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Research paper

Smart material estimation for the engineering, procurement, and construction (EPC) sector

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ABSTRACT

This study presents a novel AI-based approach that integrates deep learning techniques for symbol and text recognition with predictive modeling based on historical project data. The aim is to automate and enhance material cost estimation and procurement in Engineering, Procurement, and Construction (EPC) projects. Unlike existing methods, our approach combines data extraction from Piping and Instrumentation Diagrams (P&IDs) with predictive modeling to improve estimation accuracy. In addition, we introduce methods such as tiling and augmentation to optimize the accuracy of symbol recognition in complex and noisy industrial diagrams. We also present methods for managing diverse symbology, improving annotations, and handling background noise in actual industrial blueprints. Furthermore, we apply domain-specific knowledge rules while utilizing available historical data repositories from past engineering projects. Our findings suggest significant potential for engineering time and cost savings in large-scale EPC projects, supported by empirical analysis of development costs in relation to engineering hours saved.

1. Introduction

Engineering, Procurement, and Construction (EPC) projects, also known as Architecture, Engineering, and Construction (AEC), are characterized by their technology-driven designs and reliance on the expertise of engineering and construction teams. As noted by Songer et al. [50], clients and owner organizations are increasingly raising their expectations from EPC contractors. For these contractors, achieving project success requires managing the balance between cost, schedule, and quality, Verzuh [52]. Consequently, a precise cost estimate is essential for EPC contractors to maintain their competitive advantage, Eliufoo [15]. Numerous studies have highlighted the significance of accurate cost evaluations during the bidding phase. These evaluations significantly influence the financial outcomes of construction projects and affect their feasibility and resource allocation, Ali et al. [3]. Furthermore, the projected cost can be a crucial factor for clients when deciding whether to proceed with a project or not, Matel et al. [32].

Within the cost breakdown of EPC projects, procurement represents a significant portion of the total project costs.

While project delivery systems and information technologies have advanced significantly, most industry participants have been slow to adopt new technologies to enhance project performance to the desired levels, Songer et al. [50]. At the same time, the importance of Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL) techniques, is steadily growing in various estimation and forecasting activities, Ahmad et al. [2]. Several research papers have delved into AI applications for predicting construction costs, leveraging extensive historical tender data to identify patterns and trends, Matel et al. [32]. Many of these studies have relied on regression techniques as the standard approach to cost estimation. It is worth noting that these research efforts consistently mention the significance of risks associated with material procurement, as they can substantially impact the overall project costs, Liu et al. [30]. Furthermore, AI offers numerous advantages, including automation, intelligent and quick decision-making, reduction of human errors, and resource optimization. These benefits contribute significantly to the operations of large companies. AI also enables organizations to redirect their focus from time-consuming manual processes such as quality management, anomaly detection, and reporting, Rafsan-

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jani and Nabizadeh [40]. Although the impact of AI has been observed in various sub-fields within EPC, the development of specifically tailored approaches to seamlessly integrate human knowledge and expertise into AI applications has still been lacking, Rafsanjani and Nabizadeh [40].

The primary innovation of this work lies in combining deep learning techniques for detecting symbols and text within P&IDs with predictive modeling based on historical project data to enhance material estimation. This dual approach not only automates the traditionally manual process but also improves the reliability of estimates by refining the results using past project outcomes. Additionally, we introduce techniques such as tiling and augmentation to optimize the accuracy of symbol recognition in complex and noisy industrial diagrams. These innovations directly address long-standing challenges in the EPC sector, providing a practical and scalable solution.

1.1. Research focus

In the EPC industry, process flow diagrams (PFDs) and piping and instrumentation diagrams (P&IDs) are particularly valuable for obtaining substantial material quantity information. They contain crucial details about chemical processes, including topology, primary unit operations, control equipment, and piping data, Theisen et al. [51]. Currently, many companies still share P&IDs in PDF or scanned form during the tendering phase due to the unavailability of computer-aided files or intellectual property considerations, Dzhusupova et al. [12]. As a result, this leads to a labor-intensive and time-consuming process of manually counting materials indicated on these drawings. This practice directly increases engineering costs due to the hours spent on manual tasks, Matel et al. [32]. Furthermore, tender documents often lack comprehensive material quantity information. This gap forces project estimators to rely heavily on their individual expertise to make realistic cost predictions.

Thus, we formulated our **Research Question** as follows: **“How can we automate the extraction of material quantity information while ensuring estimation accuracy?”**

To address these challenges, we propose a two-fold solution:

- Part 1: Utilizing deep learning methods together with knowledge rules (heuristics) to extract essential information from engineering drawings.
- Part 2: Applying regression analysis to historical data derived from similar types of projects, which were previously executed within McDermott, to make accurate material cost forecasts.

The proposed solution builds upon the achievements of internal case projects conducted at McDermott, where deep learning object detection methods identify design errors, Dzhusupova et al. [11], and regression analysis predicts engineering hours, Dzhusupova et al. [12], and also benefits from recently published advancements in symbol and text recognition, which have been assessed for their suitability for real-world applications.

While our methodology can be applied to various types of engineering drawings, this study focuses specifically on P&IDs because they are the predominant document type shared during the tender phase in oil, gas, and petrochemical sectors for material quantity estimation. During detailed project execution phases, other engineering drawings (electrical, piping isometrics, instrumentation diagrams) are typically produced using smart CAD software with built-in material extraction capabilities. However, P&IDs shared during tendering are frequently provided in PDF or scanned formats due to intellectual property considerations, making automated extraction particularly valuable for early-stage cost estimation and competitive bidding processes.

This manuscript represents the extension of the conference paper “Practical Software Development: Leveraging AI for Precise Cost Estimation in Lump-Sum EPC Projects”, Dzhusupova et al. [13]. While the original conference paper introduced a preliminary concept of the solution and provided only a high level of detail regarding performance evaluation for each part, this manuscript offers a more detailed error analysis of the individual models. Furthermore, it provides an in-depth look at data processing, including annotation, augmentation, tiling, and the model development process.

While our research is ongoing, we emphasize the importance of sharing the results from the proof-of-concept phase. This contributes to the ongoing effort of information extraction from engineering blueprints using deep learning methods. It illustrates how deep learning and machine learning can be combined with knowledge rules to enhance the efficiency, accuracy, and reliability of EPC project estimations. Ultimately, our objective is to provide a valuable tool that supports decision-making during bid evaluations, reduces manual labor, and mitigates the risks associated with underestimating EPC projects. It is also worth mentioning that, while there are numerous industrial white papers discussing this topic, there is a scarcity of publicly shared feedback from actual implementations. At the same time, there is a growing academic demand for research in this field. This highlights the need for literature that explores the practical application of AI techniques to enhance outcomes in the energy industry, Waqar et al. [54]. Therefore, the additional value of this work lies in bridging the gap between academia and industry by presenting an AI-based solution that directly contributes to effective operations through improved material management.

Main Contributions

The main contributions of this work, which distinguish it from prior research, are as follows:

- Integrated Dual Approach: We present a novel solution that combines deep learning-based symbol and text recognition from P&IDs with predictive modeling using historical project data. This approach enables both automated extraction and data-driven adjustment of material quantities.
- Industrial-Scale, Real-World Validation: Unlike most previous studies that rely on synthetic datasets, our models are trained and validated on a large corpus of real industrial P&IDs from executed EPC projects, capturing authentic symbol variation, background noise, and diagram density.
- Domain-Specific Association Logic: We introduce a knowledge-rule-based method for associating symbols and text, tailored to the diverse drafting standards and practices found in industry, addressing the lack of universal standards highlighted in recent literature (e.g., Paliwal et al. [39], Kim et al. [27].
- Handling of Real-World Challenges: Our approach incorporates tiling, augmentation, and specialized model architectures to improve detection of small, overlapping, and variably sized symbols, as well as robust text detection in complex and noisy diagrams.
- Practical Impact and Cost Efficiency: We demonstrate significant potential for engineering time and cost savings in large-scale EPC projects, supported by empirical analysis of development cost versus engineering hours saved.

These innovations directly address key limitations of prior work, including limited generalizability, poor performance on real noisy data, and challenges in symbol-text association. These issues are detailed in Section 3.

The paper is organized as follows: Section 2 and 3 describe the background of the problem and related work. Section 4 outlines the research method for solution development. Sections 5 and 6 discuss the solution development and results. Future work and threats to validity are discussed in Section 7.

2. Background

2.1. Introduction to EPC projects

AEC/EPC projects encompass a wide range of industrial installations, with a primary focus on large-scale infrastructure developments

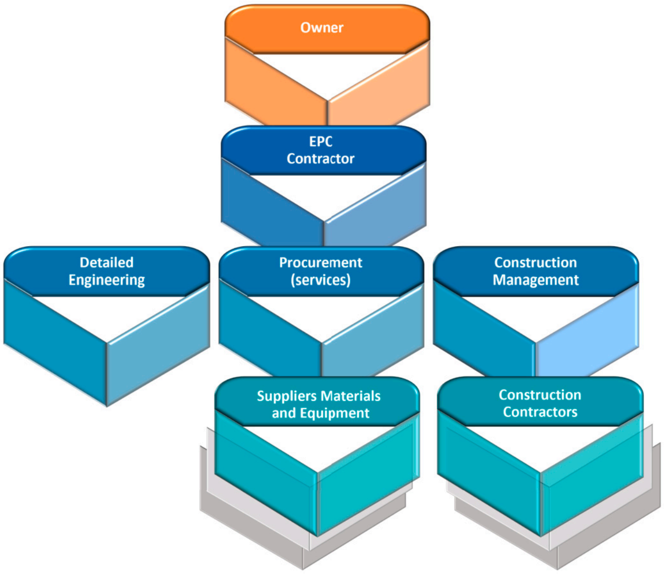


Fig. 1. Typical project organization and work breakdown structure of the large EPC projects [2]. Where the cost breakdown is a) Detailed engineering (10-20%), b) Procurement of materials & equipment (30-50%), and c) Construction and fabrication (30-50%), Berends [6].

within the private sector. The goal of AEC/EPC businesses is to design, construct, and sometimes operate capital assets. The term AEC (Architectural, Engineering, and Construction) serves as a comprehensive descriptor for the entire industry. In contrast, EPC (Engineering, Procurement, and Construction) specifically focuses on the actual construction of capital assets, AECBusiness [1].

This research explicitly narrows its focus to large EPC projects because the proposed solution is specifically designed for material procurement. This aspect is directly relevant to the construction of capital assets.

Large EPC projects are characterized by capital costs exceeding $500 million and extended execution, Berends [7]. They involve the integration of numerous technical disciplines and require extensive knowledge. These projects hold significant economic importance as they encompass various installations, such as tunnels, bridges, dams, and processing plants, Berends [6]. However, specific sectors, particularly energy—which includes petrochemicals and oil and gas—rely on them the most due to their complexity and stringent safety standards, Sholeh and Fauziyah [46], EPC contractor: financing and construction [17]. These standards often demand a high level of technical availability, typically no less than 95% throughout the facility's lifetime, which generally spans 20-25 years, Berends [6]. The typical execution model for EPC projects includes technical design, project management, engineering consulting, and general contracting, Liu et al. [30]. The project execution process involves operators who are contracted by owners to manage and operate capital assets on their behalf. Owners typically select a general EPC contractor to build the asset, AECBusiness [1]. Thus, the general contractor assumes comprehensive responsibility for the project, encompassing design, procurement of equipment and materials, construction, and commissioning of the entire project. See Fig. 1.

The energy sector is currently undergoing a substantial transformation, marked by new challenges related to environmental concerns and the rapid expansion of renewable energy sources, Franki et al. [19]. In response to the growing emphasis on sustainable practices, the utilization of AI in oil and gas projects has gained increased significance in recent years. Integrating AI-driven solutions offers a more efficient means of addressing the unique aspects of construction projects while automating various tasks. This not only facilitates timely completion but also allows human resources to focus on critical activities, Waqar et al. [54]. Moreover, AI supports sustainable growth within the sector by optimizing supply chain and material management processes. As a result, this leads to reductions in material wastage and costs, Rafsanjani and Nabizadeh [40].

The background information provided highlights the growing importance of AI in improving project outcomes in the EPC industry. However, despite these advancements, there is a gap in applying AI to automate the estimation processes involving P&IDs, which remain largely manual and error-prone. Our study addresses this gap by not only utilizing AI for symbol recognition but also enhancing the results with data-driven adjustments based on historical project performance. This approach provides a more comprehensive and practical method for cost estimation.

3. Related work

3.1. *Current research trends in symbol and text recognition on engineering drawings*

The digitization of complex engineering drawings has been a longstanding area of interest, even before the emergence of deep learning. Traditional computer vision methods are reported to underachieve due to their limited adaptability to various drafting standards and techniques, Mani et al. [31]. However, starting around 2010, there was a significant shift towards exploring neural networks and deep learning for the purpose of pattern identification in engineering blueprints, with the aim of automating their digital conversion, Dzhusupova et al. [11]. Since that time, numerous methods have been developed and tested for the detection of symbols and text within engineering drawings. In recent years, the field of P&ID symbol recognition has experienced an increase in research focused on object detection and classification methods, largely due to advancements in deep learning techniques. This shift towards deep neural networks has opened up new possibilities for digitizing or harvesting information from complex blueprints that are not available in computer-aided format.

Rahul et al. [41] introduced a two-step approach for extracting information from P&ID diagrams. Their method employed a Fully Convolutional Network (FCN) to identify and classify 11 symbols, particularly those with subtle visual distinctions between classes. Additionally, they utilized a pre-trained Connectionist Text Proposal Network (CTPN) to detect text patches and employed Tesseract OCR for text recognition. To detect lines, they applied a technique based on the Hough Transform, Duda and Hart [10]. Finally, the association of elements was achieved using rules based on Euclidean distance.

Paliwal et al. [39] introduced the Digitize-PID system, a solution for the digitization of P&ID diagrams. This system outperformed Rahul et al. in its ability to detect symbols, text, and lines. To address the challenge of identifying and categorizing intricate symbols with small differences, the authors adopted a two-step approach. First, they utilized a Fully Convolutional Network (FCN) for segmenting and obtaining region proposals for complex symbols, Shelhamer et al. [44]. Subsequently, these region proposals were processed by a Textured-Based Multi-Scale Localization Network (TBMSL-Net) which was trained for symbol classification, Zhang et al. [56].

In handling text within the diagrams, the researchers employed the CRAFT network, Baek et al. [4], for text detection, and Tesseract for text recognition. To extract lines, they utilized filters with a structuring element matrix, which proved to be more effective, particularly on noisy P&IDs, compared to the Hough transform method used by Rahul et al. The process of digitizing P&IDs involved utilizing Hough transforms for basic shape detection. This was supplemented by additional techniques for localizing complex shapes. The association was carried out by applying the k-nearest neighbors method to identify the k-closest text boxes corresponding to each symbol, followed by the application of regex rules.

Kim et al. [27] in their research, introduced a comprehensive digitization framework specifically designed for P&IDs. They proposed an end-to-end architecture that utilized the Generalized Focal Loss (GFL) network, Li et al. [28] for symbol recognition. Their approach involved employing two specialized GFL networks: one for detecting symbols above 700 pixels and another for detecting symbols below 700 pixels. To enhance the detection of closely positioned symbols, they implemented Adaptive Non-Maximum Suppression (NMS), Neubeck and Van Gool [35]. For text recognition, the authors adopted the pre-trained CRAFT network for detection purposes and utilized Tesseract for recognition tasks. Additionally, they employed RetinaNet for line detection to identify line markers and flow arrows. Recognizing continuous lines involved pixel-level traversal for straight lines and a Hough-transform method for diagonal lines. The association of symbols, text, and lines was performed using rules based on distance.

Elyan et al. [16], in their research, have developed a deep learning method aimed at identifying symbols in engineering drawings. This method addresses the limitations observed in the study by Rahul et al. [41] by demonstrating that the new approach can handle a wider variety of symbols requiring recognition. It has also improved the inconsistent accuracy of Rahul et al.'s work. The authors employed the third version of the You Only Look Once (YOLO) framework for symbol detection and recognition. Additionally, they trained a Multi-Feature Consistency Generative Adversarial Network (MFC-GAN) model to generate engineering symbols, effectively addressing the issue of class imbalance among symbols on P&IDs.

Jamieson et al. [25] focused on digitizing text from complex engineering diagrams encountered in real-world scenarios. For text detection, they employed the Efficient and Accurate Scene Text (EAST) model, while for text recognition, they utilized Tesseract v4. However, they faced challenges with their approach when dealing with intricate text representations, especially in situations where text was densely packed and positioned closely alongside other elements.

The existing research on P&ID symbol recognition has some limitations that need to be addressed. Firstly, it reports overall recognition results without specifying how well the methods perform on each type of symbol. Additionally, it is unclear whether the evaluation includes P&IDs containing symbology variations that were not part of the training data, making it uncertain whether these models can generalize. Another issue in the current literature is the limited focus on detecting vertical text lines. Many existing deep learning P&ID recognition methods rely on the EAST model for text detection, which struggles with vertical text. This indicates a need for modifications to the models to better suit the domain of application. Furthermore, the association techniques used in existing research are predominantly rule-based. However, there is no well-established set of rules in the industry for this purpose. This lack of standardization complicates the development of effective association methods.

3.2. Current trends in forecasting using historical data

In recent years, various AI-based methods have been utilized for forecasting and cost estimation in the construction and industrial sectors. These methods primarily focus on leveraging historical data to predict costs, material quantities, and project timelines. Deskera [9], Ahmad et al. [2]

Bahij et al. [5] proposes an energy consumption forecasting model using machine learning methods, specifically Linear Regression, Support Vector Machine, Decision Tree, and Artificial Neural Networks, for the industrial sector. The study finds that Linear Regression is the most efficient method for predicting energy consumption.

Khan et al. [26] introduce a hybrid energy forecasting model based on extreme gradient boosting, categorical boosting, and random forest method, focusing on pre-processing using feature engineering to improve forecasting. The model, validated with South Korea's hourly energy consumption data and shows a high forecasting accuracy.

Ghoddusi et al. [20] review the literature dedicated to applications of machine learning in areas such as predicting energy prices (e.g. crude oil, natural gas, and power), demand forecasting, risk management, trading strategies, data processing, and analyzing macro/energy trends. Their findings suggest that Support Vector Machine (SVM), Artificial Neural Network (ANN), and Genetic Algorithms (GAs) are among the most popular techniques used in energy economics papers.

Matel et al. [32] suggests that various machine learning techniques, including knowledge-based systems (KBS), evolutionary systems (ES), and hybrid systems (HS), have been widely adopted for cost estimation as they leverage extensive historical tender data to identify patterns and correlations, leading to more accurate cost predictions.

Ali et al. [3] confirms in their study the efficiency of AI algorithms such as Random Forest (RF), Support Vector Machines (SVM), and multilinear regression (MLR) in forecasting cost overruns in high-rise building projects.

Our research builds upon existing studies and extends them by integrating deep learning and predictive modeling. We combine a deep learning method for symbol recognition from P&IDs with historical data-driven predictive modeling. This dual approach is novel and enhances accuracy while automating the traditionally manual process.

3.3. Summarizing

In general, the lack of publicly accessible datasets for P&IDs has necessitated the creation of synthetic datasets, such as Dataset-P&ID. However, these datasets often fail to encapsulate the real-world complexities, including symbol variation, background noise, and diagram density, Paliwal et al. [39], Jamieson et al. [25]. This situation also restricts the availability of datasets suitable for validation, Kim et al. [27]. As a result, models are typically trained on data with clear text instances and consistent symbols, which may not accurately reflect real-world conditions, Dzhusupova et al. [12]. Moreover, linking text to symbols frequently requires specialized domain knowledge, Paliwal et al. [39]. The existence of company-specific drafting standards further complicates symbol variation, Dzhusupova et al. [12].

On the contrary, our study gains an advantage from an extensive collection of industrial data. This enables us to effectively address the challenges associated with symbol variation, noise, and density. In addition to the published work, we demonstrate methods for managing diverse symbology, improving annotations, and handling background noise in actual industrial documents. Furthermore, we apply domain-specific knowledge rules and utilize historical data repositories from prior engineering projects.

The summary of the main limitations in prior work compared to our proposed solutions is addressed in Table 1.

4. Research method

This work was conducted at McDermott, a leading Engineering, Procurement, and Construction (EPC) company with a global presence, known for undertaking large-scale projects in the energy sector. These projects adhere to a stringent safety integrity rate of 10^{-5}, indicating a limit of hazardous failures of one per every 100,000 hours of operation, IEC 61508 [24]. The research initiative was initiated by the first author and executed with the support of McDermott's engineering team under the direct supervision of the first author. The second author played a key role in the project's development, as detailed in Table 2.

In software engineering, the adoption of empirical research methods varies among scholars, highlighting methods like Action Research, which merges theory and practical application through a cyclic process of diagnosing problems, taking action, and reflecting, Sjøberg et al. [48], Easterbrook et al. [14], Wohlin et al. [55]. This method, which supports the collaborative efforts of researchers and practitioners, was deemed suitable for this study as the first two authors were part of the research team. While this approach might raise concerns about objective observation, Walsham [53], Easterbrook et al. [14], they grant unique access to empirical data due to the authors' engagement with daily operations as insiders and their responsibility to set quality standards. An external

Table 1
Gap analysis: Limitations in prior work vs. our approach.

Limitation in Prior Work	Our Approach
Reliance on synthetic data	Trained/validated on real industrial P&IDs
Symbol-text association via simple rules	Domain-specific, knowledge-based association
Poor handling of symbol variation/noise	Tiling, augmentation, robust architectures
No predictive adjustment	Regression models built on past historical EPC projects data

Table 2
Corresponding Roles in the Research Team.

Job ID within organization	Role in the research
Senior engineering manager	Artificial Intelligence Initiatives Lead (first author)
Senior engineer	Product Manager
Senior engineer	AI developer (technical lead)
Junior engineer	Software developer (front end)
2 x interns	ML/DL programmers
Junior engineer	AI developer, ML/DL programmer (second author)
Senior engineer	Data scientist
Junior engineer	Data scientist
Junior engineer	Dataset Preparation, domain expert
Senior Principal engineer	Dataset Preparation, domain expert

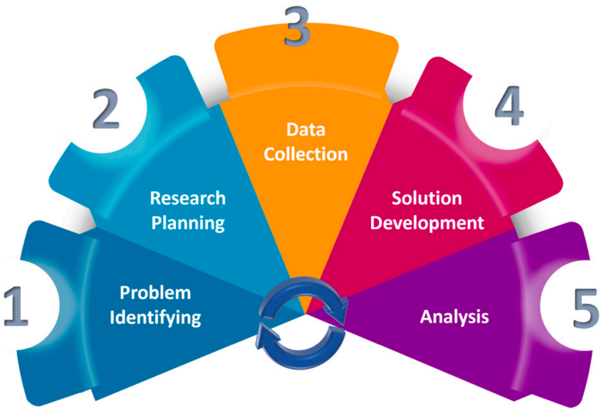


Fig. 2. Typical performed activities for action research, Coughlan and Coghlan [8], Easterbrook et al. [14], Soiferman [49].

observer would have been unable to achieve this level of involvement, especially considering the confidential nature of the data used in the study.

The study's empirical analysis was organized around a set of activities derived from established action research workflows, Coughlan and Coghlan [8], Easterbrook et al. [14], Soiferman [49], facilitating a structured, iterative exploration of findings as illustrated in the Fig. 2.

The research methodology is structured into four main stages: (1) Data Collection, (2) Solution Development and testing, and (3) Evaluation. Each stage is designed to address the research question by combining data-driven and AI-based techniques for automating material estimation from P&IDs.

4.1. Collecting the data

In contrast to many large corporations that often maintain separate platforms or databases across various offices or business units, resulting in a substantial volume of daily generated data being largely inaccessible for AI development, Mirji [33] McDermott has an advantage. The company's document management system provides access to an extensive amount of structured data accumulated from all types of projects executed over the past two decades. This access has enabled the research team and domain engineers to compile a high-quality training dataset.

Data Ownership and Provenance All training data used for symbol/text recognition models and predictive modeling constitutes proprietary intellectual property of McDermott International, Ltd. This includes real industrial P&IDs from executed EPC projects and historical project reports stored in the company's document management system. No third-party was used for core model development, ensuring protection sensitive project information. This approach ensures strict compliance with company policy and data confidentiality requirements, further protecting sensitive project and client information.

Details about data collection and pre-processing are provided in Section 5.3, as this activity has specifics for each building block of the developed proof of concept.

4.2. Solution development

To address the research question, deep learning methods were utilized to automatically identify symbols, their metadata, and interrelations within Piping and Instrumentation Diagrams (P&IDs). This forms the initial segment of the research (**Part 1**). Subsequently, historical data from archived as-built project reports were analyzed using machine learning techniques. This approach aimed to improve the accuracy of the extracted material quantities, representing the second segment of the study (**Part 2**). The comparative analysis between these two parts was expected to provide estimators with a foundation for producing more accurate material estimates.

Part 1:

The foundation of the initial part of this study was built on published research about information extraction from P&IDs, along with practical insights from a successful application developed at McDermott, as detailed by the first author in previous work, Dzhusupova et al. [11]. This earlier application leveraged a deep learning method capable of object detection and transfer learning to identify specific patterns on engineering drawings and categorize them for quality checks. The development process, including data preparation, model selection, and deployment, established a solid base for the current research.

To tackle the distinct challenges of P&IDs, which include the presence of small symbols, their similarity, unstructured text, and overlaps between text and symbols, a thorough examination of optical character, object, and text recognition methods was performed. This review, referenced in section 3, aimed to identify models that are not only open source but also straightforward to use and maintain. Furthermore, it was essential to choose models that could be adapted to overcome specific limitations highlighted in the literature. These limitations could significantly impact the precision and reliability of recognizing elements on real-life (non-synthetic) industrial P&IDs.

Data annotation for the symbol and text recognition models was performed using offline open-source image annotation tools that recorded the object's class and position. The training process of the models was conducted in the Google Colab environment, Google [21], utilizing the T4 GPU, NVIDIA [36], for both symbol and text recognition training.

Part 2:

The empirical data supporting the second part of this research is derived from the experience gained through another previously developed and successfully deployed application within McDermott, as cited in Dzhusupova et al. [12]. This application utilizes machine learning regression techniques to predict the engineering hours required across various disciplines for designing petrochemical or gas processing plants. Due to its successful integration within the company, the workflow used for data collection, data preparation, and feature engineering was replicated in this work.

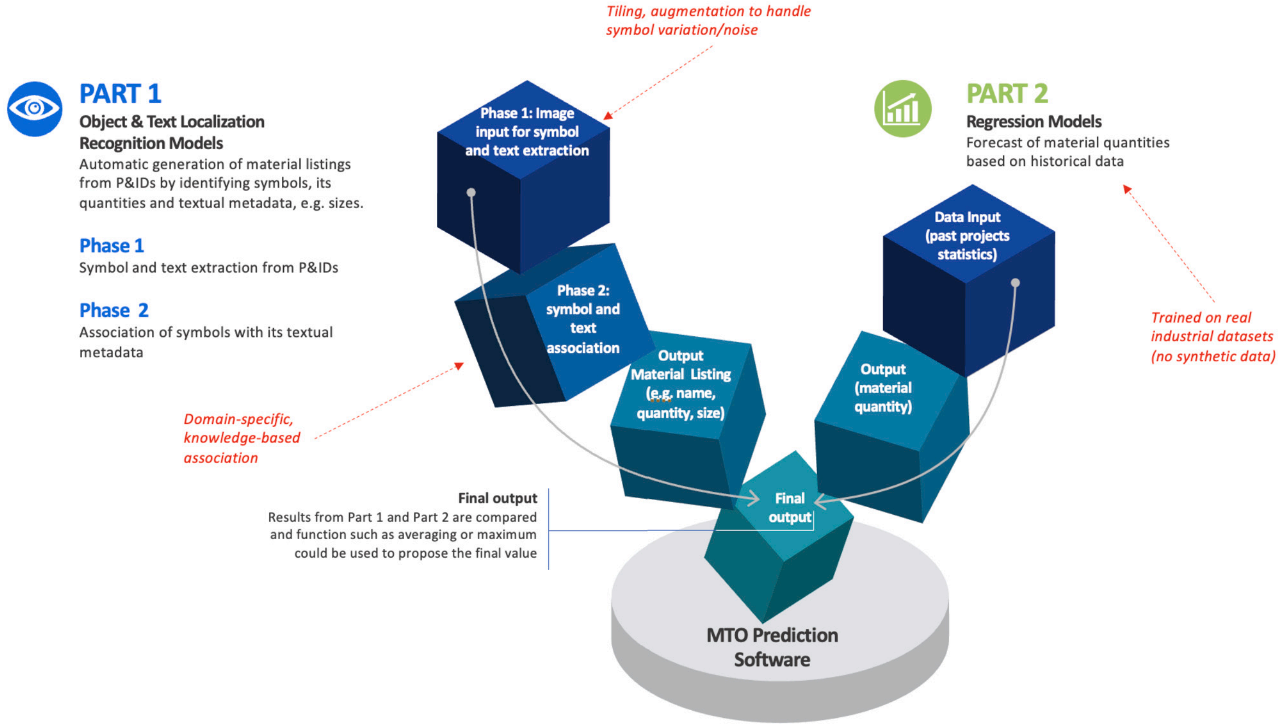


Fig. 3. Overview of the dual-stage AI-based material estimation workflow. Part 1 (left) illustrates the extraction of symbols and text from P&IDs using deep learning models, while Part 2 (right) shows the predictive adjustment of quantities based on historical project data.

Each component of our methodology directly addresses specific aspects of the research question “How can we automate the extraction of material quantity information while ensuring estimating accuracy?”:

- Part 1 (Deep Learning Extraction) addresses the “automation” challenge by automatically identifying symbols, their metadata, and interrelations within P&IDs, eliminating manual counting processes.

- Part 2 (Historical Data Analysis) addresses the “accuracy” challenge by leveraging machine learning techniques on archived project data to validate and improve extracted material quantities.

- Integration of Both Parts ensures that automated extraction is enhanced by data-driven validation, providing estimators with reliable material estimation - Material Take-Off (MTO).

More comprehensive details regarding data collection and preparation are provided in Section 5, where the development of the solution is discussed in depth.

4.3. *Analysis*

During this phase, the research team collaborated with domain experts to assess the performance of the proof of concept (POC) using new data. These domain experts were from the company’s office in The Hague, the Netherlands, as shown in Table 2. The final analysis encompassed a cost comparison between the investment in development and the monetary value of the engineering hours saved. In addition to expert review and time-saving analysis, the proof-of-concept was quantitatively evaluated using standard metrics such as accuracy, precision, recall, and F1-score for symbol and text recognition, as well as MAE and R^2 for regression model performance. All experiments were repeated three times to confirm reproducibility. Furthermore, a detailed error analysis was conducted to identify and understand the causes of incorrect or missed detections. This multi-faceted evaluation provides both statistical and practical validation of the POC’s effectiveness.

5. Development of Proof-of-Concept (POC)

This section provides an overview of how we created the proof-of-concept (POC) for our proposed solution. Firstly, it explains the fundamental concept behind the solution. Secondly, it discusses the development process of the POC itself. Afterwards, it explores the practical implementation of the POC and its evaluation, including key insights gained during the development phase.

5.1. *Proof-of-Concept description*

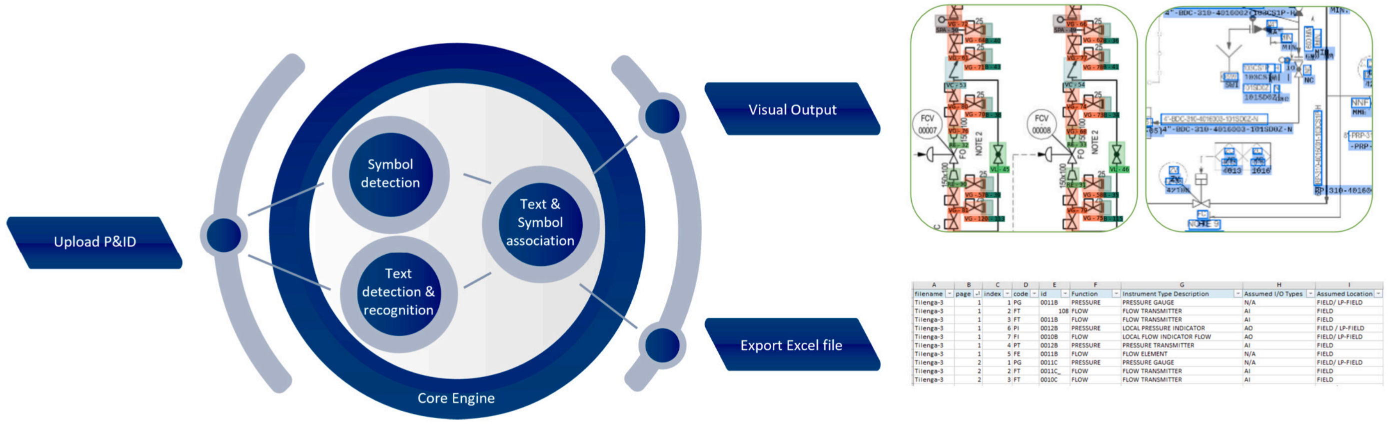
The Proof-of-Concept (POC) involves the development of software that integrates Part 1 and Part 2 (see section 4.4), enabling them to run simultaneously. The results from both parts are compared, and a unified final output is generated by utilizing certain rules, such as averaging or selecting the maximum value from each part’s output (see Fig. 3. These rules can be easily adjusted by domain experts based on the specifics of the estimated project. Below, we break down each component.

Part 1 - Material List Extraction. This component allows users to upload PDF binders and obtain visual representations of the detected symbols and text instances. These are accompanied by a table indicating equipment type, quantity, and sizes, as illustrated in Fig. 4. The user interface of Part 1 is displayed in Fig. 5.

It consists of two phases:

Phase 1: In this phase, text and symbol detection models work in parallel to retrieve their detections, including their spatial coordinates and classifications (symbol type), Kim et al. [27], Francois et al. [18].

Phase 2: After symbol and text detection, a dedicated domain-specific association logic is applied as a separate step. This logic links detected symbols with their corresponding textual metadata, utilizing heuristics and domain rules. There is no feedback loop from the detection models to the association logic; instead, the association is conducted on the outputs of detection. During this phase, text instances are associated with related symbols. Moreover, the system extracts essential metadata from text instances, such as size information. To establish an optimal



filename	page	index	code	id	Function	Instrument Type Description	Assumed I/O Types	Assumed Location
Tilenga-3	1	1	PG	0011B	PRESSURE	PRESSURE GAUGE	N/A	FIELD/ LP-FIELD
Tilenga-3	1	2	FT	108	FLOW	FLOW TRANSMITTER	AI	FIELD
Tilenga-3	1	3	FT	0011B	FLOW	FLOW TRANSMITTER	AI	FIELD
Tilenga-3	1	6	PI	0012B	PRESSURE	LOCAL PRESSURE INDICATOR	AO	FIELD / LP-FIELD
Tilenga-3	1	7	FI	0010B	FLOW	LOCAL FLOW INDICATOR FLOW	AO	FIELD/ LP-FIELD
Tilenga-3	1	4	PT	0012B	PRESSURE	PRESSURE TRANSMITTER	AI	FIELD
Tilenga-3	1	5	FE	0011B	FLOW	FLOW ELEMENT	N/A	FIELD
Tilenga-3	2	1	PG	0011C	PRESSURE	PRESSURE GAUGE	N/A	FIELD/ LP-FIELD
Tilenga-3	2	2	FT	0011C_	FLOW	FLOW TRANSMITTER	AI	FIELD
Tilenga-3	2	3	FT	0010C	FLOW	FLOW TRANSMITTER	AI	FIELD

Fig. 4. Visualization of the workflow for Part 1 - Material List Extraction. These figures are authentic industrial P&ID documents, where small text and dense symbols are characteristic of real-world engineering drawings. The purpose of including these examples is to demonstrate the AI system's ability to operate under the challenging conditions typical of actual industry practice.

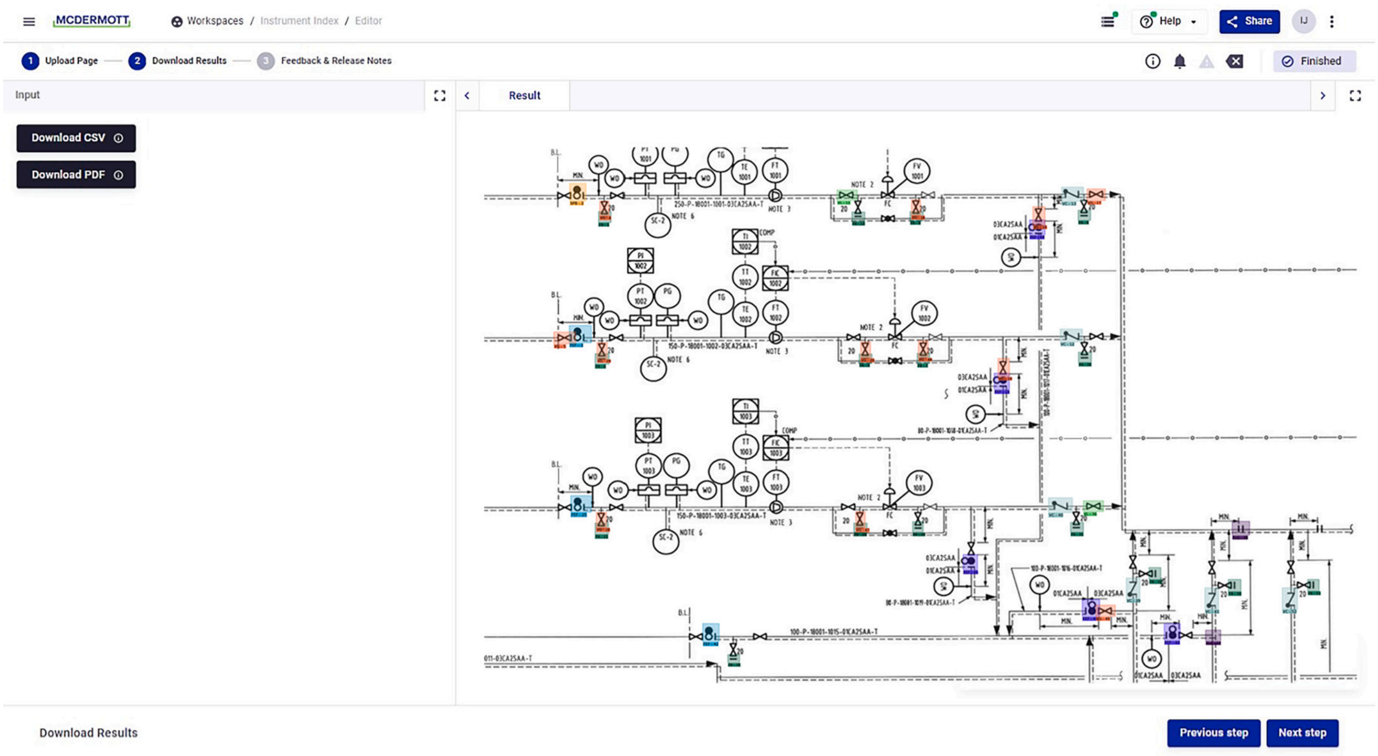


Fig. 5. User Interface for Part 1.

association, this process utilizes heuristics like the Euclidean distance between each detected symbol and text.

Part 2 - Forecast of Material Quantities. In this part of the solution, machine learning regression models are utilized to predict material quantities based on historical data derived from the project reports available at the close-out of each EPC project. The aim is to enhance the material quantities extracted from the client's drawings by aligning them with the company's experiences from past EPC projects. The user interface of Part 2 is shown in Fig. 6.

5.2. Cost-efficiency potential

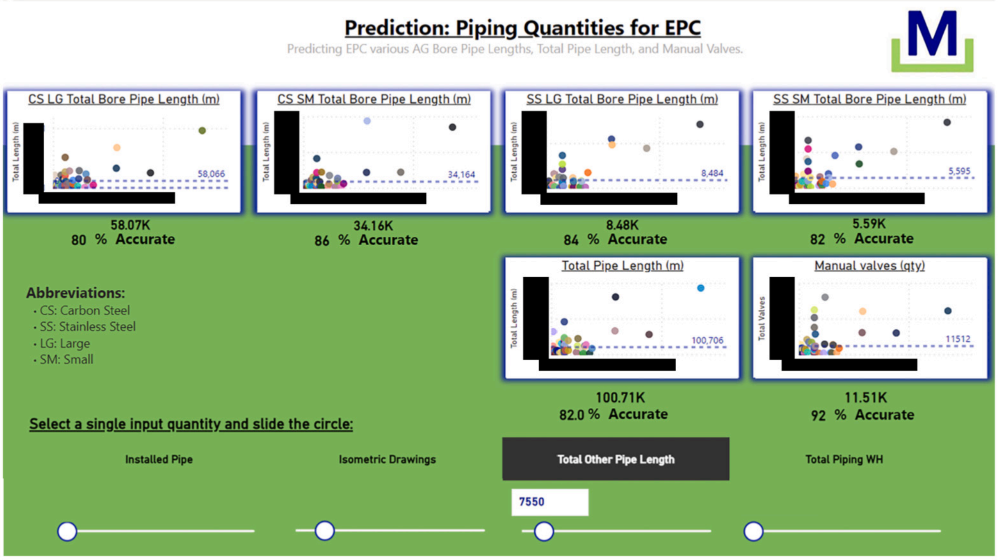
Currently, the process of generating Material Take-Offs (MTOs) for procurement cost estimation is a labor-intensive task. Engineers must meticulously examine each drawing, identify symbols, and count them before updating an MTO spreadsheet. Based on McDermott's experience, creating an MTO can consume approximately 36 hours per 10 P&IDs of a skilled engineer's time. Applying these assumptions, potential cost savings can be calculated. A typical large EPC project encompasses approximately 1,000 drawings, and the average hourly cost in a high-cost engineering environment is around \$100. This cost includes salary and various overhead expenses such as equipment, utilities, office rent, taxes, insurance, and pensions. Assuming that there are three revisions per project on average, the potential financial benefits for a large EPC contractor can be calculated as follows:

Hours saved for each revision:

$$1,000 \text{ drawings} \times \frac{36 \text{ hours}}{10 \text{ drawings}} = 3,600 \text{ hours} \tag{1}$$

Financial savings in a high-cost engineering environment per individual project would be:

$$\$100 \times 3 \text{ revisions} \times 3,600 \text{ hours} = \$1,080,000 \tag{2}$$


Prediction: Piping Quantities for EPC

Predicting EPC various AG Bore Pipe Lengths, Total Pipe Length, and Manual Valves.

CS LG Total Bore Pipe Length (m)

[redacted]

58.07K
80 % Accurate

CS SM Total Bore Pipe Length (m)

[redacted]

34.16K
86 % Accurate

SS LG Total Bore Pipe Length (m)

[redacted]

8.48K
84 % Accurate

SS SM Total Bore Pipe Length (m)

[redacted]

5.59K
82 % Accurate

Abbreviations:
- CS: Carbon Steel
- SS: Stainless Steel
- LG: Large
- SM: Small

Total Pipe Length (m)

[redacted]

100.71K
82.0 % Accurate

Manual valves (qty)

[redacted]

11.51K
92 % Accurate

Select a single input quantity and slide the circle:

7550

Fig. 6. User Interface for Part 2. Axis values are hidden due to data sensitivity.

In addition to the time aspect, the manual approach carries the risk of errors related to quantities, sizes, or materials, which can have significant financial consequences. Thus, the proposed solution not only optimizes the allocation of human resources, but also assists during crucial tender phases where precise and rapid cost estimation is essential. However, the solution does not eliminate the need for human intervention. Engineers with expertise are still required to interpret the results for the final check and verification.

5.3. Concept implementation

5.3.1. Part 1 - Material list extraction from the drawings

Symbol detection and recognition.

The task of developing a deep learning method to recognize symbols on P&IDs presents several challenges. One of the main issues is the imbalance in the frequency of symbol types within these diagrams. Common symbols are encountered frequently, while others are rare. This disparity can lead to potential bias in the recognition model towards the more common symbols, resulting in poor recognition of the rare ones. Furthermore, symbols may appear very similar to one another, which increases the risk of incorrect classification, as shown in Fig. 7.

Variations in symbol size also complicate recognition. In the same Fig. 7, it is demonstrated how a symbol with a smaller visual representation affects the recognition process. The small symbol sizes, in comparison with the full size of the P&ID, further complicate their detection and classification.

To tackle these issues, we developed an approach that involves two separate deep learning models: one for regular-sized symbols and another for downscaled symbols. The process begins by segmenting the P&IDs into overlapping images or “tiles”, Ozge Unel et al. [38] to improve the detection of objects, which are much smaller compared to the overall size of the images. These tiles are then augmented or downscaled. Tiling is discussed in detail in the “Data Preparation for symbol detection and recognition” section below. After that, the processed tiles are fed into the corresponding models. Only detections surpassing a predefined confidence threshold are retained. The detection coordinates are then repositioned to their correct location in the original P&ID image. To eliminate duplicate detections caused by the tiling and dual-model approach, the Intersection over Union (IoU) metric is employed. This metric helps filter out redundancies by retaining only the detections with the highest confidence. The complete methodology is shown as a flowchart in Fig. 8.

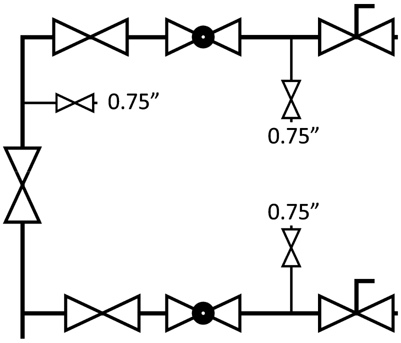


Fig. 7. A recreation of P&ID showing the similarity between different symbols and their size variability.

i) Data collection for symbol detection and recognition.

A set of 133 P&IDs from 11 different projects executed by McDermott was selected for training purposes, which contains various symbols. As previously mentioned, certain symbols in these P&IDs have different representations due to the varying standards employed across projects. The POC focuses on recognizing twelve frequently occurring symbols in Piping Material Take-Off (MTO), which represent various valves and fittings. These symbols are listed in Fig. 9.

ii) Data preparation for symbol detection and recognition.

Annotation

The data annotation for the symbol recognition model was executed in collaboration with piping engineers in LabelImg software, Lin [29]. The involvement of piping engineers was crucial, as their domain knowledge was essential for the annotation process. An example of flange connections and piping valves (Fig. 10) clearly illustrates this point: while annotating flange connections, it is important to distinguish between flanged connections and flange-nozzle assemblies. A flanged connection involves two flanges bolted together, as illustrated in Fig. 10 (right), while flange-nozzle combinations consist of a nozzle attached to a flange that is directly connected to a piece of equipment, as shown in Fig. 10 (left). Despite their visual similarities, these are considered different symbols and were treated accordingly: flange-nozzle combinations were not included in POC and, therefore, were not annotated in the dataset.

Another example is instrument valves, which must be excluded from annotation, as they are associated with instrumentation components and are not part of the piping MTO. Fig. 11 illustrates this distinction:

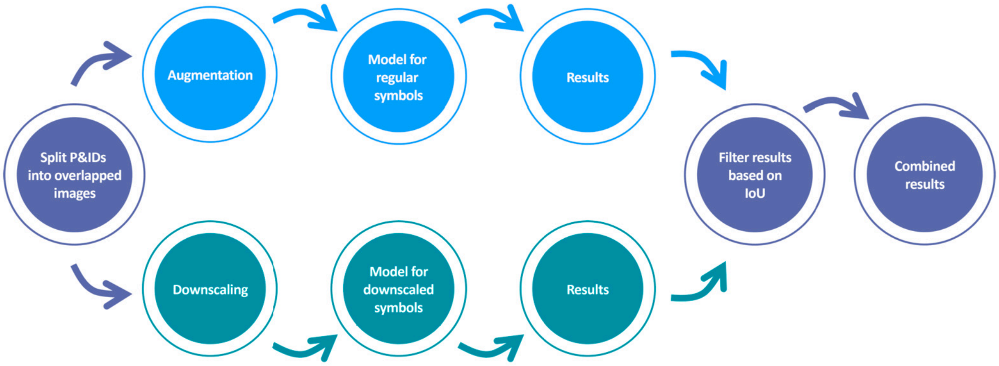


Fig. 8. Workflow for symbol recognition.

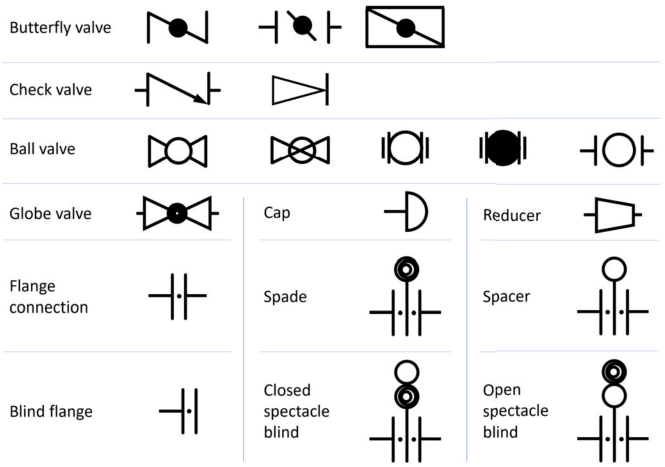


Fig. 9. Symbols used for training of the Proof-of-Concept.

Fig. 10. Flange-nozzle assembly (left) and Flanges connection (right).

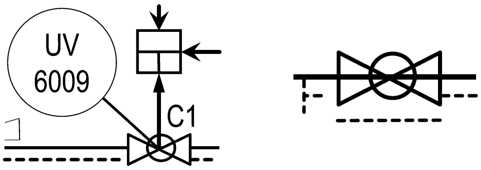


Fig. 11. Example of "instrumentation" valve connected to the instrument UV 6009 (left) and Example of "piping" valve (right).

The valve labeled "C1" in Fig. 11 (left) is connected to an instrument "UV 6009", which makes the valve an "instrumentation" valve and, therefore, should not be annotated. Conversely, the standalone valve, as shown in Fig. 11 (right), indicates that it is a "piping" valve and, therefore, was annotated.

Tiling

In the post-annotation phase, we applied "tiling" to address the challenge posed by the symbols' relatively small size compared to the full size of the P&ID. Tiling, as described in the work of Ozge Unel et al. [38], is a process that divides a larger image into smaller overlapping segments known as 'tiles'. This technique is particularly beneficial for enhancing the visibility of small objects within an image. In deeper layers of neural networks, the features of these small objects may become negligible. With tiling, each symbol occupies a larger proportion of the tile's surface area compared to its proportion in the original image, making it more detectable. An alternative approach would be the use of high-resolution P&IDs; however, this is a resource-intensive solution that would lead to increased processing times.

During tiling, each P&ID is split into smaller images with an overlap of 200 pixels. The dimensions of each tile are set to one-third the width and height of the original P&ID. In instances where tiles have reduced dimensions, they are expanded to the full size by adding white pixels to the edges. The annotations associated with each image were also split according to the tiles. Bounding boxes that are not fully captured in the tile were removed. Given the varying dimensions of P&IDs across different projects, we standardized the tiles and annotation coordinates to a consistent resolution of 860x860 pixels. This resolution was chosen as a balanced compromise, accommodating multiple project requirements without a significant compromise in image quality. Fig. 12 demonstrates an example of two overlapping tiles, where the area of overlap is marked by a red box.

Data Augmentation

The next step of the preprocessing involved exploring a data-level method to address the symbol class imbalance by using augmentation. This method identifies tiles containing underrepresented symbols while excluding overrepresented ones. For each tile, the annotations include class labels (type of the symbol) and the coordinates of the bounding boxes encompassing the symbols. Exclusion is done by checking whether the annotation file of each tile contains the class label of any of the overrepresented symbols. If the annotation file includes an overrepresented symbol, the associated tile is not augmented. To enhance the variety of symbol orientations and positions, the tiles with underrepresented symbols are augmented by applying 90, 180, and 270-degree rotations or by shifting them to the right and left by 100 pixels.

During augmentation, the coordinates in the annotation files are adjusted to reflect the transformation of the symbols within the image. This ensures that the altered position or orientation of each symbol is accurately represented in the updated annotations. Fig. 13 showcases an example of this augmentation, displaying a tile that has been rotated by 270 degrees.

Downscaling

To address variations in symbol sizes, a similar technique as described in Kim et al. [27] was applied. This method involves training separate networks to recognize both regularly sized symbols and downscaled symbols. To achieve this, a dataset consisting of downscaled versions of the original tiles was created, which also included annotations for the symbols that the model needs to recognize. These annotations were adjusted to align with the downscaled tiles. It is important to note that a set of original P&IDs containing true downscaled symbols was preserved for testing and evaluation, and it was not used during training.

iii) Model development for symbol detection and recognition.

For text detection in P&IDs, we chose VFNet due to its superior performance. VFNet's modified focal loss improves detection accuracy and precision, particularly in complex and noisy diagrams, Zhang et al. [57].

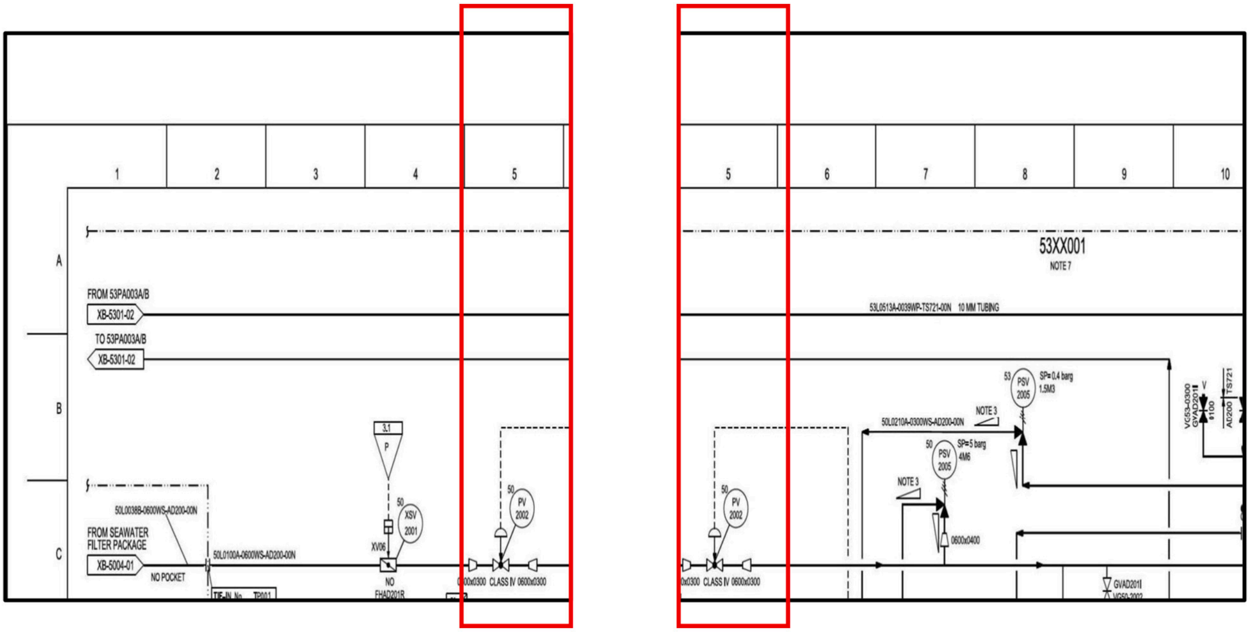


Fig. 12. An example of two overlapping tiles, where overlap is highlighted by the red box.

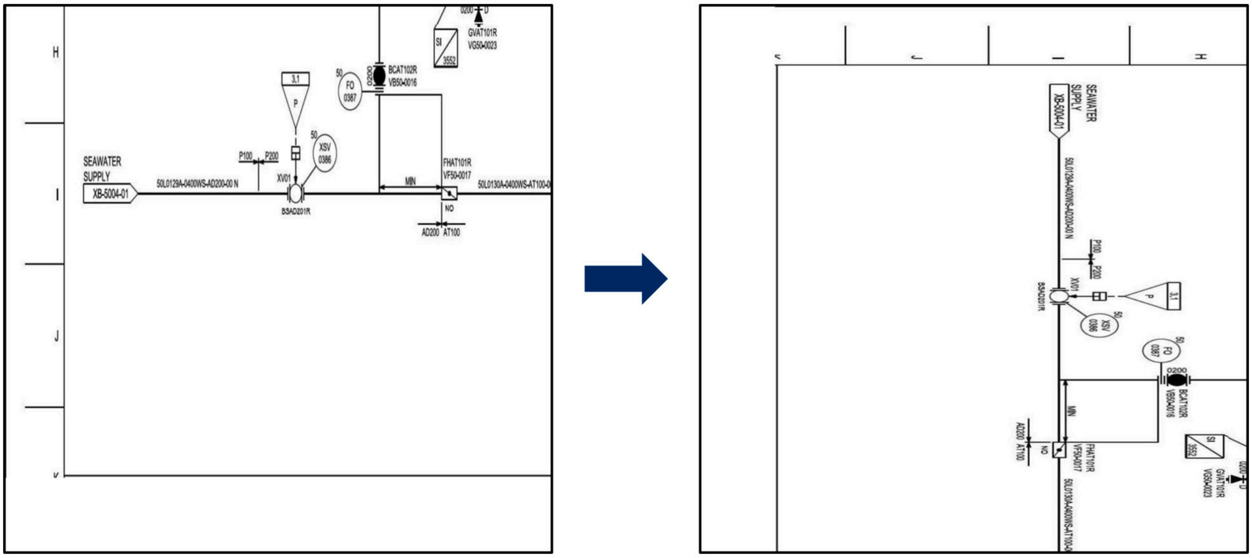


Fig. 13. Original tile (left) and Augmented tile rotated at 270 degrees (right).

This approach outperformed other models in our evaluation, making it as the most suitable choice for detecting various text orientations and densities in industrial documents.

The training process utilized the Adam optimizer, with a learning rate set at 0.0001. Training performance was evaluated using the Mean Average Precision (mAP) score, which was computed in each epoch. mAP is the average precision score across all classes. The models were trained using pre-trained weights for their respective feature extractors. The training was conducted over 25 epochs. For regular symbols, tiles generated during the data preprocessing stage were divided into training, validation, and test sets with ratios of 80%, 10%, and 10%, respectively. The test set excluded augmented tiles. Thus, the model was evaluated using only authentic P&IDs with true downscaled and augmented symbols.

Text detection and recognition.

The presence of unstructured text and the overlap of text instances with symbols or other text elements in P&IDs pose significant challenges for both text detection and recognition tasks. This overlap can create difficulties in accurately detecting and subsequently recognizing such text instances. Moreover, text on P&IDs can appear in various orientations and lengths. Notably, vertical and lengthy text instances can be particularly challenging to detect correctly, Zhou et al. [58], and any shortcomings in the detection phase are likely to lead to text recognition inaccuracies. Therefore, a deep learning method was applied again to recognize text instances of varying lengths and orientations.

i) Data collection for text detection and recognition

The training of the text detection model was conducted using a set of industrial P&IDs alongside an additional 500 P&IDs from the synthetic Digitize-PID dataset, Paliwal et al. [39]. The industrial P&ID dataset, which contains text in various orientations and lengths, provided a robust challenge for text detection. Additionally, the inclusion of the Digitize-PID dataset, which was fully annotated, served to expand the training data pool. This approach eliminated the need for extensive data annotation that would have been necessary if relying solely on industrial P&IDs.

ii) Data preparation for text detection and recognition

A proof-of-concept was developed to recognize textual information representing material sizes. Size annotation in industrial P&IDs is a labor-intensive task due to the volume of text presented in these diagrams. To improve efficiency, the Pdfminer.six library, Shinyama et al. [45], was utilized to extract sizes and their corresponding locations from the PDF versions of the P&IDs, generating preliminary annotation files. Subsequently, these files were thoroughly reviewed. Throughout this review phase, any inaccuracies or misses in the annotations were corrected by hand within Label-Studio software, Ryabinin [43].

iii) Model development for text detection and recognition

The text-processing workflow employed two separate deep-learning methods: one for detection and another for recognition. The detection phase utilized the Efficient and Accurate Scene Text (EAST) model, Zhou et al. [58], to locate text on P&IDs. For the recognition phase, these identified text areas were interpreted using the fifth version of the open-source Tesseract OCR model, OCR [37].

The EAST model provided the coordinates of the detected text, which were used to obtain crops of the respective regions containing this detected text. These crops were then passed to the Tesseract OCR to perform the recognition. For the recognition phase, Tesseract OCR leveraged an LSTM network to decode the text from the cropped images. To facilitate the recognition process, we developed the software to establish a rule that assumes the input image received by Tesseract OCR consists of individual crops corresponding to a single detected text instance.

To ensure reliable results across different types of projects, we apply quality control checks at multiple steps: (1) For symbol recognition, we set a 35% confidence threshold - any symbol predictions below this level are eliminated, (2) For text detection using the EAST method, we use a 10% confidence threshold, then apply Non-Maximum Suppression to eliminate duplicate detections of the same text by keeping only the highest confidence prediction when detections overlap by 30% or more, and (3) For text reading with Tesseract, we do not apply confidence filtering, and all results are validated across different project types and drawing standards.

Text and Symbol Association.

To enable the generation of a simplified MTO containing a material listing with its metadata, the association logic should link symbols to their corresponding sizes. Typically, the sizes of most symbols on the P&IDs are indicated as text located on one of the sides surrounding the symbol itself. Fig. 14 provides an illustration of a symbol with its size.

In the POC design, the association of the symbols with text was based on heuristics, utilizing Euclidean distance measurements. Initially, the method computed the Euclidean distance between each detected symbol and the detected text. If the distance fell below 100 pixels, the two detections were paired together. Following this initial association step, the results were refined by applying regular expressions established by domain experts. These expressions could vary for different symbol types. Moreover, any duplicate associations were resolved by retaining the association with the shortest distance.

In cases where information about the symbol's size was missing, relying solely on Euclidean distance-based heuristics became ineffective. In such situations, domain experts played a crucial role in determining alternative knowledge rules to extract size information from other text instances within the same drawing. This complexity was further heightened by the absence of universal standards in P&ID drafting across various types of projects. Consequently, when dealing with incomplete or missing information on P&IDs, domain experts must continually adapt these rules based on country standards or specific client practices.

5.3.2. Part 2 - Forecast of material quantities based on past projects

i) Data collection for material quantity prediction

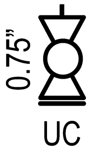


Fig. 14. An example of a Ball valve with a size indicated next to it.

Here, the research team primarily focused on gathering data by extracting key quantities from Material Take-Off (MTO) documents of McDermott's completed (as-built) EPC projects. These MTO documents are stored in a tabulated format and contain essential information about project quantities and their metadata, which were recorded at the end of the engineering phase of each EPC project. The collected data was organized based on project type (such as Refining & Petrochemical, Power Generation, Gas Processing, or LNG), location (Onshore or Offshore), and contract type (Lump Sum, Reimbursable, or Hybrid). In total, the database included key quantities from 115 EPC projects that McDermott had executed over the past two decades.

ii) Data preparation for material quantity prediction

During the data preparation, the research team had to decide how to handle the missing values. Initially, missing values were imputed by filling them with either mean or median values. However, this imputation method negatively affected model performance. Therefore, alternative approaches, such as Iterative or KNN Imputers, Zhu and Cheng [59] were explored. After consultation with domain experts, it was determined that these imputation methods often produced incorrect estimations for missing values in the number of projects, leading to poor model performance. Consequently, the decision was made to remove projects with missing values. In summary, the data preprocessing phase involved the implementation of the following activities:

(1) Removal of features containing missing values above a predefined threshold.
(2) Elimination of irrelevant categorical features by domain experts.
(3) Selection of relevant features through correlation matrices with the involvement of the domain experts.
(4) Removal of the large outliers presented in the dataset, particularly those exceeding 95% in Gaussian distribution, as they could adversely impact model performance, especially when dealing with low-quality data.

iii) Model development for material quantity prediction

Since the prediction in this case was built on tabulated data, the following regression methods were used to predict the quantity of piping material items: Linear (Polynomial), Ridge, and Lasso, Gupta et al. [22]. By employing a variety of methods, we aimed to determine the best performing one for each combination of various features. The dataset was split as 80% of the data for training purposes and the remaining 20% for testing and evaluation.

The performance of the models was evaluated using two statistical methods:

(1) Mean Absolute Error (MAE)
(2) Coefficient of Determination (R2)

The MAE measures the average of absolute differences between actual and predicted values, as shown in equation (3), where $\hat{y}$ represents the predicted y value. From the equation, the best performance occurs when MAE → 0. Although the MAE is straightforward to interpret for any given model, this metric is influenced by the scale of the feature quantities. To compare model performance across data with different scales, further analysis with the original dataset or post-processing techniques, such as Coefficient of Determination (R2) analysis, is necessary.

Table 3
Percentage of recognized symbols vs total number of symbols presented on each set of P&IDs.

Project	Accuracy
A	85.6%
B	74.2%
C	94.2%
D	94.7%

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{3}$$

The R^2 represents the proportion of the variance in the desired prediction variable, as shown in equation (4), where $\bar{y}$ is the mean y value. This results in a dimensionless score that ranges from 0 to 1, facilitating easy comparison across different project data and models. A key benefit of this approach is that it helps us determine whether the models are overfitting. If there is a significant difference between the training and test R2 scores, it indicates that the model has been overfitted, necessitating adjustments to its parameters.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \tag{4}$$

The accuracy calculations were performed according to equations (5) and (6).

$$\text{Accuracy} = 100\% - \text{Error Rate} \tag{5}$$

$$\text{Error Rate} = \frac{|\text{Observed Value} - \text{Actual Value}|}{\text{Actual Value} \times 100} \tag{6}$$

6. Results

Having outlined the methodological approach, in this section we present the results to evaluate the solution's performance.

6.1. Evaluation of Part 1

All experiments were repeated three times to assess result consistency. The obtained results were consistent, demonstrating the reliability of our methodology.

i) Evaluation of the Symbols detection and recognition

The symbol recognition model has been manually evaluated across four different projects, designated as A, B, C, and D. These projects were not included in the training dataset, which allowed us to assess the model's ability to generalize to new, unseen data. For each project's evaluation, a sample of 20 P&IDs was chosen. The results are presented in Table 3.

The observed accuracy variations between Projects A-D reflect fundamental differences in dataset characteristics relative to our training data. Projects C and D demonstrated superior performance (94.2% and 94.7% accuracy respectively) due to their high similarity with training data in terms of symbol styles, drafting standards, and drawing density. In contrast, Projects A and B (85.6% and 74.2% accuracy) contained symbol variations, drafting conventions, and graphical representations that were not adequately represented in the training dataset. These projects exhibited novel symbol orientations, company-specific drafting standards, and background noise patterns that challenged the model's generalization capabilities, resulting in increased false positive and false negative detections.

In addition to assessing overall accuracy, the model's performance was evaluated in terms of precision and recall for each individual symbol type, as illustrated in Fig. 15. The performance results showed that all symbols achieved a high recall, exceeding the 75% threshold. This indicates a low false negative rate in relation to the total number of detected symbols. It is worth mentioning that the majority of symbols also attained high precision levels, surpassing 80%. This suggests a low false positive rate concerning the total number of detected symbols. However, exceptions are observed with the "cap," "butterfly valve," and "flanged connection" symbols. These symbols exhibit a higher rate of false positive detections. Nonetheless, this is not critical, as engineers are always responsible for reviewing the model's output.

Table 4
EAST model's performance in text detection.

Metric	Score
Precision	86%
Recall	88%
F1	87%

The quality thresholds of 75% recall and 80% precision were established based on internal expert consensus and reflect McDermott's requirements for practical deployment. While there is no formal industry standard, these values are consistent with those reported as state-of-the-art in recent literature on symbol and text recognition in engineering drawings, Kim et al. [27], Paliwal et al. [39], Elyan et al. [16], Jamieson et al. [25].

ii) Evaluation of the Text detection and recognition

The performance of the EAST model in text detection (i.e. material size) was evaluated using Precision, Recall, and F1-Score metrics on a dataset consisting of 50 industrial P&IDs. The results can be found in Table 4.

Similarly, the performance of Tesseract OCR for text recognition was evaluated on the same set of 50 industrial P&IDs. This evaluation employed an end-to-end metric based on Maximum Intersection over Union (MaxIoU) and Normalized Score, as detailed in Hao et al. [23]. The normalized score result was 77%.

iii) Evaluation of the Association of symbols and texts

The performance of the knowledge rules for an association logic for symbol and text recognition was evaluated using P&IDs from the same four projects. A detailed analysis of the association's performance is provided in Table 5.

Table 5 demonstrates that the rate of correct symbol-text pair recognition is low. Error analysis revealed two primary issues that contribute to this: Firstly, missing data on the drawings (i.e. when relevant size information isn't adjacent to symbols or not indicated at all). Secondly, multiple text detection in dense and noisy diagrams where the required size information is clustered with other text or symbols. The association model, which uses distance-based heuristics, struggles when relevant size information is obscured by overlapping text, causing a high number of missed pairings.

Nevertheless, the evaluation of Part 1, which includes the localization, recognition, and association of symbols and text, indicates that the concept is functional. However, the quality of engineering drawings heavily influences the model's performance, especially concerning the association between symbols and their textual metadata. To enhance output quality, it is important to utilize high-quality drawings that do not have missing data. Future research should investigate whether refinement of the model is feasible with training on denser and noisier P&IDs.

6.2. Evaluation of Part 2

The effectiveness of the predictive models was evaluated using data from a recently completed petrochemical project, where actual material quantities were known. The proof-of-concept was trained to predict "manual piping valves" quantities based on four input features:

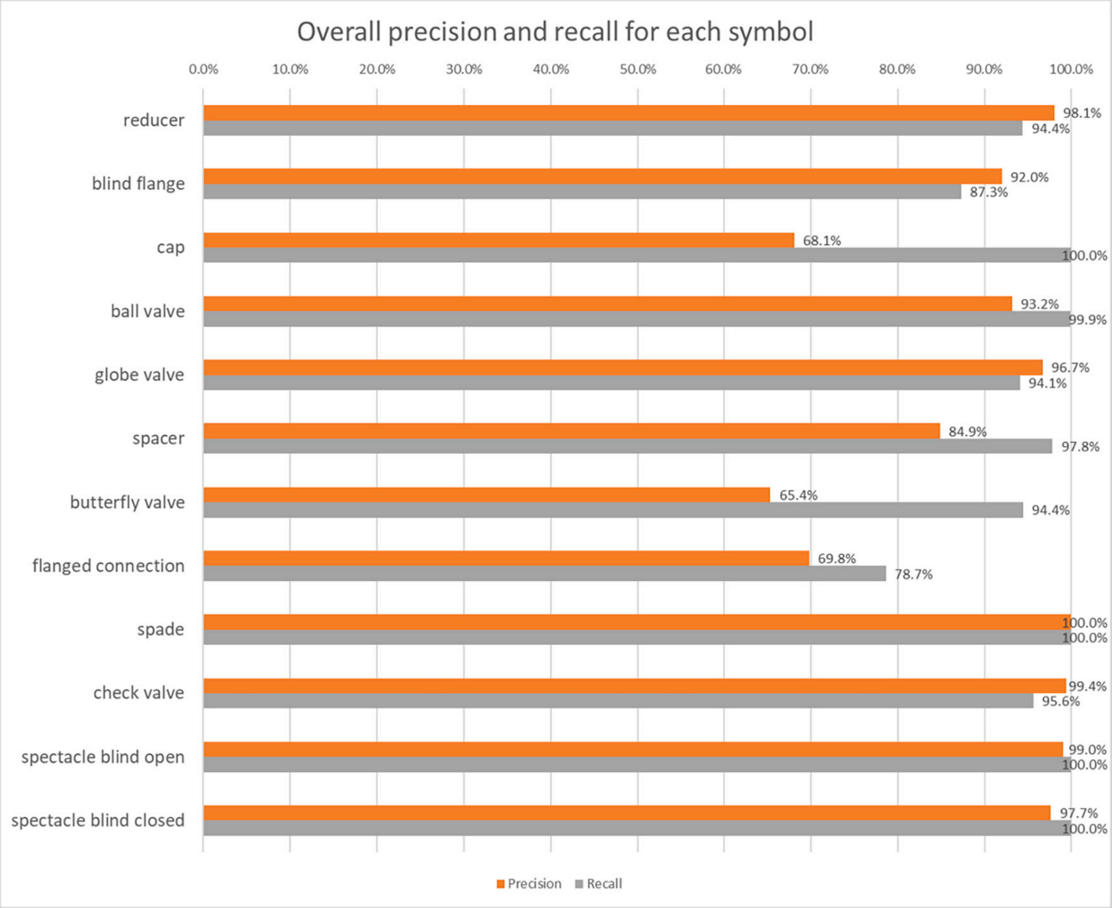


Fig. 15. Evaluation of each symbol recognition in terms of precision and recall.

Table 5
Evaluation of combined symbol and text recognition models and their association logic.

Project	A	B	C	D
Number of symbol-text pairs	73	180	75	43
Correct	44%	62%	42%	55.82%
Incorrect	12%	15%	4%	6.09%
Missing	44%	28%	54%	37.20

Table 6
Prediction of "manual piping valve" quantities based on each input feature.

Input Feature	Predicted Quantity of "manual piping valve"
Installed Pipe	9570
Amount of Isometric Drawings	11750
Total Other Pipe Length - Actuals	11510
Total Piping WH - Actuals	11953

(1) "Installed Pipe" - total length of the installed pipes, in meters (underground, above ground and non-process pipes).
(2) "Amount of Isometric Drawings" - the total amount of piping drawings that was derived from P&IDs
(3) "Total Other Pipe Length - Actuals," - total length of the installed non-process pipes, in meters.
(4) "Total Piping WH - Actuals." - the actual amount of hours spent on piping engineering and design.

These inputs were derived from the project's close-out report, along with the actual "manual piping valve" numbers. Table 6 displays the calculated estimates for manual valve quantities linked to each input feature.

The true manual valve quantity is **11578**. For this proof-of-concept tool, a threshold accuracy for acceptance was set at 70%, which the regression models achieved for most of the input features.

7. Possible application scenarios for the proposed solution

During the project's tender phase, the provided P&IDs may be incomplete or may lack the details necessary for precise material estimation. In such instances, the discrepancy between the quantities derived from Material List Extraction (Part 1) and the Forecast of Material Quantities based on previous projects (Part 2) could be significant. Domain experts must then adjust the final material quantity based on specific project characteristics such as size and location. Conversely, when drawings are sufficiently detailed, the differences between Parts 1 and 2 should be minimal. In this case, a method such as averaging or taking the maximum value could be used to determine the final figure, as shown in Fig. 3.

The solution's two components can also be used separately at different stages of an EPC project. Initially, when P&IDs lack detail, the forecasting tool (Part 2) can predict material quantities using data from similar past projects. As the P&IDs become more detailed, the material extraction tool (Part 1) can assist in generating a Material Take-Off (MTO), which is particularly useful when P&ID drafting is conducted in software that lacks this capability.

Additionally, the proposed solution can assess design maturity. A notable discrepancy between the outputs of Parts 1 and 2 can suggest that the design may not be ready for material quantity estimation and may require further refinement by designers.

7.1. Additional limitations

While this study demonstrates promising results, several limitations should be acknowledged:

1. Dependence on Data Quality: The predictive accuracy depends on the quality and completeness of historical data. Inconsistent or low-quality data could negatively impact regression model performance, necessitating additional techniques to handle data gaps.
2. Challenges with Complex Diagrams: While methods like tiling help with symbol recognition, the approach may still struggle with highly complex or noisy P&IDs, where symbols overlap or text is hard to detect.
3. Manual Validation Required: Although automation reduces manual effort, expert validation is still necessary for critical components that are not well-represented in the training data.
4. Potential Bias in Training Data: Training predominantly on data from a single source (in this case - McDermott) may introduce bias, affecting performance on other datasets. Incorporating diverse data can improve model robustness.

8. Discussion

The solution proposed in this work addresses the challenges described in the Related Work section by developing an AI models that are also trained on real-world P&IDs from construction projects, not just on synthetic datasets. This approach tackles complexities such as symbol variations, background noise, and the density of authentic blueprints. It also integrates domain-specific rules to better connect text to symbols, reflecting various drafting standards. By utilizing real data and incorporating the nuances of industry knowledge, the models aim to deliver more accurate performance in real-world conditions.

The development of the proof-of-concept has also highlighted several essential prerequisites for the effective implementation and deployment of the discussed solution. These prerequisites include:

1. The ability to manage and analyze large volumes of P&ID data.
2. A framework capable of handling lack of data by analyzing past similar projects that have been executed.
3. Sufficient computational resources for the training, evaluation and processing of P&IDs.
4. A specialized tool for image annotation, considering the sensitive nature of the data.
5. An appropriate platform for deploying and accessing the solution by engineering and procurement teams.

Moreover, the involvement of domain specialists has proven to be crucial throughout the development stages to ensure that the solution is effective in capturing key details.

8.1. Threats to validity

It is essential to highlight the necessity of a comprehensive evaluation and validation process. This process must address real-world complexities, such as symbol variation, background noise, and varying densities within diagrams. Various frameworks exist for assessing validity and identifying potential validity threats. In this context, a specific classification scheme has been adopted, as referenced in, Runeson P. [42].

Internal Validity and Reliability: The differences in symbol variation, diagram density, and noise levels across P&IDs are substantial. Noise and density, in particular, present significant challenges, sometimes complicating even human interpretation. A comprehensive assessment of P&IDs with high levels of noise and density was not within the scope of this study. Future research could explore this area, possibly necessitating new model architectures or enhanced pre/post-processing methods to mitigate these difficulties more effectively.

External Validity: This aspect focuses on the extent to which the research findings can be generalized and the relevance of these findings beyond the studied cases. Given that this research was conducted in the unique environment of McDermott and utilized its document management system, we recommend investigating the applicability of our results to various organizations or sectors.

Construct Validity: This aspect pertains to the extent to which the operational measures used effectively address the research questions. To ensure construct validity, the development and validation phases of the proposed solution involved close collaboration with domain experts and intended users, including engineers and estimators. This collaboration ensured that the research outcomes closely aligned with their needs.

8.2. Future work

While the proof of concept has been completed, our research is ongoing, and we are currently investigating various areas to focus on further:

1. *Evaluation of the final software performance.* While in this work, we focus mainly on evaluating individual models, for future work it is necessary to evaluate the complete software that integrates Parts 1 and 2, does the comparison of their results and suggests a final material quantity value.
2. *Expanding Symbol Recognition.* Currently, our models are trained to identify the 12 most common symbols found in P&IDs. By adding more symbols to our recognition list, we can further decrease the time engineers spend on Material Take Off (MTO) production. Additionally, this expansion might help to rectify some of the misidentifications that the models currently make.
3. *Improving the Training Dataset.* To overcome the limitations identified earlier, it's essential to broaden our training dataset with a wider variety of symbols and text instances from different P&IDs. This expansion will allow the model to better differentiate between the target symbols and those that look similar, thus reducing errors in classification. Moreover, including symbols in combination with text and various markups in training examples will improve the model's ability to recognize symbols in more complex settings.
4. *Improving Text Recognition.* It could be beneficial to explore other detector networks with architectures that handle better vertical and long text instances. Also, more post-processing techniques could be utilized to improve the clarity of the detected text regions before passing them to the OCR. Additionally, the text recognition results could be post-processed using more heuristics or computer vision techniques, such as clustering.
5. *Comprehensive Model Comparison.* Systematic comparisons of alternative deep learning architectures for both symbol and text recognition tasks could be conducted. It could include evaluating other object detection models (YOLO variants, Faster R-CNN, RetinaNet) against VFNet for symbol recognition, and comparing alternative text detection networks (CRAFT, TextBoxes, DBNet) against EAST for text detection, Shteriyanov [47]. Such comparisons would provide empirical justification for model selection and potentially identify superior architectures for specific P&ID characteristics.
6. *Improving Association.* When equipment metadata are not available next to its symbols, an alternative method could be considered, such as linking equipment to the pipe size on which the equipment is installed (as the equipment has the same size as the pipe it is installed on). This can be done by using flow direction arrows to track the pipes, which can then be connected to their respective pipeline numbers. These numbers are typically found on the same page and include crucial information such as sizes and other metadata related to the material items connected to that line. In addition, it is required to investigate whether model refinement is feasible by training on dense and noisy P&IDs.
7. *Further Improving the Regression Models.* The performance of the regression models may significantly depend on the size of histor-

ical projects data. Therefore, incorporating additional projects data shall further enhance its performance.

(8) *Leveraging Large Language Models (LLMs)* Future research to investigate the application of Large Language Models (LLMs) to further improve text extraction and semantic association between symbols and text, building on recent advances in AI for the AEC sector, Nabizadeh Rafsanjani and Nabizadeh [34], i.e.: a) Text Interpretation - Improving extraction of semantic relationships between symbols and text through natural language processing of P&ID annotations and associated project specifications. b) Association Rule Generation - Automating the development of context-aware symbol-text linkage rules using LLM-based analysis of drafting standards across different projects/clients

While this study demonstrates the feasibility of the proposed approach, future work may focus on quantitative comparisons with existing methods, including statistical significance tests and confidence intervals. This will provide a more comprehensive evaluation of the solution's performance. It will validate its advantages across different datasets and scenarios, and further reduce the risks of cost overruns and other negative project outcomes caused by inaccuracies in initial cost estimation.

9. Conclusion

In this study, we utilized AI to enhance material cost estimation for large-scale EPC projects. These projects are typically complex and require specialized knowledge, where material procurement significantly influences the project's budget. When engineering documents are not available in computer-aided files, the estimation process becomes manual and time-consuming. It also heavily relies on the expertise of estimators. Therefore, our objective was to create a tool that reduces manual workload and decreases the risk of underestimating material costs.

This research contributes by developing a solution that merges machine learning and deep learning with industry-specific knowledge rules for the oil, gas, and petrochemical sectors, enhanced by McDermott's expertise in EPC projects. While further enhancements are needed, sharing initial results demonstrates the viability of the concept and its immediate value. This approach is particularly relevant for industrial applications, aiming to reduce engineering time and costs. It also promotes the integration of AI to improve the quality and efficiency of project execution in general.

CRediT authorship contribution statement

Rimma Dzhusupova: Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Vasil Shteriyanov:** Visualization, Software, Formal analysis, Data curation. **Jan Bosch:** Writing – review & editing. **Helena Holmström Olsson:** Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used AI-powered writing assistance integrated within the Overleaf LaTeX editor to improve language clarity and readability. After using this tool, the authors thoroughly reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Rimma Dzhusupova, Vasil Shteriyanov reports a relationship with McDermott International Inc that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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