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Transformative Trends: A Progressive Examination of P&ID Advancements

Sushma K. R., Bhaskara P., Divijesh P., Rashmi K. R.

[1]Assistant Professor
Department of Electronics and Communication
Coorg Institute of Technology
[2]Assistant Professor
Nitte (Deemed to be University)
Department of Mechanical Engineering
NMAMIT, Nitte
[3]Assistant Professor
Nitte (Deemed to be University)
Department of Mechanical Engineering
NMAMIT, Nitte
[4]Assistant Professor
Department of Electronics and Communication
SMVITM, Bantakal

Abstract—This compilation of research studies showcases sig- nificant strides in engineering diagram recognition and digitization across diverse domains, addressing intricate diagram categories like Piping and Instrumentation Diagrams (P&IDs), scene text in images, and point symbols on scanned topographic maps. Employing a versatile array of methodologies, encompass- ing deep learning, neural networks, digital image processing, and innovative algorithmic fusion, these studies consistently surmount the challenges posed by complex visual data. These methods consistently attain remarkable levels of accuracy and efficiency, bolstering applications ranging from plant design to information extraction, symbol recognition, text detection, and line extraction. While certain papers meticulously detail their algorithmic under- pinnings and techniques, others present holistic frameworks for the comprehensive digitization of intricate engineering drawings. Collectively, these research endeavors underscore the burgeoning influence of advanced technology in enhancing the efficiency, precision, and automation of multifaceted tasks across diverse industries, from manufacturing to geographic information sys- tems. These insights pave the way for future advancements, opening new horizons in the realms of engineering and document digitization.

Index Terms—Engineering Diagram, Recognition, Digitization, Piping and Instrumentation, Diagrams (P&IDs), Deep Learning Information Extraction

I. Introduction

Process and Instrumentation Diagrams (P&IDs) are foun- dational documents in the realm of the process industry, playing a pivotal role as visual schematics that provide cru- cial guidance for plant design, procurement decisions, and construction operations. These meticulously crafted diagrams capture the essence of complex industrial processes, delineat- ing equipment, materials, and fluid flow with precision. In their digital form, P&IDs have become indispensable tools for plant operators, engineers, and designers. However, the transition from image-based P&IDs to digital versions poses a significant challenge. [5]

The urgency of this transition arises from several quarters. In the modern era, characterized by digital transformation across industries, P&IDs are no exception. Digital P&IDs offer unprecedented accessibility, accuracy, and automation potential, revolutionizing plant management and optimization. Yet, a considerable portion of P&IDs remains in image format, bound by contractual agreements, legacy storage practices, and the need for digitization in aging facilities.

The conventional path to digitization involves labor- intensive manual efforts, where human operators painstakingly recreate digital P&IDs while referring to their image-based counterparts. Although effective, this process is prone to errors, time-consuming, and relies heavily on operator pro- ficiency. Innovative solutions are urgently needed to expedite and enhance the digitization process, ensuring accuracy and consistency while reducing the human resource burden.

This research paper embarks on a journey into the trans formative realm of technology-driven P&ID recognition and digitization. It explores a diverse landscape, encompassing the digitization of Process and Instrumentation Diagrams, the extraction of scene text from images, and the identification of point symbols on topographic maps. At the heart of these endeavors lies the fusion of cutting-edge deep learning and image-processing algorithms.

The research endeavors detailed within this collection share a common challenge - the scarcity of labeled data, a re- curring limitation in the training of deep learning models. Nevertheless, the ingenious solutions that emerge offer a glimpse into the potential of future applications. Moreover, the amalgamation of techniques showcases the adaptability of these algorithms, capable of unraveling intricate diagram structures.

This study presents a novel method for symbol and text recognition, underpinned by the prowess of deep learning technology. The approach assumes pristine P&ID images, untainted by noise or distortion, generated through special- ized authoring programs. The method's journey involves pre- processing P&ID images, discerning symbols and text with remarkable acuity along with a count of detected symbols, and elegantly storing the outcomes.

To fuel our research and model development, we meticu- lously curated a diverse dataset comprising distinct P&IDs. The preparation of this dataset was approached from three unique perspectives:

1) Holistic P&ID Labeling: Our first approach involves considering the entire P&ID diagram as a unified entity. Leveraging the LabelImg tool, we meticulously label the entirety of the diagram, marking it as a whole, and subsequently save it in the YOLO format.
2) Segmented Square Images: In the second approach, we import P&IDs into our custom code, expertly dividing them into square images of varying dimensions. Subse- quently, these segmented images are diligently labeled using LabelImg and preserved in YOLO format, offering a more granular perspective.
3) Manual Symbol Cropping: Our third approach entails the manual cropping of symbols and their interconnected networks from the P&ID images. These meticulously curated symbol images are then subjected to labeling through LabelImg, providing distinct insights into sym- bol recognition.

Symbol detection is at the core of our investigation, where we explore the capabilities of YOLOv5, YOLOv8, and AlexNet. Additionally, our research delves into text recognition, utiliz- ing Tesseract OCR as a foundational tool. Furthermore, we embark on a journey into the Craft algorithm, broadening the horizons of our text recognition endeavors. These algorithms consistently deliver remarkable precision and recall rates, illu- minating symbols, lines, and text with unparalleled accuracy. [21]

Our study introduces a pioneering methodology for sym- bol and text recognition, underpinned by cutting-edge deep learning technology. Our dataset curation encompasses three distinct approaches, enabling a multifaceted exploration of P&ID recognition. Symbol detection, text recognition, and symbol counting are the focal points of our investigation, with the utilization of state-of-the-art models and algorithms. This research endeavors to pave the way for advanced digitiza- tion techniques in the realm of Process and Instrumentation Diagrams, with far-reaching implications for industry and innovation.

II. Literature Survey

Wei Gao et al. (2020) [4] and colleagues utilized Faster RCNN, specifically ResNet-50, to automatically extract com- ponent information from Piping and Instrumentation Diagrams (P&IDs) in Nuclear Power Plants (NPPs). They addressed the challenge of detecting small symbols by employing data aug- mentation techniques and introducing a feature grouping strat- egy. For text detection, they introduced the SegLink model. Their efforts yielded an impressive 98% Average Precision rate in component detection, with high success rates in component- text and component-pipe mapping. Importantly, their versatile framework has applications beyond nuclear power, making it potentially valuable across various industries.

A. Boccaccio et al (2019) [18] presents an Augmented Reality (AR) framework for handheld devices, enhancing users' understanding of plant data typically conveyed through printed Piping and Instrumentation Diagrams (P&ID). The framework adds interactive virtual elements (hotspots) to the

P&ID, simplifying identifying components within the same category, such as pumps. Users can tap hotspots to access multimedia data, including technical details, 3D CAD models, and 360° images, all sourced from the factory database. A milling plant's cleaning section is used as a case study. This AR tool reduces intervention time, improves accuracy, and eases cognitive load when comprehending plant layouts, offering promising applications in industrial settings.

Shubham Paliwal et al. (2021) [27] introduced "Digitize- PID," an end-to-end solution for automatically converting scanned Piping and Instrumentation Diagrams (P&ID) into structured, machine-readable formats. The paper employs ad- vanced techniques, including kernel-based line detection and deep learning-based symbol recognition, to address the chal- lenges in P&ID digitization. Additionally, the authors provide a novel synthetic dataset, Dataset-P&ID, for evaluation pur- poses. The results demonstrate that Digitize-PID outperforms existing methods for P&ID digitization.

Arroyo et al.(2016) [33] tackle the challenge of modernizing plant facilities in the process industry by proposing a method for automatically deriving qualitative plant simulation models from legacy piping and instrumentation diagrams (P&IDs). These digital plant models are crucial for simulating and val- idating engineering solutions. The authors emphasize the un- tapped potential of existing engineering documentation, which remains underutilized due to its non-computer-interpretable nature. Their method leverages optical recognition and se- mantic analysis to convert P&IDs into object-oriented plant descriptions and, subsequently, into qualitative plant simu- lation models. These models find application in tasks like validating base control functions during factory acceptance testing. Unlike existing approaches, this method does not rely on a computer-interpretable plant description, significantly reducing time and modeling efforts during (re)engineering tasks. The authors envision its application in Greenfield and Brownfield projects across industries such as chemical, pharmaceutical, oil and gas, and power generation. Future work will focus on enhancing recognition robustness, filtering irrelevant information, and developing an integrated software tool for commercial distribution.

A. *Preprocessing*

Yoochan Moon et al.(2021) [2] and colleagues utilized image-format piping and instrumentation diagrams (P&ID) for the identification of different line types and flow arrows. They began by preprocessing the diagrams, removing the outer border and title box. To effectively detect continuous lines, line signs, and flow arrows, they applied a combination of techniques, including line thinning, pixel processing for horizontal and vertical lines, and the Hough transform for diagonal lines. For training, they optimized their data and used RetinaNet, achieving impressive results with an average precision of 96.14% and an average recall of 89.59%. These findings highlight the efficacy of their approach in accurately categorizing components within P&ID diagrams, which is crucial for engineering and industrial applications.

Sierla, Seppo, et al (2020) [3] featured the integration of Piping and Instrumentation diagrams with 3D pipe routing to develop a unified digital plant model. For the automatic generation of graphs required for matching the 2D and 3D data sources, the authors have employed graph-matching tech- niques. To address disparities between the graphs derived from both sources, they proposed preprocessing algorithms, such as piping simplifications. By using these preprocessing steps, the authors anticipate that the graph matching technique will provide results that are consistent in structure and level of detail, although a specific accuracy value wasn't mentioned.

Stinner et al. (2021) [8] delve into the significant role of buildings in contributing to CO2 emissions, noting the potential for mitigation through modern building automation system controls such as model predictive control (MPC). A prerequisite for effective MPC implementation is a mathe- matical model or "digital twin" that predicts the building's future behavior. Despite their utility, setting up these digital twins in existing buildings often entails laborious processes, particularly in integrating various technical components. This study introduces an automated method to discern symbols and connections in Piping and Instrument Diagrams (P&ID) from buildings. Recognizing the diversity of standards in P&ID symbols for building energy systems, the authors collated data from multiple sources and standards. Their approach, which integrates symbol recognition, line recognition, and connection derivation, achieved an impressive average precision of 93.7%. The concluding remarks highlight the potential of technical building equipment plans as insightful sources for understand- ing building energy systems. The generated digital twins, while showcasing immediate utility, also lay the foundation for future optimization algorithms aimed at enhancing energy utilization. The team envisions broadening the applicability of these twins in areas like control code generation, fault detection, and integration into building automation systems. Lin et al. (2023) [11] developed an engineering drawing recognition system to address inconsistencies in the presen- tation of engineering drawings and to reduce human inter- pretation errors. Utilizing the geometric dimensioning and tolerancing (GD&T) method, in tandem with technologies like PyTorch, OpenCV, and the YOLO deep learning model, the researchers segmented 2D engineering drawings to accurately identify components such as dimensions, tolerances, and geo- metric symbols. The model, trained on real-world engineering drawings with mixed features, demonstrated an 85% accuracy rate in detecting views, 70% in detecting annotations, and 80% in text and symbol recognition. This approach aids in reducing product verification time, eliminating manual entry errors, and preventing subsequent quality control issues.

Kang et al.(2019) [31] introduced an automated method for recognizing and digitizing design information in Piping and Instrumentation Diagrams (P&ID) drawings. Using digital image processing techniques like template matching and the sliding window method, they identify symbols, lines, and text in P&IDs and store them in a structured database. This digitized data is then mapped to predefined intelligent P&ID information, enabling the creation of high-quality intelligent P&ID drawings. This method significantly boosts productivity by automating tasks like drawing creation, material calcula- tion, and equipment lists, resulting in improved accuracy and efficiency compared to manual methods, making it valuable for plant engineering companies seeking to reduce time con- sumption and errors in their design processes.

Tan et al.(2016) [34] and their team introduced a novel framework for automating the identification of components within raster-format Piping and Instrumentation Diagrams (P&IDs). Their approach centers on detecting contours and utilizes the Local Binary Pattern (LBP) descriptor combined with the Spatial Pyramid Matching (SPM) concept for en- hanced visual analysis. By calculating L1 distances between LBP-based descriptors of image patches, comparisons are made. To make this framework work, it requires at least one example image per component type, along with their corresponding LBP and SPM descriptors. They employ a linear sliding window approach to identify potential candidates from sub-images within the original P&ID, and then verify these candidates against the entire symbol library using nearest neighbor-based classification. Notably, this method achieved outstanding performance on a challenging dataset created in collaboration with industry experts from the marine and offshore sector, underscoring its effectiveness in component identification within P&IDs, a crucial task in industries where such diagrams are prevalent.

B. *Symbol Detection*

Eun-Seop Yu et al. (2019) [1] featured piping and instru- mentation diagrams (P&ID) to identify the symbols, charac- ters, lines, and tables. For symbols, the authors have employed the AlexNet algorithm to detect and recognize the symbols in P&ID drawings. For characters, the authors used the connec- tionist text proposal network (CTPN) algorithm for detection. Traditional image processing techniques were applied for P&ID line and table detection. By using these algorithms, the authors can obtain 91.6% accuracy for symbols, 83.1% for characters, and 90.6% for lines.

Hyungki Kim et al. (2020) [5] featured Piping and In- strumentation Diagrams (P&IDs) in the process industry to identify symbols and texts. For symbols and text recognition, the authors employed deep-learning technology, specifically the GFL method. The procedure entailed initial processing of P&ID images, followed by the identification of symbols and texts. Subsequently, the results of this identification were archived. Using this technique, they secured a precision of 0.9718 and a recall of

0.9827 for symbols. For text, the precision was 0.9386, with a recall of 0.9175.

Elyan et al. (2020) [7] featured engineering drawings, particularly P&ID, to identify symbols in various engineering domains. For symbols, the authors employed an advanced bounding-box detection method to localize and recognize the symbols. Additionally, they introduced a Deep Generative Adversarial Neural Network (GAN) to handle class-imbalance challenges in symbol representation. By using these combined techniques, the authors achieved an impressive 94% accuracy in symbol recognition.

Khan et al. (2020) [9] addressed the intricate landscape of graphic symbol recognition, highlighting the pivotal role these symbols have played since the advent of written scripts. Their study offers a comprehensive overview of existing models and methodologies tailored for symbol representation, descrip- tion, and classification.The research divides various symbol recognition techniques into four primary groups: statistical, structural, syntactical, and hybrid approaches. A recurring difficulty identified in these methods is determining the best features suitable for detecting graphical symbols, especially considering the natural inconsistencies in their designs and forms. Additionally, the intricate nature of the issue often leads to computational challenges. The study highlights ongoing issues in the field, including pinpointing symbols, dividing them, representing them for feature extraction, and challenges linked to matching and categorization, such as adaptability, resilience, and effectiveness.The study accentuates the vast applicability domain of graphic symbol recognition, implying its potential utility across various fields of image processing and pattern matching.

Khomenko et al. (2023) [10] delved into the challenge of classifying non-digital documents, such as scanned or photographed items, into electronic document management systems using optical character recognition (OCR). To address this, they simulated the OCR process within organizational regulatory documents. Their comprehensive study spanned from laying out the structure of departments for electronic doc- ument management to the intricate processes involved in OCR, including image processing, segmentation, and recognition. Crucial image processing steps such as alignment, blurring, binarization, contour finding, and line removal were detailed. They also evaluated image blur techniques and proposed the Kenny operator for improved image binarization. The segmentation phase was divided into string, word, and character stages, with an innovative algorithm based on average image pixel brightness proposed. Moreover, they analyzed various popular online and desktop-based OCR tools, ultimately sug- gesting the use of artificial neural networks for the recognition stage.

Dong-Yeol Yun et al. (2020) [12] featured Piping and In- strument Diagrams (P&IDs) which are vital for understanding plant components such as valves, lines, and instruments. Rec- ognizing the complexity of manual interpretation, Yun and his team proposed an automated solution. Their method is three- pronged: initially, they used image processing to highlight po- tential regions with symbols; then, they applied unsupervised learning methods like k-means and deep adaptive clustering to filter out irrelevant symbols; and finally, a convolutional neural network was employed to classify and extract the symbolic information. Their results indicated a notable efficiency in symbol identification and extraction, paving the way for more streamlined P&ID interpretations.

Rahul, Rohit, et al. (2019) [13] have delved into the realm of Piping and Instrumentation diagrams (P&IDs), crucial representations for engineering processes. Traditional methods have led to these diagrams being manually generated and subsequently stored as image files. Such a format necessitates digitization for effective inventory management and schematic component referencing. Modern P&IDs encompass diverse resolutions and are often riddled with noisy textual data. Key challenges in their digitization involve pinpointing symbols, which often possess subtle visual disparities, and discerning pipelines, especially given their propensity to merge and di- verge variably. While no known systems offer a comprehensive solution for extracting data from P&IDs, the evolution of deep learning brings newfound optimism to addressing this issue. Rahul, Rohit, et al. introduce an innovative approach that intertwines conventional vision methodologies with cutting- edge deep learning models. Their strategy emphasizes the accurate identification and isolation of various P&ID elements, including pipeline codes, symbols, and inlets/outlets. After detection, the associated components are linked with the pertinent pipeline, and this information feeds into a tree-like structure capturing the entirety of the piping schematic. Their method, when assessed on genuine P&ID sheets sourced from an oil company, showcased encouraging outcomes.

Shouvik Mani et al. (2020) [14] featured Piping and Instru- mentation Diagrams (P&ID) commonly used across sectors like manufacturing and oil and gas. Typically, these diagrams reside in image files with minimal metadata, rendering their content unsearchable and isolated from other systems. To address this limitation, the authors introduced a pipeline for the automatic digitization of P&IDs. They incorporated computer vision techniques for symbol detection, text-symbol associ- ation, and symbol interconnection through lines. For symbol identification, a Convolutional Neural Network was employed, achieving over 90% precision and recall. The connectivity between symbols was discerned using a graph search method. This transformation from unstructured diagrams to structured data allows for applications such as diagram search and equipment-to-sensor mapping, ultimately laying the ground- work for a comprehensive digital twin of a facility. This can further facilitate advanced predictive maintenance driven by machine learning.

Mitsuo Ishii et al.(2007) [15] developed an automatic sys- tem for inputting diagrams that can interpret handwritten pip- ing and instrument diagrams, recognizing symbols, characters, and lines. Given the inherent complexities of such diagrams, which can have over 200 varied symbols and diverse line types, the authors introduced several processing techniques. These include high-accuracy vector representation, distortion shaping, and a two-stage segmentation for differentiating lines, symbols, and characters from the vectorized image. The sys- tem integrates decision tree methodology with pattern match- ing to facilitate symbol recognition and employs a recognition dictionary generated through automated distortion of patterns. This flexible system allows for the registration of new symbols and can recognize intricate handwritten diagrams. In tests using real design diagrams, the system achieved a recognition rate above 95% and processed A3-sized diagrams in 3 to 8 minutes using a large-scale computer.

Luoting Fu and Levent Burak Kara (2011) [16] investigated the recognition of freehand sketched symbols employing a three-step neural network training methodology. Their ap- proach commenced with the creation of an extensive dataset of unlabeled synthetic samples derived from a limited set of annotated training examples. Subsequently, they initiated the training process by pre-training a Deep Belief Network (DBN) using these generated samples, followed by fine-tuning the DBN utilizing the available limited labeled samples. When compared to traditional supervised methods, their approach demonstrated a significant reduction in error rates, indicating its efficacy in sketch symbol recognition.

Frans C. A Groen et al (1985) [17] featured electrical diagrams to identify symbols using probabilistic matching. The symbols' skeletons are graphically represented. By de- termining the graph's pose, encompassing factors such as orientation, translation, and scale, using a search process aimed at minimizing transformation errors, the observed graph is subsequently compared to class models to calculate the likelihood of a match. The outcomes, subjected to testing on both computer-generated and hand-drawn symbols, both with and without a template, exhibited error rates spanning from under 1% to 8%.

Taekyong Lee et al (2019) [20] introduces a vital challenge in managing P&IDs, where these crucial design documents are often converted to non-editable PDF formats for data transfer, resulting in inefficiencies during modifications. To streamline this process, engineering companies often resort to manual re-conversion of P&ID images into CAD formats. To address this issue and pave the way for automated P&ID conversion, this study presents methods for the automatic detection of symbols and text within P&ID images. Various detection techniques, including geometrical and deep learning- based approaches, are explored for identifying elements such as texts, instrumentation symbols, and equipment symbols in P&ID images. The results demonstrate the effectiveness of combining these approaches to detect diverse elements in P&ID images efficiently.

Christo S. Christov (2022) [21] offers a concise insight into the significance of Piping and Instrumentation Diagrams (P&IDs) across industries like oil, energy, and construction. These engineering drawings, including Process Flow Diagrams (PFD) and Sequence Diagrams (SD), are vital for understand- ing complex system connections. Despite their importance, open-source research on P&IDs is limited, and the challenge lies in their extensive nature, often spanning hundreds to thousands of pages. This article explores the extraction of essential information from P&IDs, such as material take-off and inventory management, using object detection models to tackle real-world data complexities and enhance symbol detection reproducibility, contributing to advancements in this field.

S. Belongie et al (2002) [22] This paper presents a novel method for shape similarity measurement and its application in object recognition. It involves finding correspondences between points on two shapes and using them to calculate an aligning transformation. Shape contexts, descriptors capturing point distributions, help solve the correspondence problem. Similar shapes have similar shape contexts, aiding in cor- respondence matching. The dissimilarity between shapes is computed from matching errors and the aligning transform magnitude. Object recognition is framed as nearest-neighbour classification. The approach is demonstrated on silhouettes, trademarks, digits, and the COIL dataset with promising results.

Kim et al. (2021) [23] introduced an advanced deep learn- ing approach aimed at symbol and text recognition within high-density piping and instrumentation diagrams (P&IDs). Their method encompasses three primary phases: image pre-processing, symbol and text recognition, and result storage, making it adaptable to symbols of varying sizes and complex- ities pertinent to the process industry. To bolster their deep neural network, the authors standardized the training dataset and symbol taxonomy, drawing from diagrams provided by a local Korean firm. Impressively, the model yielded outstanding outcomes, boasting a precision rate of 97.18% and a recall rate of 98.27% for symbols, along with a precision rate of 93.86% and a recall rate of 91.75% for text recognition. This research bears the potential to significantly streamline plant design processes and enhance decision-making within the process industry.

Wenjun Huang et al.(2023) [28]investigation revolves around the intricate challenge of recognizing point sym- bols within scanned topographic maps (STMs), which serve as repositories of vital geographic information. Their ap- proach introduces a novel deep convolutional neural network (DCNN)-based model to address the complexities arising from the intricate map elements and unique symbol structures. Toenhance recognition and positioning accuracy, their model incorporates atrous spatial pyramid pooling (ASPP) and leverages k-means++ clustering. The inclusion of data augmenta- tion techniques further strengthens the model's capacity for generalization. Empirical experiments underscore the model's superiority and efficiency in comparison to traditional algo- rithms. Notably, the ASPP-YOLOv4 model achieves remark- able recognition and positioning accuracies, boasting a mean average precision (mAP) of 98.11% and a mean intersection over union (mIoU) of 0.876. While this research significantly advances STM processing and symbol recognition, it also points to future areas of exploration, such as challenges related to tessellation, folded maps, data conversion, handling undirected symbols, and expanding the dataset for a more comprehensive point symbol recognition system.

Ong Kai Bin et al.(2022) [29] explore symbol recog- nition within engineering diagrams, emphasizing the chal- lenges posed by the need for substantial training datasets for Convolution Neural Networks (CNN). To overcome this constraint, they suggest an innovative fusion of CycleGAN and CNN, enabling the artificial generation of symbols and thereby augmenting the training dataset. Their study focuses on engineering symbols, particularly in Piping and Instrument Diagrams (P&IDs). Experimental results demonstrate the pro- posed method's remarkable efficacy, achieving up to 92.85% accuracy for symbol recognition, outperforming baseline and alternative methods, even with gradually reduced training samples. The study highlights the significance of maintaining a balanced dataset quantity and outlines future work involving spatial transformations in the CycleGAN architecture and the extension of recognition capabilities to cover all types of symbols in engineering drawings, enhancing accuracy and robustness.

Ishii et al.(2007) [15] introduce an automated diagram input system designed to read and identify symbols, characters, and lines from handwritten piping and instrumentation dia- grams. These diagrams often comprise more than 200 different symbols of varying sizes, posing a significant recognition challenge. The system employs diverse diagram processing techniques, including vector representation, distortion correc- tion, and hierarchical segmentation. Symbol recognition is accomplished through a decision tree and pattern matching, with an automatic generation of a recognition dictionary for training purposes. The system exhibits satisfactory perfor- mance, with processing times ranging from 3 to 8 minutes for A3-sized diagrams and achieving a recognition rate exceeding 95 percent. Future work is recommended to address the wide array of handwriting distortions commonly encountered in such diagrams and to enhance recognition accuracy.

C. *Text Detection*

Liao et al. (2016) [24] introduced TextBoxes, a novel text detection method based on a single deep neural network designed for scene text. TextBoxes demonstrate exceptional accuracy and efficiency, eliminating the need for extensive post-processing, with the exception of standard non-maximum suppression. This method surpasses competitors in terms of text localization accuracy and boasts remarkable speed, capable of processing images in a mere 0.09 seconds per image. Additionally, when combined with a text recognizer, TextBoxes outperforms state-of-the-art approaches in word spotting and end-to-end text recognition tasks. The model's full convolutional nature ensures stability and efficiency in generating word proposals, even in cluttered backgrounds. This research offers great potential for applications in text de- tection, word spotting, and end-to-end recognition, with future prospects for handling multi-oriented text and integrating with network systems.

Baek et al.(2019) [25] introduce a novel neural network- based approach for scene text detection. They focus on character-level analysis and affinity to improve text repre- sentation, overcoming the lack of character-level annotations by leveraging synthetic image data and an interim model. The proposed CRAFT detector outperforms existing methods on challenging datasets, excelling in detecting complex text shapes. It provides character region and affinity scores and demonstrates strong generalisation without fine-tuning. The authors also propose weakly-supervised learning to address data scarcity issues and aim to explore end-to-end training for broader scene text spotting applications, making a significant contribution to text detection and recognition.

Byung Chul Kim et al. (2022) [26] focused on the digi- tization of Piping and Instrumentation Diagrams (P&ID) in image format with the goal of identifying symbols, text, and lines. To recognize symbols, the authors employed a GFL-based deep neural network. Additionally, they utilized the CRAFT deep neural network for detecting text regions and employed the Tesseract engine for character recognition. Traditional image processing techniques were also applied to detect P&ID lines. The outcomes were notably impressive, with symbol recognition achieving an accuracy rate of 96.65%, text recognition at 92.16%, and line recognition at 87.91%.

D. *Line Connectivity*

Maximilian F. Theisen et al. (2023) [6] featured the dig- itization of process flow diagrams (PFDs) in the chemical engineering domain. For unit operation detection, the authors employed a deep learning-powered object detection model, specifically Faster R-CNN. Additionally, they introduced a pixel-based search algorithm to determine the connectivities between the detected unit operations. With the training dataset comprising over 1000 PFDs from varied sources, the algorithm was designed to recognize 47 distinct classes that represent various drawing styles of unit operations. By implementing this approach, they achieved an Average Precision of 50 percent (AP50) of 88% for line detection and an Average Precision (AP) of 68% for detecting unit operations.

Moon et al. (2023) [30] introduce an improved technique for extracting line elements from image-format Piping and Instrumentation Diagrams (P&IDs) by utilizing an enhanced continuous line detection algorithm. This algorithm optimizes the line extraction process by incorporating differential filters and identifying continuous lines in both vertical, horizontal, and diagonal orientations, effectively handling the difficulties posed by short diagonal lines. Through evaluations conducted on nine P&IDs, the results reveal an overall average precision and recall of 95.26% and 91.25%, respectively, showcasing the algorithm's robustness in line extraction. This research offers a promising avenue for advancing P&ID digitization, with prospective endeavors aimed at tackling more intricate P&IDs, addressing detection intricacies, and further reducing line detection duration by incorporating deep learning tech- nologies.

E. *Optimization*

Mohit Gupta et al (2022) [19] introduces a method for creat- ing synthetic labelled datasets for P&ID diagrams, addressing the challenge of obtaining large, costly labelled datasets for AI and ML model development. Using data augmentation, the framework facilitates quick and cost-effective dataset generation, enhancing context recognition. Testing with valve symbols shows promising results. This approach is efficient, eliminates the need for expert annotation, and future work aims to expand its capabilities to detect all symbols and ac- commodate drawing style variations from different contractors, alongside pipeline detection for improved project management efficiency.

Moreno-Garc´ıa et al.(2018) [32] address the increasing importance of digitizing complex engineering drawings used in various industries. They highlight the potential of these legacy drawings as rich sources of information and discuss the challenges of automatically analyzing and processing them, emphasizing the need for advanced digital image processing methods.The paper outlines a comprehensive approach for the digitization of complex engineering drawings, substantiated by a thorough review of relevant literature, machine learn- ing methods, and machine vision algorithms. It specifically delves into the contextualization of digitized information from piping and instrumentation diagrams (P&IDs) and explores the application of emerging machine vision trends like deep learning, particularly convolutional neural networks (CNNs), within this domain. While recognizing the potential of CNNs, the authors acknowledge the challenges posed by the avail- ability of labeled data and the diversity of image quality standards for complex engineering drawings. They suggest hybrid approaches that combine heuristic-based processes and document image recognition with deep learning methods for improved digitization and contextualization outcomes.

III. Methodology

Our approach to P&ID (Piping and Instrumentation Dia- gram) analysis is distinguished by its systematic methodology, commencing with rigorous data collection and the conversion of PDFs into image formats. Employing advanced computer vision techniques, our model is meticulously trained on a curated dataset, enabling precise recognition of symbols, text, and lines within these images. This proficiency empowers our system to automate symbol detection, text extraction, and line identification with exceptional accuracy. To ensure the utmost precision, our model undergoes a meticulous fine- tuning process that incorporates human expertise for error correction and data refinement. The output module synthesizes these findings into user-friendly tabular summaries, providing valuable insights into complex industrial configurations. Our comprehensive approach integrates data preprocessing, robust algorithms, and human involvement, ultimately enhancing system reliability and effectiveness.

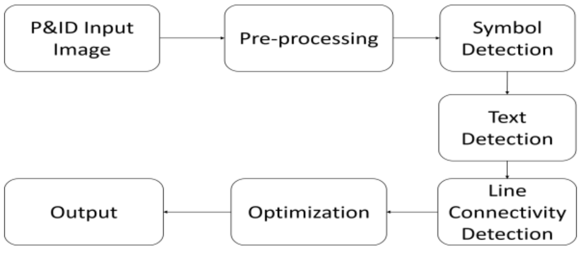

Fig. 1. Proposed System Architecture.

IV. Conclusions

Our research underscores the transformative potential of advanced technology in enhancing the accuracy and effi- ciency of Process and Instrumentation Diagram (P&ID) dig- itization. Leveraging cutting-edge deep learning models and image processing algorithms, we've demonstrated substantial improvements in accuracy and recall rates for symbol and text recognition within P&IDs. Our innovative approaches, including diverse dataset curation and algorithm integration, play a pivotal role in achieving these remarkable results. By harnessing the power of technology-driven solutions, we not only expedite the digitization process but also minimize errors and human resource burdens. As industry and innovation converge, our research offers a promising glimpse into a future where P&ID digitization is synonymous with precision and automation, ushering in a new era of efficiency and accessibility in plant management.

V. Contribution Of Authors

SG, SB, TT, MP; all authors have equally contributed in the making of this manuscript. DU supervised the study and provided critical feedback during the drafting of the manuscript.

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