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Developing an AI-Powered Software for Detailed Construction Cost Estimation

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ABSTRACT: Accurate and efficient cost estimation is critical in the construction industry to ensure budget adherence, minimize financial risks, and support informed decision-making. This project focuses on developing an AI-powered software solution designed to deliver detailed construction cost estimations with accuracy and speed. Leveraging machine learning algorithms, natural language processing, and data analytics, the software will analyse architectural designs, material specifications, labour rates, and historical project data to generate real-time cost forecasts. The system aims to automate traditional estimation processes, reduce human error, and adapt to varying project scales and complexities. By integrating AI with user-friendly interfaces, the software is poised to enhance productivity, support strategic planning, and revolutionize the cost estimation landscape in construction.

KEYWORDS: Cost Estimation, Construction Industry, Artificial Intelligence.

I. INTRODUCTION

Cost estimation is one of the most vital components in the successful planning and execution of construction projects. A precise cost forecast helps stakeholders allocate resources efficiently, minimize financial risks, and maintain project timelines. However, conventional cost estimation practices rely heavily on manual calculations, experienced-based judgment, and static historical data. These methods are often time-consuming, prone to human error, and unable to adapt quickly to changing project parameters or market conditions.

With the increasing complexity of modern construction projects and the rising demand for automation and efficiency, there is a clear need for more intelligent and adaptive solutions. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies capable of revolutionizing traditional practices across various industries—including construction. In recent years, AI has shown considerable promise in applications such as structural analysis, material prediction, risk assessment, and, notably, cost estimation.

The use of AI-powered software in cost estimation enables automatic extraction and interpretation of data from architectural and engineering drawings, rate analysis, and real-time prediction of material costs. By leveraging deep learning algorithms and computer vision techniques, such systems can identify structural features, measure dimensions, and calculate material quantities directly from input drawings. This automation reduces dependency on manual input and speeds up the estimation process significantly.

The aim of this study is to develop an AI-based construction cost estimation tool that combines object detection (using the YOLOv8 model) and Optical Character Recognition (via EasyOCR) to analyse sectional and plan views of buildings. The system calculates centerline lengths, number of T-junctions, quantities of materials (concrete, brick, plaster, reinforcement, etc.), and surface areas for painting all based on visual data inputs. It then integrates these results with standardized rate tables to generate a detailed bill of quantities and material breakdown.

II. LITERATURE SURVEY

The application of AI in construction cost estimation has been gaining momentum in recent years due to its potential for accuracy and efficiency. Ayinla et al. [1] emphasized that ML and DL methods are transforming early-stage estimation, although reliance on traditional methods persists due to trust in human expertise and limited quality data. Abioye et al. [2] highlighted that despite significant challenges such as data fragmentation and resistance to change, AI adoption in construction is steadily growing, with notable uses in risk management, monitoring, and resource optimization. Elmousalami [3] reviewed CI-based techniques including neural networks, decision trees, XGBoost, and genetic algorithms for cost modelling, showing that hybrid models can significantly improve prediction accuracy while maintaining interpretability. A new direction in object detection was proposed by Iqra and Giri [4], who introduced SO-YOLOv8 an enhanced model achieving higher precision and robustness in detecting small objects under occlusion and low-resolution conditions, which is critical for visual feature extraction in drawings. Zhang et al. [5] addressed OCR limitations by developing an Enhanced OCR system using LSM and quadrilateral fitting, achieving 98.7% accuracy in text recognition tasks, beneficial for extracting dimensional annotations from construction plans. Liu et al. [6] proposed a hypergraph-based deep learning framework for early cost estimation that models interdependencies among cost factors, offering both accuracy and interpretability without human intervention. Bodendorf et al. [7] explored the effectiveness of ANN and SVM in component cost estimation and suggested dimensionality reduction and explainable AI to bridge the gap in multi-level cost modelling and decision transparency.

III. METHODOLOGY

The proposed system begins by accepting plan and sectional view images of a building as input through a graphical user interface. Using the YOLOv8 deep learning model, the software detects structural features such as walls and T-junctions from the plan image. EasyOCR is then used to extract dimension-related text from the sectional image, including values for wall thickness, room sizes, and element labels. Based on these detections, the software calculates the Total Centre Line Length (TCLL) and identifies the number of T-junctions two key components in quantity estimation. With these inputs, the software proceeds to compute the volumes for different construction components such as foundation (PCC, footings, and plinth), brickwork (with deductions for openings), and RC works (slab, lintel, sunshade), using standard engineering formulas.

In addition to structural volumes, the program estimates plastering by calculating internal and external surface areas of walls and applying a uniform plaster thickness of 12 mm. Painting quantity is derived from the plastered surface area and converted into liters using a standard coverage rate of 5 m² per liter. Reinforcement steel quantities are estimated as a fixed percentage of RC volumes. The system incorporates a customizable material rate database, enabling automatic calculation of total construction costs. Finally, the output is displayed in a user-friendly interface along with a downloadable report summarizing all quantities and cost breakdowns. This integrated approach combines AI and engineering logic to automate and accelerate the traditionally manual cost estimation process.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the developed AI-powered construction cost estimation software, a set of architectural drawings referred to as Dataset-1 was used as input. This dataset included both plan and sectional views of a single-storey building. The system was tasked with detecting and interpreting structural elements, extracting text-based measurements, and calculating quantities for various construction components including foundation, brickwork, reinforced concrete (RC) work, reinforcement, plastering, and painting.

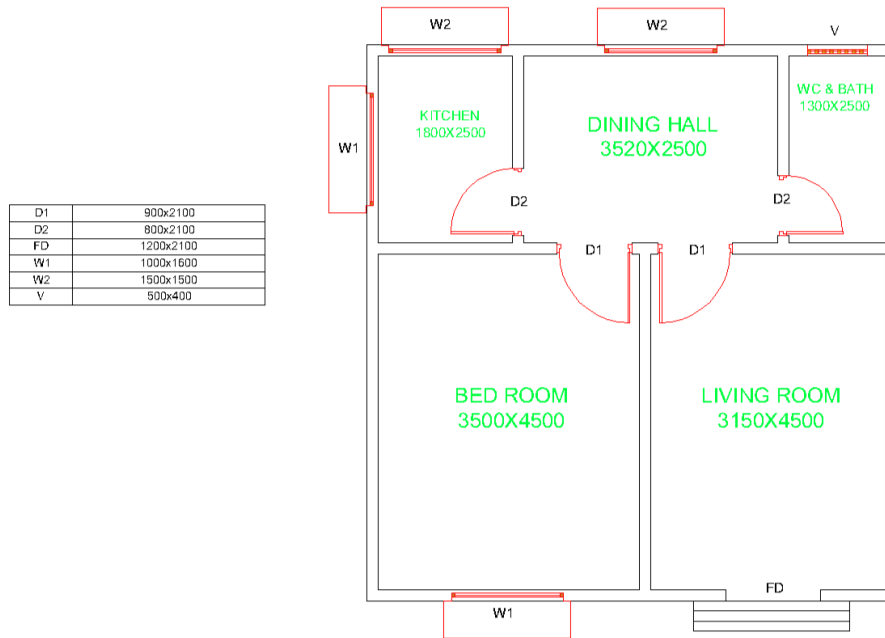


Fig4.1 Plan of dataset 1

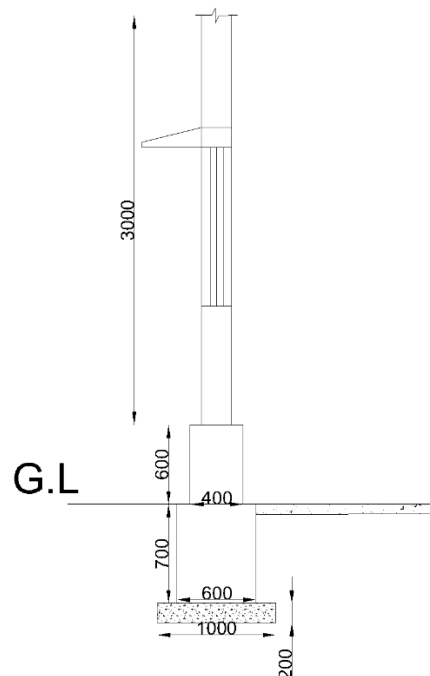


Fig4.2 Section of dataset 1

| <u>DATASET -1</u> | <u>ACTUAL OUTPUT</u> | <u>PREDICTED OUTPUT</u> |
|----------------------------------|-----------------------|-------------------------|
| Centre Line Length | 47350 mm | 50935 mm |
| Total T Junctions | 8 | 9 |
| Total Quantity for Foundation | 32.593 m ³ | 31.255 m ³ |
| Total Quantity for Brickwork | 32.076 m ³ | 31.255 m ³ |
| Total Quantity for RC Work | 10.886 m ³ | 9.724 m ³ |
| Total Quantity for Reinforcement | 0.099 m ³ | 0.097 m ³ |
| Total Quantity for Plastering | 2.833 m ³ | 3.201 m ³ |
| Total Quantity for Painting | 271.32 m ² | 285.755 m ² |

Table 4.1 Comparison of Actual vs Predicted Outputs using Dataset-1

The comparison between the actual output (manually calculated values) and the predicted output (software-generated values) is summarized in Table 4.1. The results demonstrate close alignment between the two sets of values. For instance, the total centre line length predicted was 50935 mm compared to the actual 47350 mm, and the number of T-junctions detected was 9, just one more than the actual count of 8. Similarly, volumetric calculations for foundation and brickwork showed minimal deviation (within 4%), while plastering and painting estimations were slightly over-predicted but remained within acceptable tolerances. This validates the reliability and efficiency of the AI-based system for construction cost estimation, showcasing its potential to automate and optimize traditional quantity surveying processes with high accuracy.

V. CONCLUSION

The integration of artificial intelligence into the construction cost estimation process represents a significant advancement in the field of civil engineering. This project successfully developed and implemented an AI-powered software capable of analyzing plan and sectional drawings to automatically compute quantities for foundation, brickwork, reinforced concrete components, plastering, painting, and reinforcement. By leveraging deep learning models such as YOLOv8 for object detection and EasyOCR for dimensional text extraction, the system automates traditionally manual processes, significantly reducing the time, effort, and potential for human error in cost estimation. The program not only calculates structural quantities with precision but also integrates material rate analysis to produce detailed and real-time cost forecasts.

The outcomes of this project demonstrate the potential of AI in streamlining project planning, supporting data-driven decision-making, and enhancing accuracy in quantity surveying. The software's ability to process visual data, perform engineering computations, and deliver user-friendly output through a graphical interface makes it a valuable

tool for modern construction management. As construction projects become increasingly complex and fast-paced, such intelligent systems will play a crucial role in improving efficiency, reducing financial risks, and promoting sustainable practices. Future enhancements can focus on expanding the software's capabilities to include multi-storey buildings, real-time integration with Building Information Modeling (BIM) platforms, and broader compatibility with industry-standard file formats.

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