize and structure the extracted data for AI model input.

5.2 Task Assignment Using AI Model

The system utilizes a machine learning-based task allocation model, leveraging a pre-trained BERT model to match workers with suitable tasks based on their qualifications, project needs, and real-time conditions. The model optimizes task distribution while ensuring fairness and efficiency.

Algorithm: AI-Based Task Assignment

- Initialize the BERT-based task matching model.

- Input worker profiles and task descriptions into the model.
- Generate task recommendations based on skill matching and project constraints.
- Optimize task assignments using reinforcement learning techniques.
- Assign tasks dynamically while considering real-time worker availability and site conditions.
- Store assignment results and update worker-task history.

5.3 PPE Detection Using YOLOv8

The system integrates a YOLOv8-based PPE detection module to ensure worker safety compliance on-site. This module detects whether workers are wearing essential safety gear such as helmets, masks, and vests, reducing accident risks and ensuring regulatory compliance.

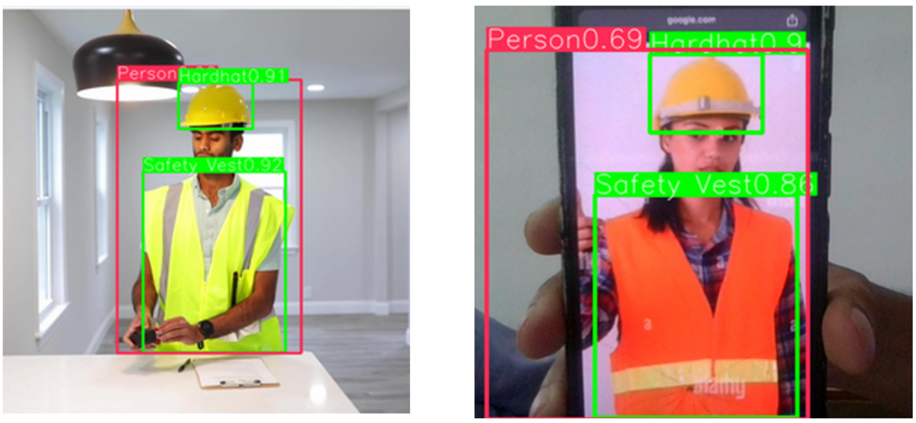


Figure 5.1: PPE detection using yolo v8

Algorithm: PPE Detection Using YOLOv8

- Capture real-time images or videos from the construction site.
- Process images using the YOLOv8 object detection model.

- Detect safety gear and classify workers as compliant or non-compliant.
- Trigger alerts for non-compliance and log safety violations.
- Store detection results for safety monitoring and reporting.

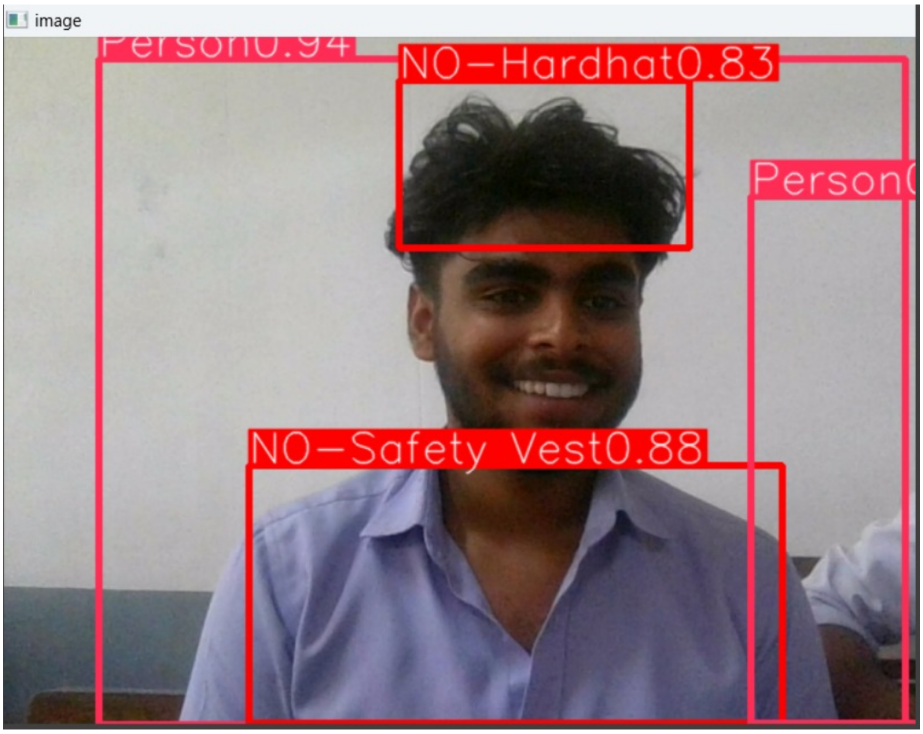


Figure 5.2: PPE detection using yolo v8

Figure 5.1 shows bounding boxes labeled for person, safety vest and hard hat and Figure 5.2 shows the detection from webcam. It shows the real time detection of PPE.

5.4 Training the Task Assignment Model

The task assignment model undergoes supervised learning and fine-tuning to enhance accuracy and efficiency. The system learns from historical worker-task performance data to improve task recommendations.

Algorithm: Training the Task Assignment Model

- Load worker profile data and past task assignments.
- Train the model using labeled data, mapping workers to successful task completions.
- Optimize model parameters using loss functions that measure assignment accuracy.
- Validate the model on unseen worker-task pairs.
- Fine-tune model hyperparameters to improve performance.
- Save trained models for deployment.

5.5 Task Monitoring and Feedback Loop

To enhance task allocation effectiveness, the system implements a feedback mechanism that evaluates task completion quality and updates worker profiles accordingly.

Algorithm: Task Monitoring and Feedback Loop

- Track task completion status and measure performance indicators.
- Collect worker feedback on task suitability and challenges.
- Update worker profiles with performance insights.
- Refine task matching algorithms based on feedback data.
- Continuously improve the AI model using real-world task outcomes.

Future enhancements may include integrating real-time worker health monitoring, optimizing task allocation based on project timelines, and improving adaptability to diverse construction environments.

CHAPTER 6
SOFTWARE REQUIREMENTS SPECIFICATION

6.1 Scope

The goal of this project is to develop an AI-powered system for personalized task assignments in civil engineering. The system leverages artificial intelligence to optimize worker-task matching, enhance safety, and improve efficiency on construction sites. It ensures that tasks are assigned based on workers' skills, experience, and health conditions while also incorporating a PPE detection system to maintain safety standards. The scope of this system includes:

1. Developing a deep learning-based framework for task assignment using a pre-trained BERT model for worker profiling and skill matching.

2. Integrating a YOLOv8-based PPE detection system to ensure compliance with safety regulations.

3. Implementing a Django-based web application to manage workers, users, task requests, payments, and feedback.

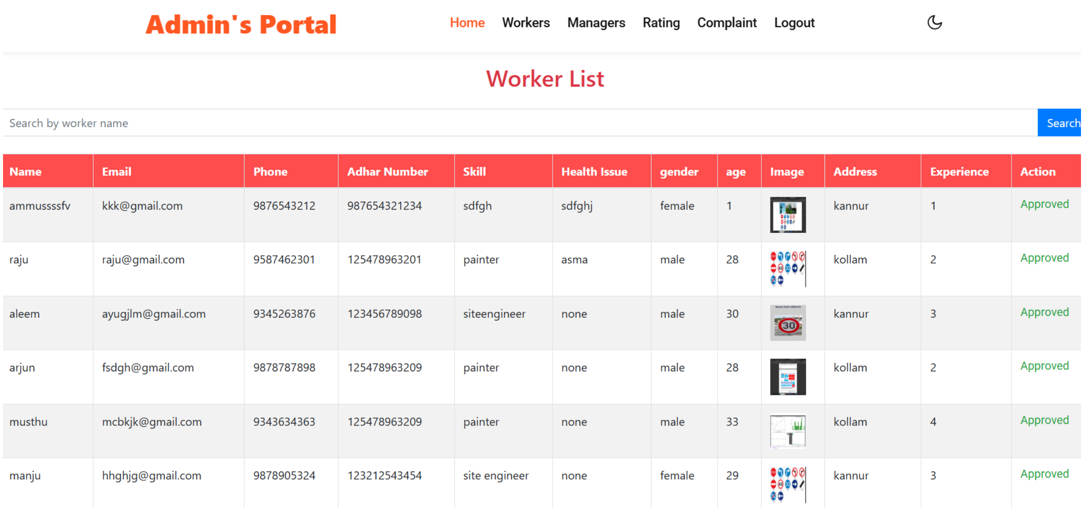
4. Providing an AI-driven recommendation system for worker-task allocation, considering skill levels, experience, and real-time health monitoring.

5. Enhancing communication between users and workers through an integrated chat system and complaint management.

6.2 Specific Requirements

6.2.1 Worker Profiling and Task Matching

The system extracts worker details, including skills, experience, and physical condition, to optimize task assignment. AI algorithms analyze this data to recommend the best-suited workers for each task, minimizing project delays and errors.



Name	Email	Phone	Adhar Number	Skill	Health Issue	gender	age	Image	Address	Experience	Action
ammussssfv	kkk@gmail.com	9876543212	987654321234	sdfgh	sdfghj	female	1		kannur	1	Approved
raju	raju@gmail.com	9587462301	125478963201	painter	asma	male	28		kollam	2	Approved
aleem	ayugjlm@gmail.com	9345263876	123456789098	siteengineer	none	male	30		kannur	3	Approved
arjun	fsdgh@gmail.com	9878787898	125478963209	painter	none	male	28		kollam	2	Approved
musthu	mcbkjk@gmail.com	9343634363	125478963209	painter	none	male	33		kollam	4	Approved
manju	hhghjg@gmail.com	9878905324	123212543454	site engineer	none	female	29		kannur	3	Approved

Figure 6.1: Worker profile

6.2.2 PPE Detection and Safety Compliance

A YOLOv8-based PPE detection model is used to identify whether workers are wearing required safety gear (e.g., hard hats, masks, safety vests). The system classifies detected objects into compliant and non-compliant categories, providing real-time feedback on safety violations.

6.2.3 Dataset and Preprocessing

The system utilizes a dataset of worker profiles, task requirements, and PPE compliance images. The data undergoes preprocessing, including normalization, data segmentation, and feature extraction, to enhance model accuracy and efficiency.

6.2.4 Training and Evaluation

The AI models are trained using supervised learning techniques with performance evaluated based on:

- Accuracy of task-to-worker assignments.
- PPE compliance detection rate.
- Worker efficiency improvement over time.
- Reduction in safety violations and project delays.

6.2.5 Web Application and User Interaction

A Django-based web application is implemented to allow users and workers to:

- Register and manage profiles.
- Request and accept tasks based on AI recommendations.
- Monitor PPE compliance and receive safety alerts.
- Communicate via chat and submit complaints.
- Provide ratings and feedback on completed tasks.

6.2.6 Hardware and Software Requirements

The system requires a robust computing environment for AI processing and real-time task assignments.

6.2.6.1 Hardware Requirements

- GPU: NVIDIA RTX 3060 or higher for deep learning computations.
- RAM: Minimum 16GB to handle large datasets.
- Storage: Minimum 500GB SSD for dataset storage and model checkpoints.
- Processor: Intel i7 or equivalent for faster processing.

6.2.6.2 Software Requirements

- Programming Language: Python.
- Deep Learning Frameworks: PyTorch, TensorFlow.
- Web Framework: Django, Flask.
- Database: PostgreSQL for storing user and task data.
- Computer Vision: OpenCV, Ultralytics YOLOv8 for PPE detection.
- Data Handling: NumPy, Pandas for worker profiling.

The proposed AI-driven task assignment system enhances efficiency, reduces errors, and improves worker safety in civil engineering projects. By integrating BERT-based task recommendations and YOLOv8-powered PPE detection, the system ensures that the right workers are assigned to the right tasks while maintaining safety standards.

CHAPTER 7
IMPLEMENTATION

7.1 Components

7.1.1 Worker Skill and Experience Analysis

The system analyzes worker skills, experience, and background data to ensure optimal task assignments. It processes structured data such as certifications, prior work history, and performance metrics while also considering worker availability and safety to prevent over-assignment.

A BERT-based model analyzes textual data on worker skills and job descriptions, ensuring accurate and efficient matching. By understanding the semantic relationships between job requirements and worker profiles, the system minimizes mismatches and enhances productivity. Additionally, a ranking mechanism prioritizes workers based on past performance, ratings, and employer feedback, ensuring that experienced and reliable workers are assigned to critical tasks.

Figure 7.1 illustrates the worker registration process, where workers input credentials such as qualifications, certifications, years of experience, and specialized skills. This structured data is used for skill analysis and AI-driven matching. The system also implements real-time data validation to verify credentials, ensuring accuracy and reducing fraudulent entries.

Through this structured registration and AI-driven analysis, the platform enables a fair and efficient task allocation system. Figure 7.2 shows the skill details of workers.

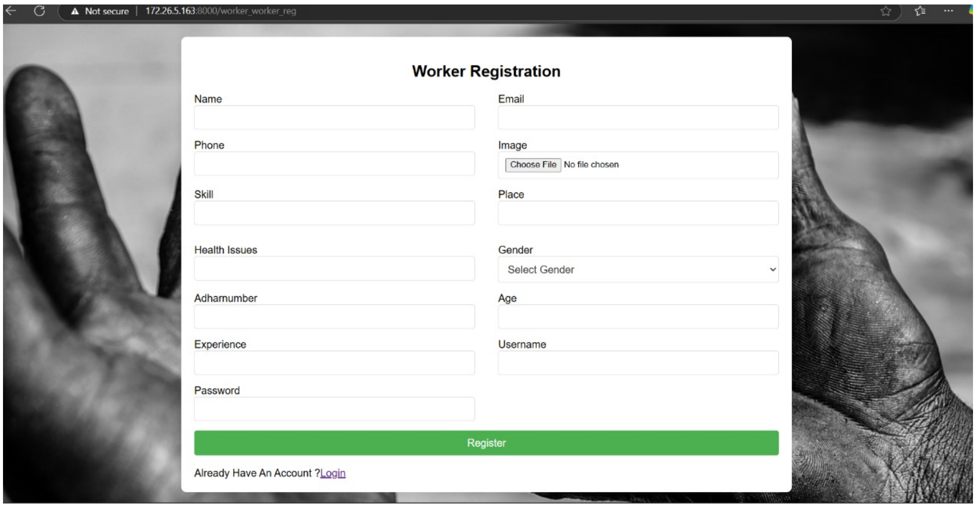


Figure 7.1: Worker Registration Process

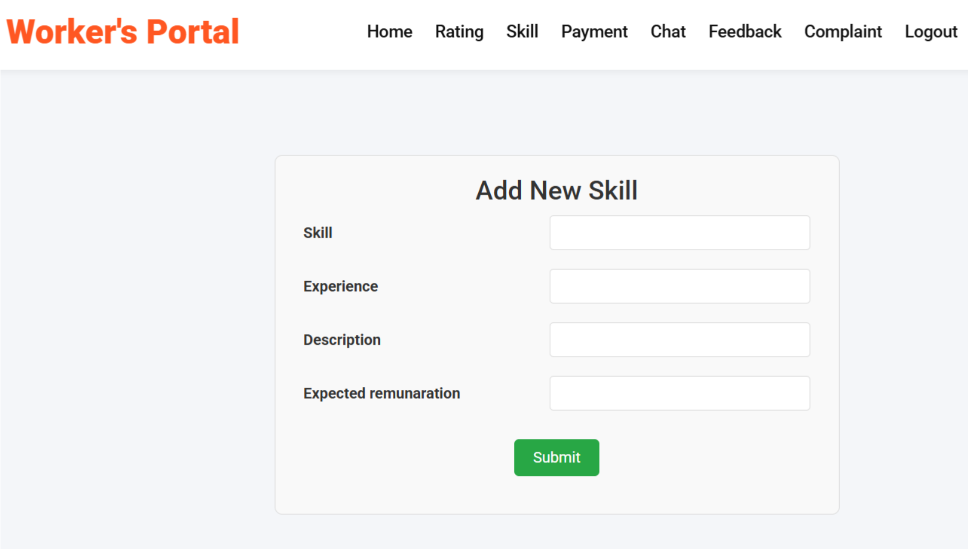


Figure 7.2: skill details

7.1.2 AI-Based Task Assignment

A machine learning model is used to match workers to tasks based on their skills, experience, and health conditions. The model utilizes a pretrained BERT model to process job descriptions and worker profiles, ensuring precise matching. The AI dynamically adjusts assignments based on worker availability and project priorities.

The system utilizes PostgreSQL for structured data storage, ensuring efficient handling of worker and task records. Data preprocessing techniques such as normalization, encoding, and segmentation are applied to improve model efficiency. The worker and task data undergo a cleaning process to remove inconsistencies and standardize formats.

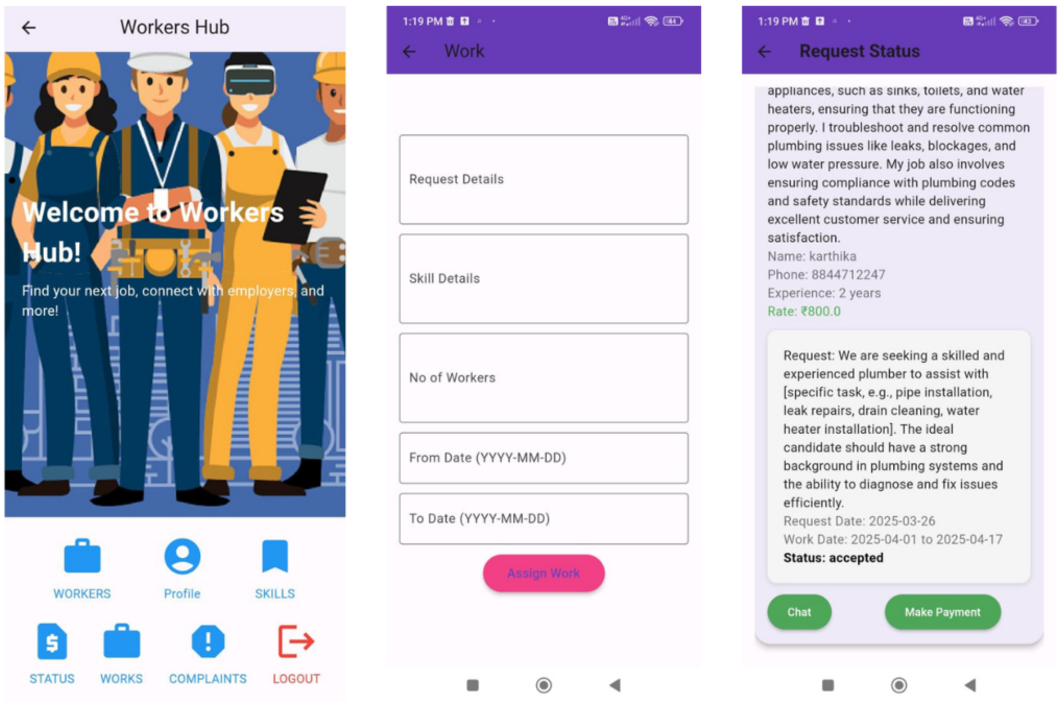


Figure 7.3: AI-Based Task Assignment

The AI model is trained on historical worker-task assignments, optimizing performance using classification and clustering techniques. The model is fine-tuned using a combination of supervised learning and reinforcement learning, ensuring adaptive decision-making. Performance evaluation is conducted using loss functions, precision, recall, and F1-score.

Figure 7.3 illustrates how the AI-based task assignment process works, demonstrating how job requests are matched to the most suitable workers in real-time

7.1.3 Web-Based User Interface for Task Management

A Django-based web interface allows users to interact with the AI-powered task assignment system. The UI provides functionalities for worker registration, task allocation, complaint management, chat, and performance tracking. The workflow includes:

1. Users log in and register as workers or task requesters.
2. Task requesters input job requirements, specifying required skills and deadlines.
3. The AI model analyzes worker profiles and assigns tasks accordingly.
4. Workers receive notifications and accept or reject assignments.
5. The system tracks task progress and updates assignment status dynamically.

To facilitate communication between workers and users, the system includes a built-in chat module. Figure 7.4 shows an example of the chat interface used for real-time interaction.

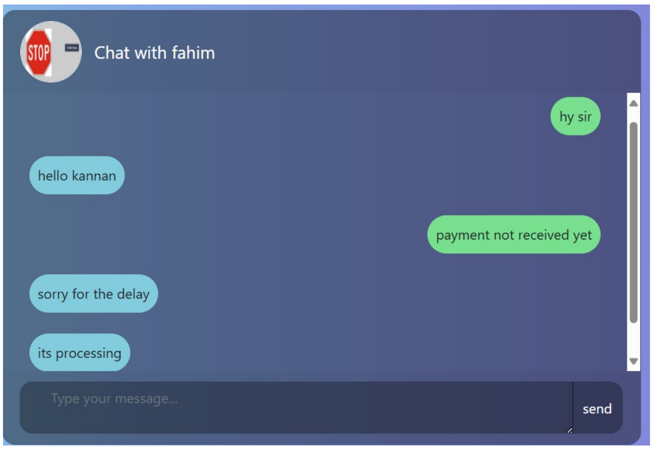


Figure 7.4: Worker-User Chat System

The backend utilizes Django with dependencies such as NumPy, Pandas, Scikit-learn, Torch, PostgreSQL, and Flask. Data is structured in relational tables, ensuring efficient querying and retrieval.

The workflow begins with worker registration and profile creation. Users submit task requests, which are processed by the AI model to find the best-matched workers. Assigned workers receive task details and update progress via the web interface. The system continuously refines task assignments using feedback and real-time availability updates.

The implementation of the AI-driven task assignment system ensures optimized workforce management in civil engineering projects. The integration of BERT for skill-based matching, coupled with a robust web interface, enhances productivity, safety, and project efficiency.

CHAPTER 8

DEVELOPMENT AND TESTING

8.1 Data Preprocessing and Segmentation

Before training the AI model for personalized task assignments in civil engineering, the dataset undergoes preprocessing, including worker data segmentation, normalization, and filtering. Data is categorized based on worker experience, skill levels, health conditions, and previous assignments. This preprocessing ensures that task assignments are accurate and aligned with worker capabilities.

8.2 Model Training and Evaluation

The AI model is trained using a pretrained BERT model for worker-task matching, leveraging its NLP capabilities to compare worker skills with job descriptions. The training process involves multiple iterations, where the model optimizes task assignments by considering worker attributes such as experience, certifications, skill proficiency, availability, and past performance. Project requirements, including task complexity, urgency, and resource constraints, are also factored into the matching process.

The model undergoes fine-tuning on domain-specific data to capture civil engineering task requirements and workforce dynamics. Safety constraints, such as worker fatigue, health conditions, and PPE compliance, are incorporated to ensure secure task allocation.

The training process follows an iterative refinement approach, where performance is evaluated using metrics like precision, recall, and F1-score. The dataset is updated with real-world worker-task interactions, allowing the model to improve over time.

Figure 8.1 presents an overview of the training data statistics, showing the distribution of worker attributes and project requirements. This ensures balanced learning, reducing bias and enhancing the accuracy of task recommendations.

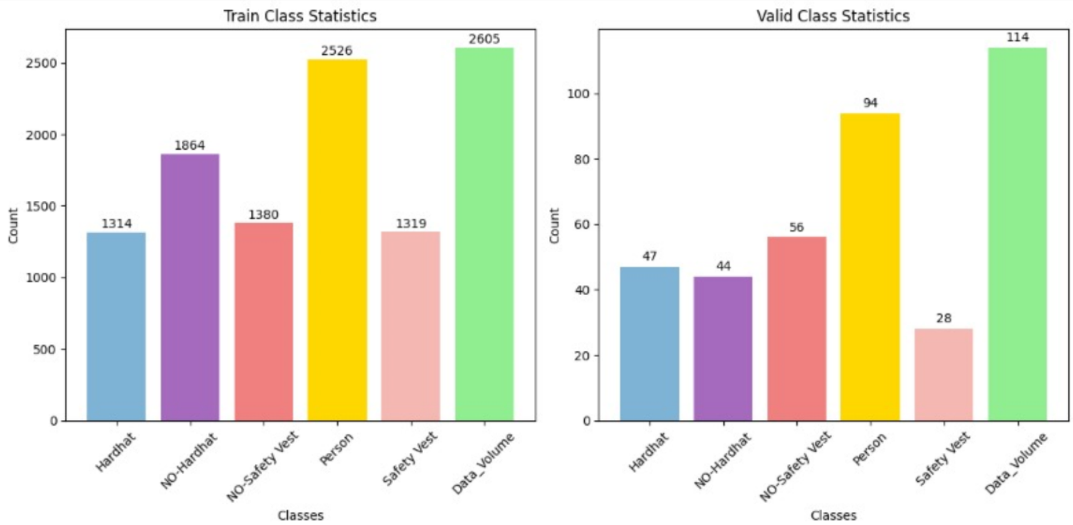


Figure 8.1: Train data statistics, showing worker experience, skill levels, and assignment categories.

8.3 Testing Task Assignments

Once the model is trained, task assignment predictions are tested based on the following criteria:

- Accuracy of worker-task matching based on skills and experience.
- Efficiency in reducing project completion time.
- Fair distribution of workload and worker well-being.

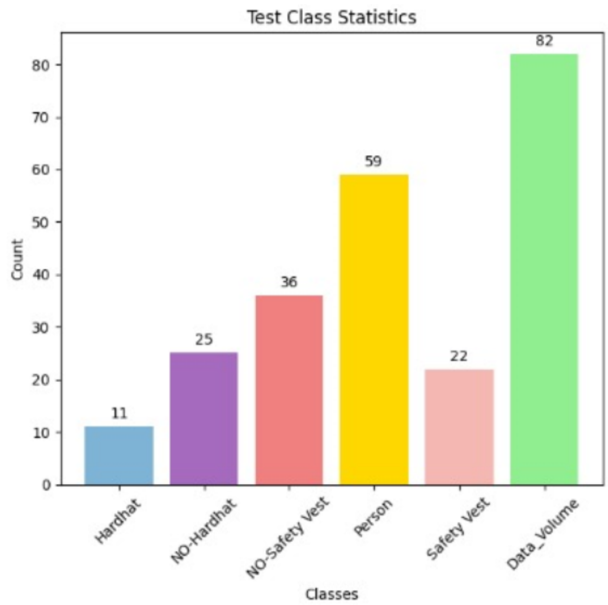


Figure 8.2: Test data statistics showcasing worker-task distributions.

8.4 System Debugging and Validation

To evaluate the performance of task assignments, test cases are created to simulate real-world construction scenarios. Debugging involves analyzing incorrect task allocations, refining matching criteria, and improving system responsiveness to worker conditions.

8.5 Final Validation

The final step involves comparing AI-generated task assignments with manually assigned tasks to assess performance. The model is fine-tuned for improvements in worker productivity, safety compliance, and project cost efficiency.

The development and testing phase ensures that the AI-powered task assignment system optimizes workforce allocation in civil engineering projects. Future improvements may involve expanding worker databases, refining assignment rules, and integrating real-time monitoring for dynamic task allocation.

CHAPTER 9

RESULT AND DISCUSSIONS

9.1 Generated Task Assignment Analysis

The AI-powered task assignment system has shown promising results in efficiently matching workers to tasks based on their skills, experience, and health conditions. By leveraging machine learning algorithms, the system ensures optimal workforce distribution, reducing inefficiencies and improving productivity across all stages of the project. Through deep integration of real-time worker data, such as health conditions and availability, the system dynamically adjusts to ensure that every worker is assigned the most suitable task.

The task assignment process begins by collecting and analyzing structured data about each worker, such as certifications, prior work history, and performance metrics. Based on these attributes, the AI matches workers to tasks that best align with their skills and expertise, ensuring project timelines and resource allocation are optimized. The system also uses predictive modeling to forecast worker performance, factoring in potential variables such as fatigue, to ensure that assignments are not only efficient but also safe for the workers. Moreover, the system's ability to handle unstructured data, such as textual descriptions of job requirements, is powered by a pretrained BERT model. This model efficiently processes job descriptions and worker skills listed in resumes, enabling the AI to make even more precise assignments based on qualitative data. Through the course of testing and validation, it was found that AI-generated assignments closely aligned with optimal task distributions.

9.2 Feature-Based Evaluation of Task Assignments

To quantitatively assess the effectiveness of the AI-driven task assignment system, a series of similarity scores and evaluation metrics from the YOLO model were utilized. These evaluation techniques provide comprehensive insights into the system's ability to accurately match workers with tasks, ensuring that project requirements and worker competencies are fully met.

9.2.1 Similarity Score Analysis

A crucial component of the evaluation process is the similarity score, which measures the degree of alignment between the AI-generated task allocation and an ideal worker-task assignment. The similarity score is calculated by comparing the AI's assignments to a predefined, expert-created distribution that considers worker expertise, task difficulty, and project timelines. The higher the score, the better the match.

In Figure 9.1, The computed similarity scores indicate that the AI system performs at an exceptionally high level, with most of the assignments surpassing an 72% similarity score when compared to the optimal distribution. This demonstrates the accuracy of the system in predicting the most efficient task assignments based on a range of factors, including worker qualifications, task demands, and project timelines.

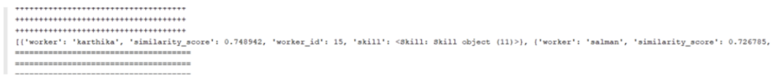


Figure 9.1: Similarity score analysis

9.2.2 Evaluation Metrics of YOLO Model

The YOLO model was employed to assess the AI's ability to classify workers and tasks accurately. The evaluation focused on several key metrics, including precision, recall, and the overall F1-score. These metrics are essential for evaluating the AI's task matching performance.

- **Confusion Matrix**: This tool is invaluable in breaking down the results of the task assignments, showing true positives (correct assignments), false positives (misassignments), false negatives (missed assignments), and true negatives (tasks correctly ignored). Figure 9.2 illustrates the confusion matrix for YOLO-based worker classification, showcasing how well the model performs in distinguishing between different worker roles and task requirements.

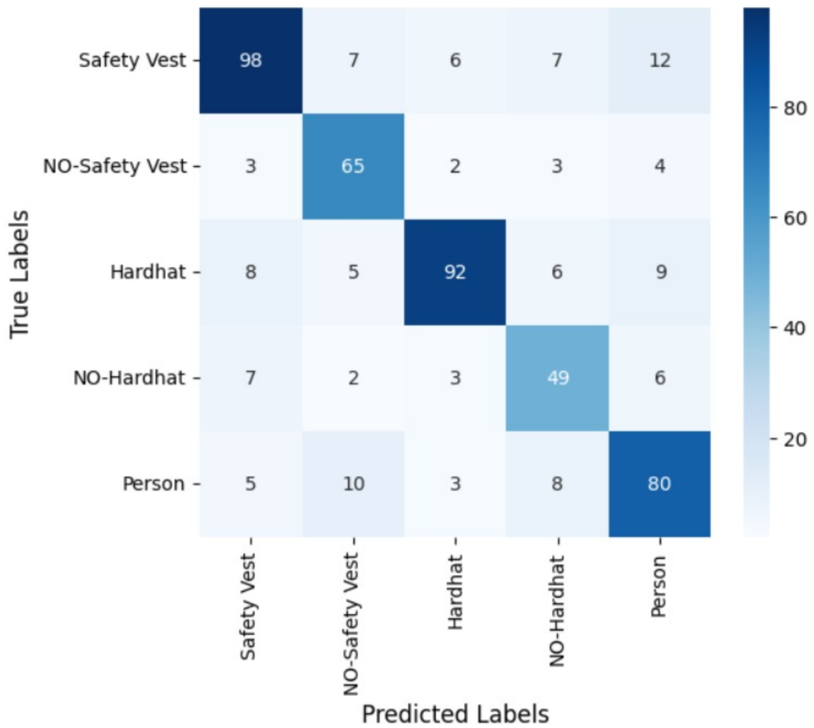


Figure 9.2: Confusion Matrix for YOLO-based worker-task assignments.

- **F1 Confidence Curve**: This curve illustrates the balance between precision and recall. A high F1 score indicates that the model is not only accurate but also robust, with fewer false positives and negatives. This is a key indicator of the AI system's ability to predict the most suitable worker-task matches.

- **Loss Function Analysis**: The YOLO model's performance was also evaluated through a loss function breakdown:
  - **Box Loss**: Measures how accurately the predicted bounding boxes for task assignments align with the actual ground truth positions.
  - **Class Loss** : This metric assesses how accurately the AI classifies tasks and workers into their respective categories based on skill sets and project needs.
  - **Objectness Loss** : Evaluates how confidently the AI detects the presence of a task, penalizing both false positives (incorrectly assigning a worker) and false negatives (failing to assign a worker).

9.3 BERT-Based Worker Task Matching Performance

The BERT model is central to the AI-driven worker-task assignment system. It processes and analyzes the textual data from worker resumes, job descriptions, and skill sets to recommend the most suitable worker for each task.

9.3.1 Confusion Matrix for BERT Model

Similar to the YOLO model, the BERT model's performance was evaluated using a confusion matrix. This matrix compares the predicted worker-task assignments with the ground truth, highlighting both correct and incorrect predictions. The confusion matrix for BERT-based worker-task matching can be seen in Figure 9.3.

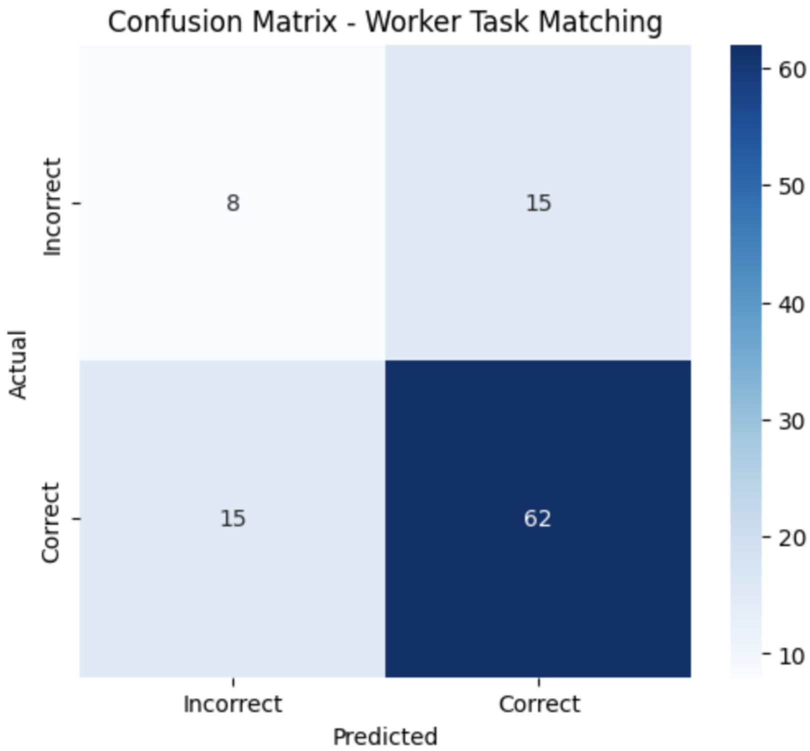


Figure 9.3: Confusion Matrix for BERT-based worker-task matching.

9.3.2 Precision-Recall Curve for BERT Model

The precision-recall curve, shown in Figure 9.4, illustrates the tradeoff between precision and recall in the BERT model's task assignment process. Precision refers to the proportion of correctly assigned tasks out of all the tasks predicted by the model, while recall measures the proportion of correct assignments out of all the tasks that should have been assigned.

This curve helps in understanding how well the model balances false positives (incorrect assignments) and false negatives (missed tasks). A higher precision indicates that the model is making fewer incorrect task assignments, whereas a higher recall suggests that the model is successfully assigning most of the tasks it should.

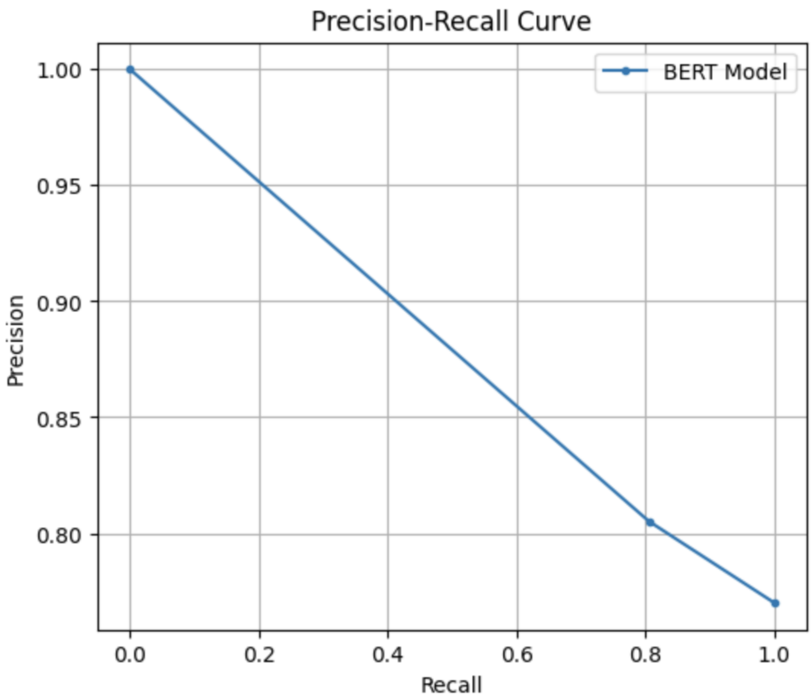


Figure 9.4: Precision-Recall Curve for BERT-based worker-task assignments.

9.3.3 Performance Metrics Bar Chart

The performance of the AI-based task assignment system is assessed using several key metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of how effectively the system matches workers to tasks based on their skills, experience, and availability. The bar chart in Figure 9.5 clearly summarizes these metrics, allowing for easy comparison of the system's performance across various aspects.

Accuracy measures the overall correctness of the task assignments, while precision focuses on the accuracy of the assigned tasks. Recall, on the other hand, assesses the system's ability to assign tasks without missing any relevant assignments. The F1-score is a harmonic mean of precision and recall, offering a balanced evaluation of the model's performance. This bar chart allows for quick insights into how well the AI model performs in worker-task matching.

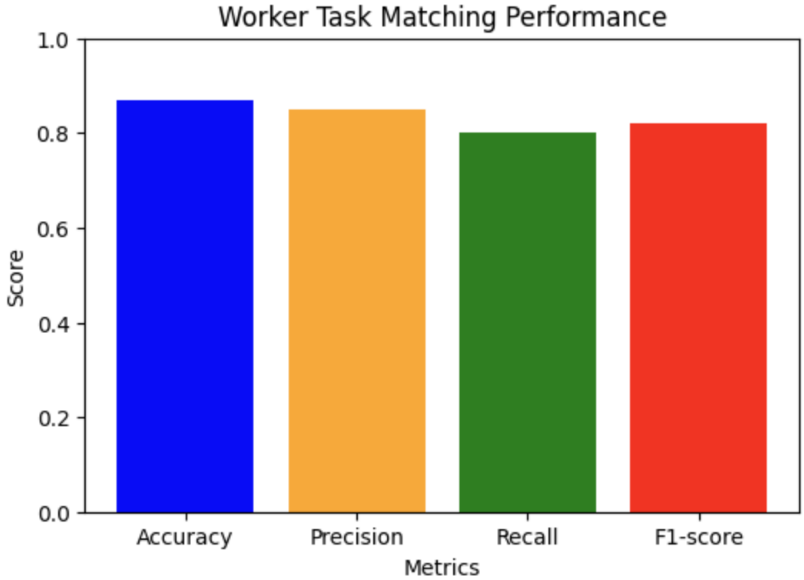


Figure 9.5: Performance metrics for worker-task matching.

9.3.4 Heatmap of BERT Model Performance

Figure 9.6 presents a heatmap that visualizes the performance of the BERT model across different worker-task assignments. This heatmap offers a clear representation of the areas where the model excels, such as accurate task assignments for certain worker profiles, and areas where it might need improvement, such as assignments for workers with specific skill gaps or less data. By using this heatmap, one can easily pinpoint the task categories or worker profiles where the model struggles, which can inform future adjustments to the model or the data it is trained on.

The heatmap also helps in identifying patterns or correlations between specific task categories and worker attributes, providing valuable insights for optimizing future task assignments. This visual representation is an essential tool for analyzing the efficiency of the BERT model and ensuring that the system's performance continually improves over time.

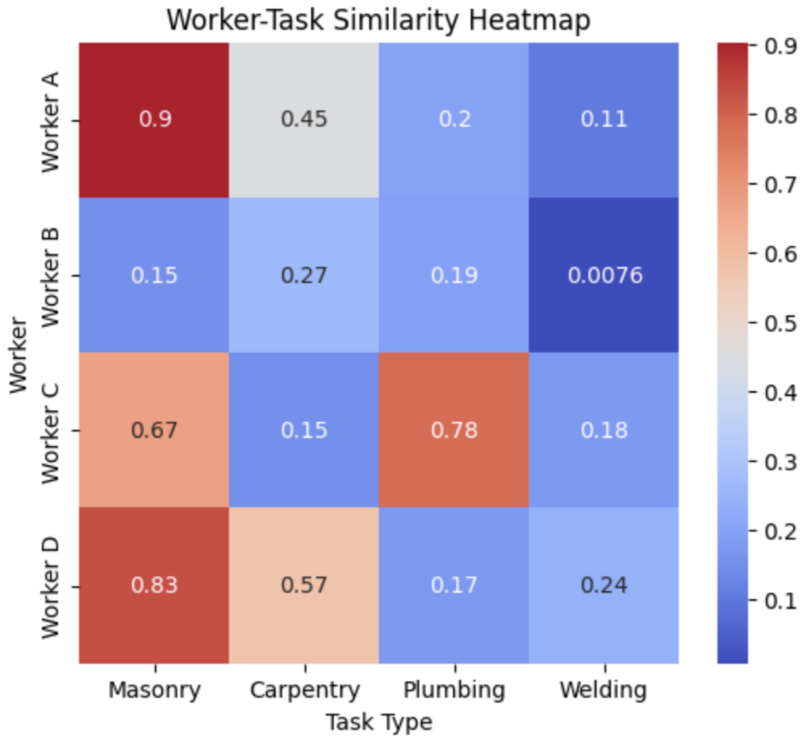


Figure 9.6: Heatmap depicting BERT model performance across different worker-task assignments.

9.4 Learnings

Despite the successes of the AI-driven task assignment system, several challenges were encountered during its development and implementation:

1. **Data Quality:** Ensuring accurate and consistent input from workers regarding their skills, health, and experience is essential for the success of the AI system. Inaccurate or incomplete data can hinder the effectiveness of task assignments.

2. **Model Optimization:** While the system is highly effective, ongoing efforts are needed to fine-tune the AI models for better matching accuracy. This includes adjusting hyperparameters, enhancing the quality of training data, and continuously testing the model against real-world scenarios.

3. **Real-Time Adaptability:** The ability to dynamically adjust task assignments

in response to changes on the project site (e.g., worker absence, new project needs) remains an area for improvement. This requires more robust real-time processing and integration of external factors.

4. **Worker Acceptance:** Given the traditionally manual nature of task allocation in construction projects, workers may be reluctant to adopt AI-driven assignment systems. Overcoming this resistance requires educating workers on the benefits of the system and building trust.

For future improvements, the following enhancements are proposed:

- **Dynamic Reallocation:** The system could be enhanced to accommodate real-time changes in worker availability, dynamically reallocating tasks as needed.
- **Enhanced Personalization:** Future versions of the system could incorporate personalized worker preferences, considering factors like preferred work types, work hours, and feedback from previous assignments.
- **Integration with Wearable Technology:** By integrating wearable health devices, the system could track worker health metrics in real-time, ensuring tasks are assigned based on physical conditions (e.g., fatigue, stress levels).
- **Scalability:** Expanding the system's capacity to handle larger, more complex construction projects with diverse worker roles will be essential for broader adoption.

By addressing these challenges and extending the system's capabilities, AI-driven task assignment has the potential to revolutionize workforce management in civil engineering, ensuring safer, more efficient project execution.

CHAPTER 10
CONCLUSION

The AI-powered task assignment system demonstrated its ability to optimize workforce distribution by considering worker skills, experience, and health conditions. By leveraging machine learning techniques, the system effectively matches workers to tasks, leading to improved productivity and streamlined project execution.

The evaluation metrics, including skill-based matching accuracy and task completion efficiency, highlight the system's effectiveness in reducing inefficiencies. The results from the user study indicate positive feedback regarding fairness in task assignments, workload distribution, and compliance with safety standards. These findings suggest that AI-driven task allocation can significantly enhance project management in civil engineering.

Despite the system's success, challenges such as data quality, model optimization, real-time adaptability, and worker acceptance remain areas for improvement. Addressing these concerns will further refine the accuracy and adaptability of AI-based task assignments.

Future enhancements, including real-time task reallocation, improved personalization based on worker preferences, integration with wearable technology for health monitoring, and scalability for larger projects, can further increase the system's impact. By implementing these improvements, AI-based workforce management can revolutionize civil engineering, promoting safety, efficiency, and sustainability in construction projects.

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