BarChartAnalyzer: Digitizing Images of Bar Charts

A Preprint

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Abstract

Charts or scientific plots are widely used visualizations for efficient knowledge dissemination from datasets. However, these charts are predominantly available in image format. There are various scenarios where these images are interpreted in the absence of datasets used initially to generate the charts. This leads to a pertinent need for data extraction from an available chart image. We narrow down our scope to bar charts and propose a semi-automated workflow, BarChartAnalyzer, for data extraction from chart images. Our workflow integrates the following tasks in sequence: chart type classification, image annotation, object detection, text detection and recognition, data table extraction, text summarization, and optionally, chart redesign. Our data extraction uses second-order tensor fields from tensor voting used in computer vision. Our results show that our workflow can effectively and accurately extract data from images of different resolutions and of different subtypes of bar charts. We also discuss specific test cases where BarChartAnalyzer fails. We conclude that our work is an effective and special image processing application for interpreting charts.

1 Introduction

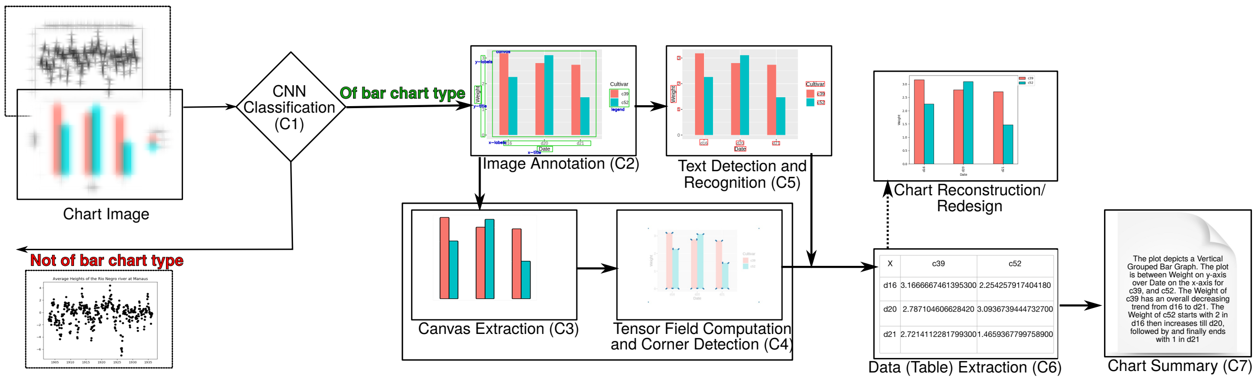
Chart Image
CNN Classification (C1)
Of bar chart type
Not of bar chart type
Image Annotation (C2)
Text Detection and Recognition (C5)
Chart Reconstruction/ Redesign
Canvas Extraction (C3)
Tensor Field Computation and Corner Detection (C4)
Data (Table) Extraction (C6)
Chart Summary (C7)

X	c39	c52
d16	3.1666667461395300	2.254257917404180
d20	2.787104606628420	3.0936739444732700
d21	2.7214112281799300	1.4659367799758900

The plot depicts a Vertical Grouped Bar Graph. The plot is between Weight on y-axis over Date on the x-axis for c39, and c52. The Weight of c39 has an overall decreasing trend from d16 to d21. The Weight of c52 starts with 2 in d16 then increases till d20, followed by and finally ends with 1 in d21

Figure 1: Our proposed workflow for data extraction from a given image of a chart using our proposed semi-automated BarChartAnalyzer (BCA), with seven components (C1-C7), for applications including chart reconstruction and redesign. Significant components include C1 for classifying the chart image to bar charts and its subtypes, C2-C4 for feature extraction, C5 for text detection for data contextualization, and finally C6 for generating the data table.

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Data can be interpreted better when presented as visualizations, wherein one of the simplest and most ubiquitous forms is the class of charts. Chart representation specifically is a widely used approach, which is evident from the inclusion of the basic understanding of simple charts in the curriculum of primary school education. Simple charts, *e.g.,* bar charts, scatter plots, etc., are commonly found in documents (textbooks, publications), print media (newspapers, magazines), and on the internet; and are most prevalent in image format. There are use cases of redesign and reconstruction of charts for getting high-resolution images for applications such as generating accessible reading materials for differently-abled students. The chart redesign also enables students with learning difficulty to understand data using alternative designs. These applications pose a problem when the source data for the charts is not available alongside the chart image for ready consumption. Thus, data extraction in the form of semi-structured tables [1] from these chart images is a relevant problem, specifically in the space of improving assistive technologies.

Amongst all statistical plots, bar chart representation is the most commonly used one for visual summarization. Since the design space for charts is large, in terms of chart types and their formatting, we focus on bar charts here. Bar charts have subtypes, depending on the data type and user requirement, such as simple, stacked, grouped bar charts, to name a few. Stacked and grouped bar charts help visualize multi-class or multi-series data. The grouped bar chart gives inter-and intra-class trends, and the stacked bars give part-to-whole information for multiple classes.

The redesigning of multi-series charts is a motivating application, as they are relatively difficult to interpret [2]. The redesign entails the requirement of source data that is used to generate the original plot as well as information about classes/multi-series being represented in the image. The state-of-the-art in reasoning over scientific plots includes bar charts [1, 3], where object detection using convolutional neural networks (CNN) for bars may fail for specifically the stacked bars. Hence, we revisit the image processing method exploiting spatial locality for object detection [4]. We, thus, propose a semi-automated workflow (Figure 1), called BarChartAnalyzer, that can take an image as input, identify the bar chart, sub-classify it to bar chart type, and then perform data extraction. The extracted data can be further used for reconstruction to get customized charts of high-resolution image quality, as well as for redesigning the complex to simpler charts.

Our contributions in this work are in:

- proposing a complete semi-automated workflow for digitizing images of bar charts and its seven subtypes, including stacked bar charts,
- identifying appropriate state-of-the-art algorithms for text recognition in bar charts,
- generating training dataset for bar chart images covering all seven subtypes, and a complement set “others”,
- proposing a flowchart for templatizing text summary of bar charts from its images, and
- conducting a systematic study of limitations in our workflow for specific test cases.

2 Related Work

Chart analysis is generally divided into smaller tasks such as chart type classification, data extraction and optionally, reconstruction or redesign, and summarization. Revision is a system that performs tasks like identifying chart type, extracting visual elements, and encoded data by creating feature vectors and identifying geometric structures in pixel space [5]. WebPlotDigitizer is another system that provides both automatic and manual procedures to extract data from given chart images [6]. However, the tool requires extensive user interaction for aligning axes to select data points. It works for simple bars but fails for stacked and grouped bar charts in giving class information.

Machine learning models have been effectively used for classification and/or object detection problems in chart analysis. Beagle is a web-based system for classifying charts in scalable vector graphics format [7]. Text type classification has been done using feature vector generated using the geometric property of text along with mark type classification using a fine-tuned AlexNet [8]. FigureSeer uses a similar fine-tuning approach [9]. A convolutional neural network (CNN) model used for chart classification, can also used for object detection, *e.g.,* for chart objects such as bars in the source image [3]. ChartSense uses GoogleNet for chart classification for line, bar, pie, scatter charts, map, and table types [10]. ChartSense further uses the connected components method to extract bar objects, using the x-axis as a baseline in the image. While this method works for simple bar charts, the charts with bars of multiple series (*e.g.,* grouped bars) get incorrectly identified as belonging to the same series. The existing methods using object detection-based approach have not been shown to work for all subtypes of bar charts, *e.g.,* stacked bars, for which training data is currently unavailable.

Text detection is important for chart inference. Automated data extraction for bar charts has been done by identifying graphical components and text regions independently [11]. Chart data is further extracted using inference.

Chart analysis has been used for applications of automated question-answer systems. PlotQA is one such solution for reasoning over scientific plots that uses a more accurate neural network for object detection for visual elements, such as bars [1]. However, manual drawing of bounding boxes around bars fails for complex bar types, such as stacked bars. Hence, we use the method that exploits spatial locality using second-order tensor fields for corner detection [4] in our proposed system. While PlotQA is an example of an approach where data is extracted, an alternative approach for chart question answering (CQA) is through the use of Transformers for answering questions from charts directly, *e.g.,* Structure-based Transformer using Localization, STL-CQA [12].

Textual summary of a chart is a relevant task for its interpretation. While its relevance may appear counter-intuitive as the charts are visual summary of data, its text summarization is useful for the visually impaired users to read its images, usually embedded in documents. Linguistic constructs have been used to generate a chart summary with the help of semantic graph representation [13]. Three types of features have been selected from charts, namely, salience, trend, and rank, that encode details like increasing or decreasing trend, any specific colored bar showing highly prominent detail. However, we have found the summary output of the system to have a limited description. Summaries, especially for bar charts, have also been generated by calculating differences using existing attributes in chart images and providing the core message represented by the selected chart [14]. The iGRAPH-Lite system generates a short summary explaining the visual description of the chart itself but does not provide insight into the information provided by visualization using the chart [15].

3 Proposed Workflow & Implementation

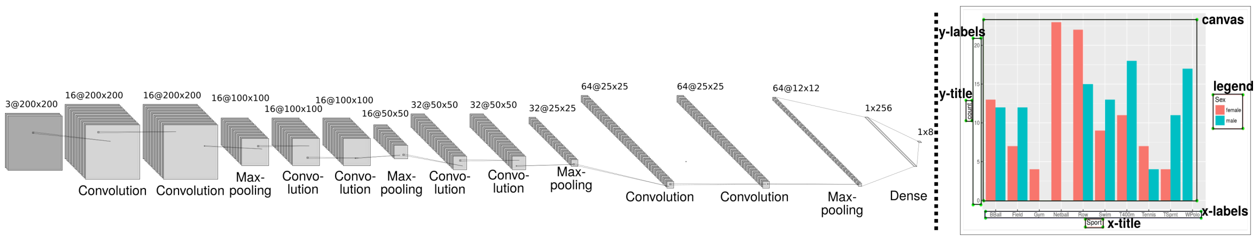


Figure 2: (Left) The architecture diagram of our CNN-based classifier for identifying bar chart subtypes. (Right) Human-guided annotation of the chart image, where the chart canvas is used for object detection.

We propose a workflow that extracts data from a given chart image, BarChartAnalyzer, which has seven main components (Figure 1), namely, chart subtype classification, chart image annotation, canvas extraction, tensor field computation, text recognition, data table extraction, and chart summarization.

Chart Subtype Classification (C1): Data is represented using different chart types based on the number of variables and user requirements. For example, scatter plots and bar chart representations visually encode the data differently, which require different approaches for chart analysis. In the case of bar charts, there are subtypes available in the design space, namely, simple bars, grouped bars, stacked bars, and of different orientations, depending on design requirements. Since the process of data extraction from a given chart image depends on its chart type, identifying both the type and subtype information is the first step of our workflow.

Image classification is a widely studied problem in computer vision, and it has been done using different CNN-based classification models such as AlexNet, GoogleNet. These models were trained and tested for a set of natural images provided during the ImageNet challenge [16]. The natural images contain characteristics other than the shape of the object as well, like texture, finer edges, color gradients, etc. However, compared to natural images, the chart images are sparser and more structured with repeating patterns. Hence, the models that work for natural images do not work effectively for chart images.

The chart objects such as bars, scatter points, and lines are distinguishable based on their shape and geometry, unlike objects found in natural images. The chart subtypes for bar charts also have similar geometry through chart objects. Overall, contour-based techniques for chart subtype classification are inefficient. Some of the pre-trained models have been used for chart type classification of images by imposing certain constraints, *e.g.,* training with a small image corpus; however, the classification outcomes have low accuracy. The classifier in ChartSense has used GoogleNet [10] and has been trained on different chart types. This model classifies subtypes, such as grouped and simple bars, also, since the features are similar in both subtypes. However, other subtypes of our interest, namely, stacked bar charts, have not been explored. On the other hand, mark-based chart classification has been used [8], where the classifier is trained to recognize specifically five mark types: bars, lines, areas, scatter plot symbols, and other type. This classifier is limited to identify the chart type without extension to subtypes. Thus, we explore all bar chart subtypes, including the stacked bar charts and histograms, that have not been explored at all in the state-of-the-art.

Our classifier is inspired by the VGGNet (Visual Geometry Group Network) architecture [17], which is widely used for object detection and segmentation tasks on image databases, such as KITTI [18], an image benchmark dataset for road-area and ego-lane detection [19]. We choose the VGGNet architecture as it is efficient in feature extraction from images, and addresses the issue of depth in convolutional networks. It is also simple to implement for a new model, with the flexibility of adding more VGG blocks. The VGGNet architecture has a stack of convolutional layers (Figure 2) that generalizes the deep learning tasks. Our CNN model is a combination of the convolutional, pooling, and fully connected layers. The convolutional layers are responsible for extracting features by convolving images using kernels or filters. Our classifier uses max-pooling to reduce computation by reducing the spatial size by half. The tailing layers in our classifier are the fully connected layers that take the results of the pooling/convolutional layer and assign it a label/class. Our classifier identifies the bar chart subtype of an input image. This classification also results in checking if the given image is of bar chart type, as the workflow downstream accepts only bar charts, rejecting the others.

Our chart image dataset consists of images of seven different subtypes of bar charts, namely, simple, grouped/clustered, and stacked bar charts of horizontal and vertical orientations and histograms. For training our CNN model, the training dataset consists of images of these seven subtypes, and additionally an "other" category. The "other" category of images consists of scatter plots, line and pie chart images, which are commonly found charts, that are not bar chart subtypes. Histograms are included as one of the subtypes of bar charts since some of the plotting tools, *e.g.,* Google sheets and Microsoft Excel®, use bar charts for histogram plots. Also, we observe that the geometry of bins in histograms is the same as columns/bars in the bar charts. Our CNN-based classifier requires input images of fixed size for training; hence, we first resize the images in the dataset to 200×200 size. The image resizing and classifier implementation has been done using Python imaging (PIL) and Keras libraries, respectively. Our CNN model for chart sub-type classification is novel in its application for classifying bar chart subtypes. Our classifier assigns class labels to an input image specifying the bar chart subtype and its orientation, except in the case of histograms, *e.g.,* "horizontal grouped bar", "vertical stacked bar".

Image Annotation (C2) and Canvas Extraction (C3): Image annotation is usually performed to prepare training datasets for computer vision-related problems like object detection, segmentation, etc. The idea behind image annotation is to provide labels to different regions of interest (ROI) in the images. These predefined labels are used to detect and extract regions of interest. As this task requires contextual labels and appropriate associations between labels and ROIs, human-guided annotation of images is a straightforward image annotation approach.

For chart images, manual marking and annotation of bounding boxes for ROIs have been widely used [3, 1]. Different labels are decided for components of chart images based on their role in the visualization, such as canvas, x-axis, y-axis, x-labels, y-labels, legend, title, x-title, and y-title. We use LabelImg [20] as a tool to mark and annotate bounding boxes for ROIs of a chart image. LabelImg is a Python tool with a graphical user interface (GUI) for interactively selecting an image, drawing a bounding box for an ROI, annotating the ROI, and labeling the ROI. We use the label *Canvas* for the ROI that contains the chart objects such as bars, lines, or scatter points and is defined as *chart canvas*, which is one of the chart image components [4]. The annotation is generated as an XML file that is processed to extract the canvas region as well as for text localization. The former is used for chart extraction (C3), and the latter for text detection (C5). Figure 2 (right) shows a sample annotated bar chart.

The canvas extraction step (C3) includes image preprocessing methods to remove the remaining elements other than chart objects such as gridlines, overlaid legends, etc. The subsequent step (C4) on tensor field computation is sensitive to the presence of these extraneous elements, which lead to erroneous results. Image processing techniques marker-based watershed segmentation and contour detection algorithm have been used to remove such components in the chart canvas effectively [4]. These steps also fill hollow bars, as required, since the tensor field is computed effectively for filled bars. Highly pixelated edges in aliased images lead to uneven edges in each bar object. This issue is addressed by using the contour detection method to add a fixed-width border to bars [4]. Overall, we perform these steps to extract a chart canvas containing chart objects used in C4.

Tensor field Computation (C4): Tensor fields have been widely used to exploit geometric properties of objects in natural images [21] using structure tensor and tensor voting. We use local geometric descriptor as a second-order tensor for tensor vote computation [22] that further leads to corner detection in case of bars for a given bar chart. Structure tensor T_s at a pixel provides the orientation of the gradient computed from the local neighborhood, computed as:

$$T_s = \mathcal{G}_\rho * (G^T G), \text{ where } G = \begin{bmatrix} \frac{\partial I}{\partial x} & \frac{\partial I}{\partial y} \end{bmatrix}$$

is the gradient tensor at the pixel with intensity I; convolved (using $*$ operator) with Gaussian function $\mathcal{G}$ with zero mean and standard deviation ρ. The tensor vote cast at x_i by x_j using a second-order tensor K_j in d-dimensional space is, as per the closed-form equation [23]: $S_{ij} = c_{ij}R_{ij}K_jR'_{ij}$,

$$\text{where } R_{ij} = (I_d - 2r_{ij}r_{ij}^T);\ R'_{ij} = (I_d - \tfrac{1}{2}r_{ij}r_{ij}^T)R_{ij},$$

I_d is the d-dimensional identity matrix; unit vector of direction vector $r_{ij} = \hat{d_{ij}}$, with $d_{ij} = x_j - x_i$; σ_d is the scale parameter; and $c_{ij} = \exp\big(-\big(\sigma_d^{-1}.\|d_{ij}\|_2^2\big)\big)$. The gradient T_g can be used as K_j [24].

Anisotropic Diffusion: As the tensor votes T_v in normal space have to encode object geometry in tangential space, we perform anisotropic diffusion to transform T_v to tangential space [22, 4]. The eigenvalue decomposition of the two-dimensional T_v yields ordered eigenvalues, $\lambda_0 \geq \lambda_1$, and corresponding eigenvectors v_0 and v_1, respectively. Anisotropic diffusion of T_v using diffusion parameter δ, is:

$$T_{\text{v-ad}} = \sum_{k=0}^{1} \lambda'_k.v_kv_k^T, \text{ where } \lambda'_k = \exp\Big(-\frac{\lambda_k}{\delta}\Big).$$

Diffusion parameter value ($\delta = 0.16$) is widely used [25, 4].

Saliency Computation: The saliency of a pixel to belong to geometry features of line- or junction/point-type is determined by the eigenvalues of $T_{\text{v-ad}}$ [4]. We get the saliency maps at each pixel of an image of its likelihood for being a line- or junction-type feature, C_l and C_p, respectively, $C_l = \frac{\lambda_0-\lambda_1}{\lambda_0+\lambda_1}$ and $C_p = \frac{2\lambda_1}{\lambda_0+\lambda_1}$,
using eigenvalues of $T_{\text{v-ad}}$ of the pixel, such that, $\lambda_0 \geq \lambda_1$. The pixel with $C_p \approx 1.0$ is referred to as a critical point or degenerate point in the parlance of tensor fields. Our goal is to find all the critical points in the chart canvas in the C4 step.

DBSCAN Clustering: The critical points of chart image computed from tensor field computation form sparse clusters at the corners of each bar [4]. These pixels are localized using density-based clustering, DBSCAN [26], and cluster centroids are computed by adjusting hyperparameters of DBSCAN clustering to specific chart types. These cluster centroids are treated as corners of the bar. Using the positional layout or arrangement of these corner points based on the specific chart type and subtype, we heuristically compute the height of each bar in pixel space.

Text Recognition (C5) and Information Aggregation for Data Extraction (C6): The data we have extracted from the chart image, using tensor field computation, is in the image (or pixel) space. However, the extracted data has to be in the data space for accurately summarizing, and optionally, reconstructing the chart. Hence, to transform the data from the pixel space to the data space, we now combine the data in pixel space with the text information in the image. We perform text detection to get x-axis and y-axis labels and compute the scale factor between the pixel and data spaces. The recognition of other textual elements, namely, plot title, legend, x-axis, and y-axis titles, also plays a crucial role in analyzing chart image, *e.g.,* the information is used in summary (C7).

Tesseract-OCR is known for its popularity in text detection and recognition [27]. It works effectively with scanned document images with a clean background with regular font, plain layout, and single uniform color. However, Tesseract fails for text images with different colors, sizes, orientations, curvy fonts, and different languages, along with interferences or issues in the text, such as low resolution, exposure, noise, motion blur, out-of-focus, varying illumination, etc. Here, chart images may have text with numerical characters, small text font size, formatting, and blurry appearance. Yet, few of these cases are solved by improving image resolution, varying orientations in text regions like axis labels and chart title in a chart image are falsely recognized. Also, Tesseract tends to incorrectly detect non-textual elements, such as arrows, color boxes in legend, etc., in the image.

We explore the use of deep-learning-based OCR, namely Character Region Awareness for Text Detection, CRAFT [28] for effective text area detection, including arbitrarily-oriented text. This approach is designed for relatively complex text in images, and it works by exploring each character region and considering the affinity between characters. A CNN designed in a weakly-supervised manner predicts the character region score map and the affinity score map of the image. The character region score is used to localize individual characters and affinity scores to group each character to a single instance. So, the instance of text detected is not affected by its orientation and size. The text orientation is inferred from the detected text boxes and is then rotated to horizontal orientation for the extraction.

The CRAFT text detection model can be followed by a unified framework for scene text recognition that fits all variants of scenes, called the scene text recognition framework, STR [29]. Being a four-stage framework consisting of transformation, feature extraction, sequence modeling, and prediction, STR resembles the combination of computer vision tasks such as object detection and sequence prediction task, and hence, uses a convolutional recurrent neural network

(CRNN) for text recognition. We find that the CRAFT model, along with the STR framework, works efficiently to retrieve labels and titles of the chart image better than Tesseract OCR.

In our workflow, we transform the data extracted in pixel space to data space and add appropriate textual information for the variable name and bar width to extract the data table in C6. For both stacked and grouped bar charts, we identify class or series information using the legend to add to the extracted data table. However, BarChartAnalyzer can only be used to distinguish bars and stacked segments differentiated based on color, but those differentiated using texture will not give correct output with our workflow.

Chart Summarization (C7): Today chart images are increasingly used in mass media and other print media for knowledge dissemination. However, such information encoded in the graph remains inaccessible to the visually impaired. While we aim to retrieve the data table from the chart image, the users with the need to access the encoded information may not find this data table useful. Instead, the brief, significant details of this data and/or chart itself are useful. Thus, our next step is to generate a summary of the chart image based on its retrieved data table and the chart image, thereby allowing the user to know enough about the chart image before having the option to access the data table to learn more about the chart.

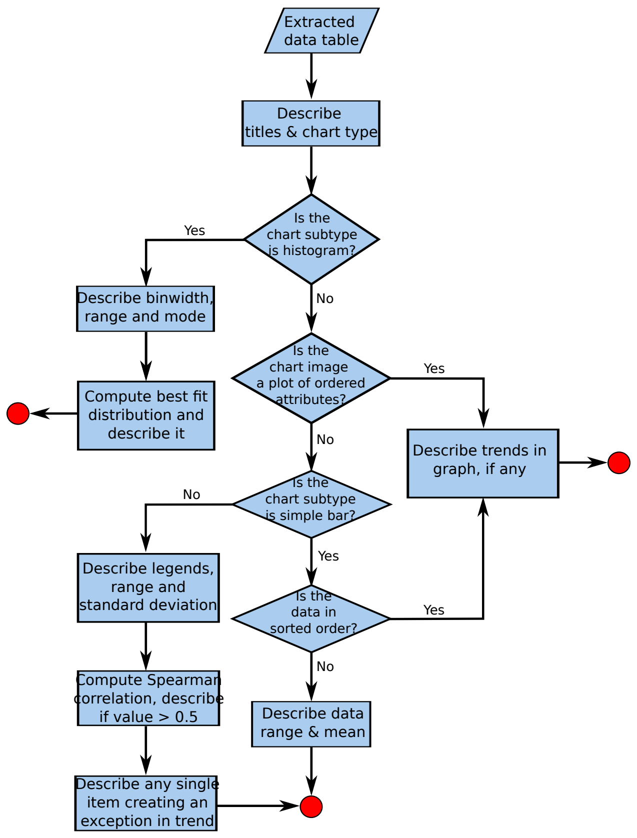
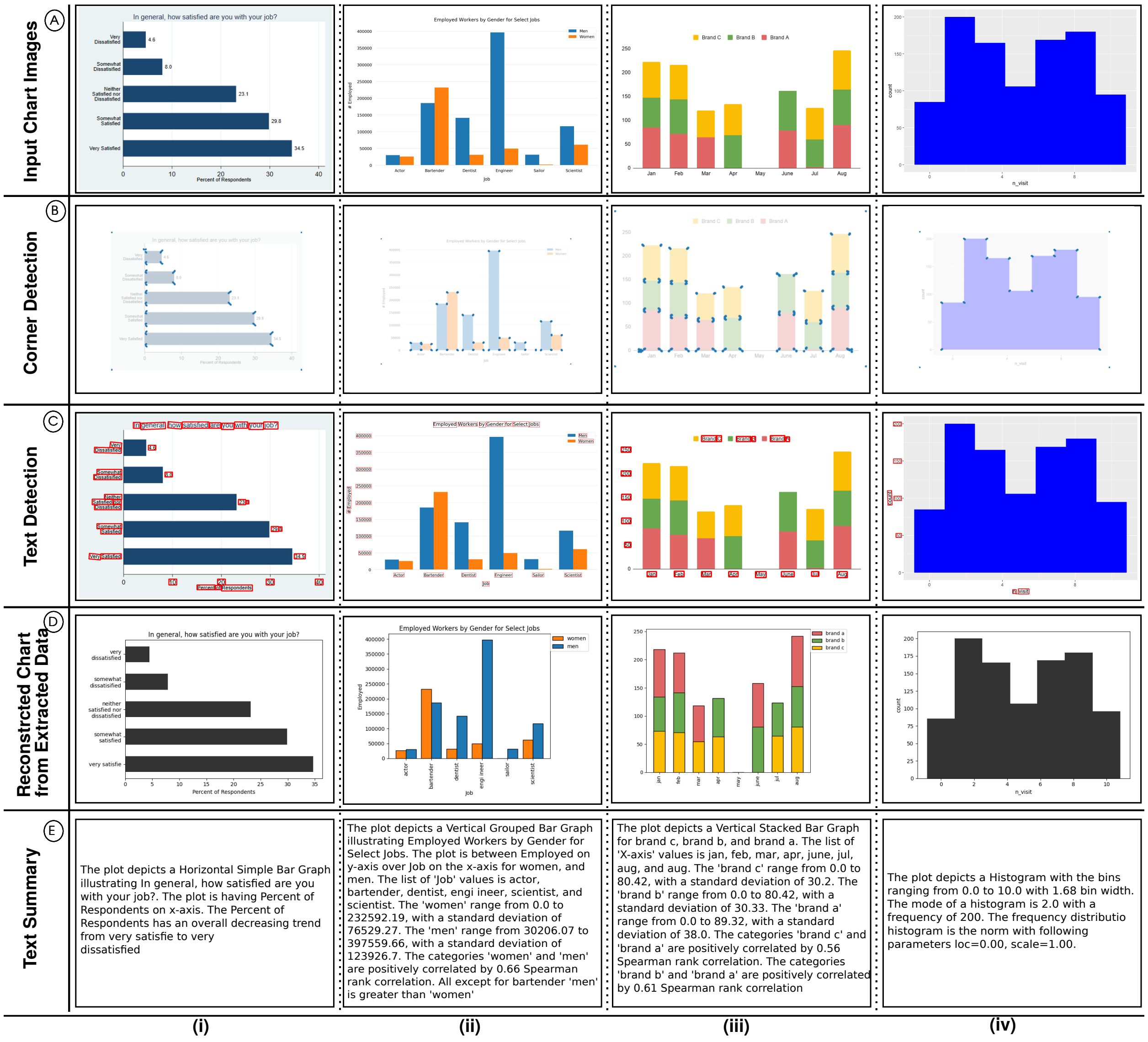

Extracted data table
Describe titles & chart type
Is the chart subtype is histogram?
Yes
No
Describe binwidth, range and mode
Compute best fit distribution and describe it
Is the chart image a plot of ordered attributes?
Yes
No
Describe trends in graph, if any
Is the chart subtype is simple bar?
No
Yes
Describe legends, range and standard deviation
Is the data in sorted order?
Yes
No
Compute Spearman correlation, describe if value > 0.5
Describe data range & mean
Describe any single item creating an exception in trend

Figure 3: The proposed flow chart of sentence structure formation for chart summary generation in text format (C7).

An effective summary should be accurate and concise for readers to consume. We present a well-built sentence structure to generate a summary of bar charts using the data table retrieved from the chart image in a way that captures the core information of the data table. The sentence structure is heuristically produced based on features identified from the extracted data. Based on this sentence structure produced, the summary for the intended graph image is generated. The features of the chart used in summary depend on its type and subtype. For the histogram type chart, we focus on features like the type of distribution, range, and mode. For bar charts with categorical variables, we check for ordinal variable type, *e.g.,* age, date, day, month, and year in the image, and extract the variable-based trend patterns in the chart image. Apart from these, we consider the statistical descriptors, such as the range of attributes, correlation between them, standard deviations, and mean values based on cases mentioned in our proposed flowchart (Figure 3). We, thus, generate the chart summary using the template abstracted in the flowchart.

4 Experiments & Results



The plot depicts a Horizontal Simple Bar Graph illustrating In general, how satisfied are you with your job?. The plot is having Percent of Respondents on x-axis. The Percent of Respondents has an overall decreasing trend from very satisfie to very dissatisfied

The plot depicts a Vertical Grouped Bar Graph illustrating Employed Workers by Gender for Select Jobs. The plot is between Employed on y-axis over Job on the x-axis for women, and men. The list of 'Job' values is actor, bartender, dentist, engi ineer, scientist, and scientist. The 'women' range from 0.0 to 232592.19, with a standard deviation of 76529.27. The 'men' range from 30206.07 to 397559.66, with a standard deviation of 123926.7. The categories 'women' and 'men' are positively correlated by 0.66 Spearman rank correlation. All except for bartender 'men' is greater than 'women'

The plot depicts a Vertical Stacked Bar Graph for brand c, brand b, and brand a. The list of 'X-axis' values is jan, feb, mar, apr, june, jul, aug, and aug. The 'brand c' range from 0.0 to 80.42, with a standard deviation of 30.2. The 'brand b' range from 0.0 to 80.42, with a standard deviation of 30.33. The 'brand a' range from 0.0 to 89.32, with a standard deviation of 38.0. The categories 'brand c' and 'brand a' are positively correlated by 0.56 Spearman rank correlation. The categories 'brand b' and 'brand a' are positively correlated by 0.61 Spearman rank correlation

The plot depicts a Histogram with the bins ranging from 0.0 to 10.0 with 1.68 bin width. The mode of a histogram is 2.0 with a frequency of 200. The frequency distributio histogram is the norm with following parameters loc=0.00, scale=1.00.

Figure 4: The key steps in our BarChartAnalyzer workflow of corner detection (C4), text detection (C5), data extraction (C6), chart reconstruction, and chart summary (C7) of the source input chart images. We observe the ordering of the series could be reversed in (ii) the grouped and (iii) stacked bar charts, even though the data is extracted accurately.

In C1 of the BarChartAnalyzer, we have trained the CNN model for classification using 1000 images belonging to eight types of charts, namely, the seven subtypes of bar charts and a complement set, "others", consisting of chart images of line charts, scatter plots, and pie charts. The training set excludes images for charts with textured, hollow, or hand-drawn bar objects. The training accuracy for our classifier is currently at 85%. For testing, we have used a dataset of 50 chart images each from these eight types. For experiments, we generated a dataset that includes bar chart images of these eight types from two sources, namely images downloaded from the internet and synthetically generated images. The latter is from bar charts generated using Python plotting library, `matplotlib` from known data tables.

The results from the BarChartAnalyzer for a subset of our experiments are shown in Figure 4. The images are first classified, and only those of bar charts and its subtypes pass through the BarChartAnalyzer. The source images are given in Figure 4(A). The tensor field analysis on extracted canvas detects the corner of the bars using critical points identified by the saliency value calculation. The results of pixels identified by corner detection are shown in Figure 4(B). The critical points are detected at the top and bottom corners of bars and at the bar segment junctions

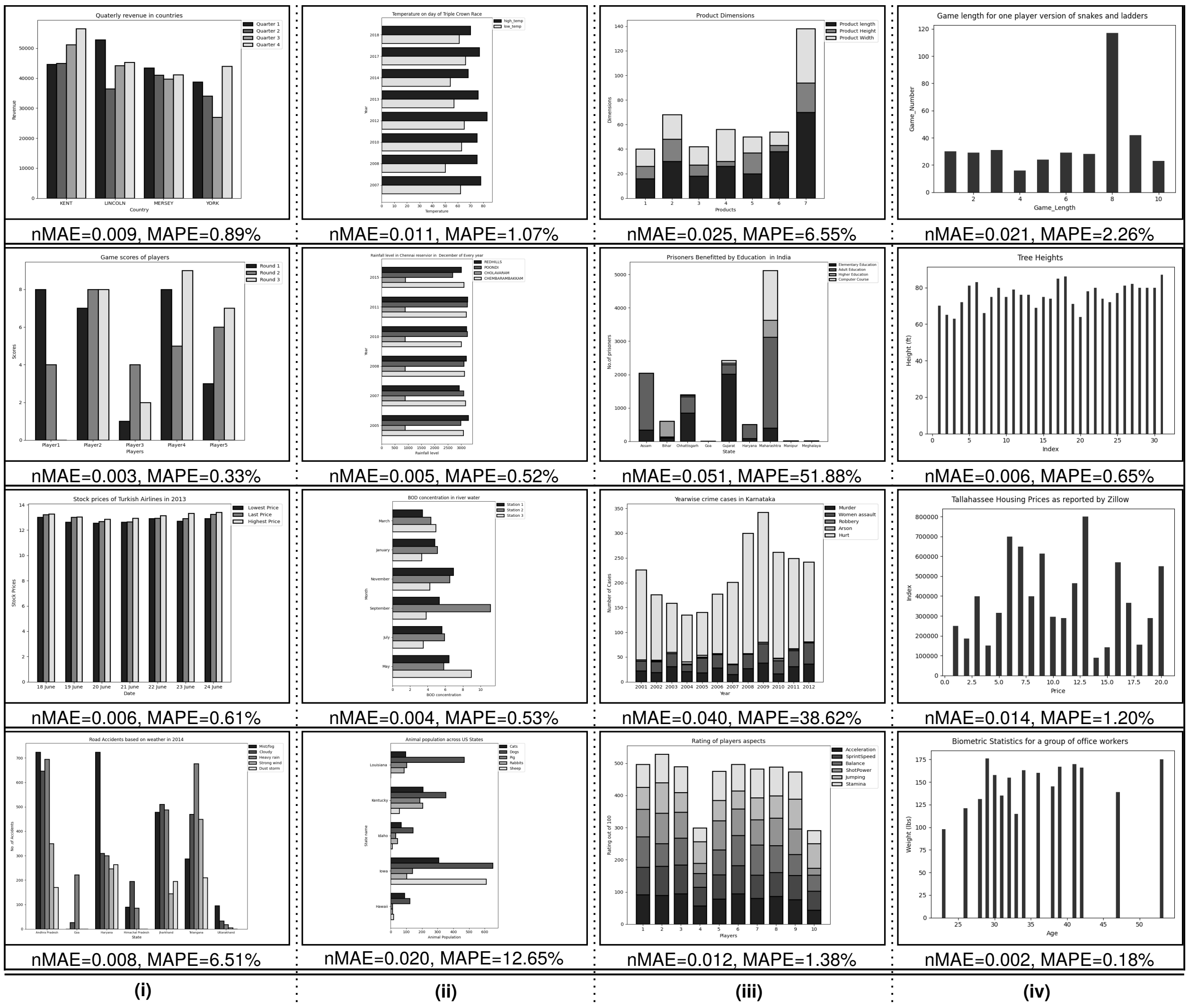
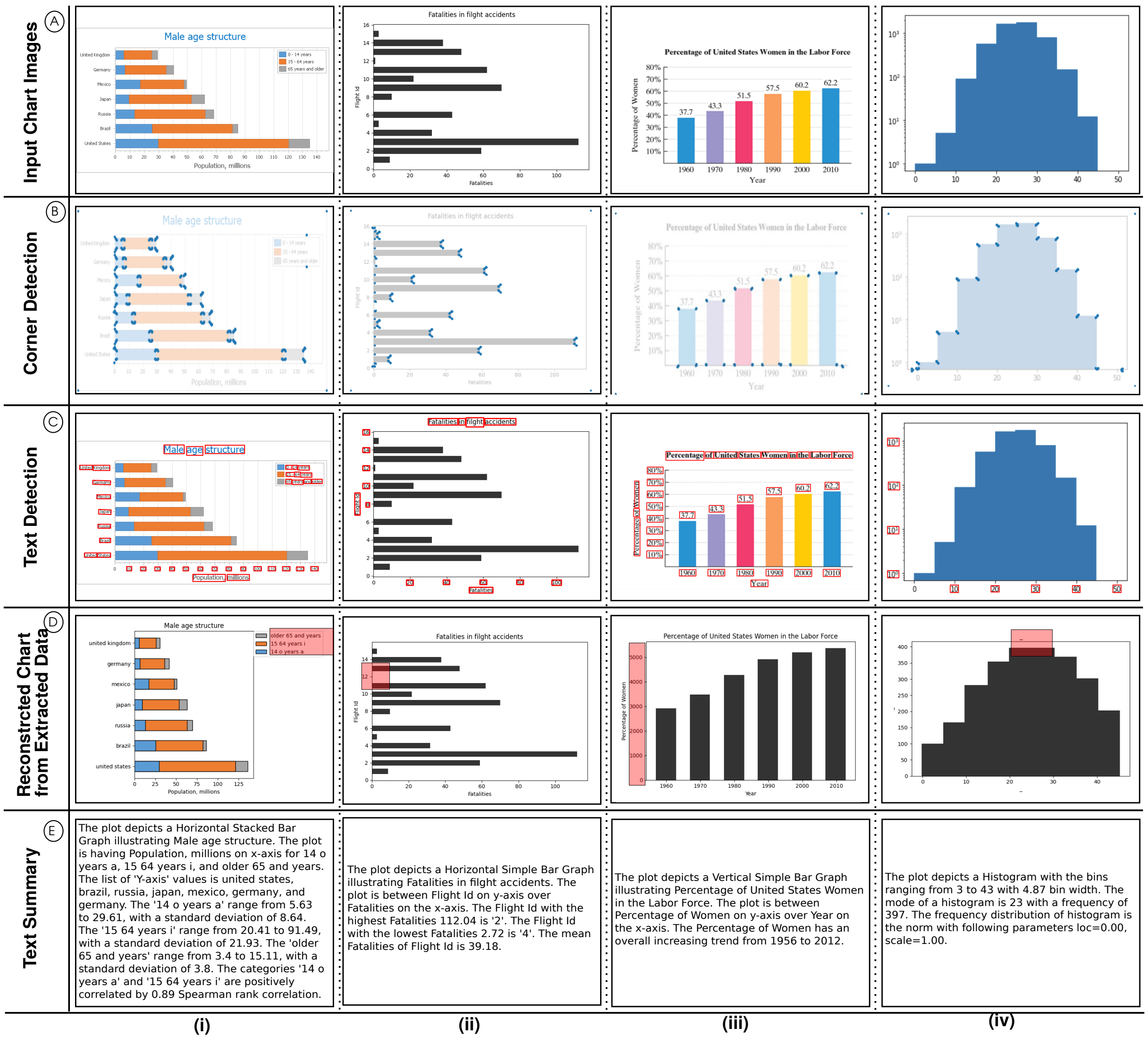


Figure 5: Reconstruction of synthetically generated bar chart images with their error evaluation in normalized mean absolute error (nMAE) and mean absolute percentage error (MAPE).

in the stacked bar chart. The histogram displays the distribution of such points at the junction where the transition between bins occurs. The visualization of critical points at corners also guides us in deciding the hyperparameters for DBSCAN, *e.g.,* distance (eps), minPts.

The OCR based text detection model [28] works with 0.95 F1 score on ICDAR 2013 dataset. The model fails to detect certain text components during testing, as shown in Figure 4(C, ii). Our workflow addresses this limitation while performing data extraction based on pixel scaling and the intervals retrieved from the detected text/values. Our reconstructed charts in Figure 4(D) can be visually compared with the original images in Figure 4(A).

Color is an important property of the images of the multi-series bar charts like grouped and stacked bar, as color is a visual encoding of the metadata of the series. In such cases, color represents the identity of the class or series the data item belongs to. But, in the case of simple bar charts and histograms, the use of color is cosmetic. Our algorithm preserves the source color value only in the case of it being a visual encoding, where we use the color value identified in the legend for the bars during reconstruction. In the cases where color is not used as a visual encoding for the chart, we use a default color value, *i.e.,* black, during reconstruction. Thus, color is preserved in reconstruction for charts in Figure 4(ii, iii), but not in Figure 4(i, iv). However, even where color is preserved, the order of rendering the series is not guaranteed to be preserved, as shown in Figure 4(ii, iii), as ordering of the classes or series is not an important property in the multi-series bar charts.



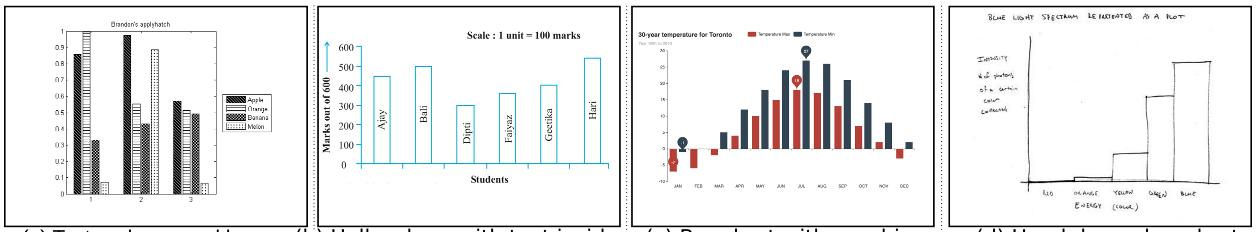
The plot depicts a Horizontal Stacked Bar Graph illustrating Male age structure. The plot is having Population, millions on x-axis for 14 o years a, 15 64 years i, and older 65 and years. The list of 'Y-axis' values is united states, brazil, russia, japan, mexico, germany, and germany. The '14 o years a' range from 5.63 to 29.61, with a standard deviation of 8.64. The '15 64 years i' range from 20.41 to 91.49, with a standard deviation of 21.93. The 'older 65 and years' range from 3.4 to 15.11, with a standard deviation of 3.8. The categories '14 o years a' and '15 64 years i' are positively correlated by 0.89 Spearman rank correlation.

The plot depicts a Horizontal Simple Bar Graph illustrating Fatalities in fllght accidents. The plot is between Flight Id on y-axis over Fatalities on the x-axis. The Flight Id with the highest Fatalities 112.04 is '2'. The Flight Id with the lowest Fatalities 2.72 is '4'. The mean Fatalities of Flight Id is 39.18.

The plot depicts a Vertical Simple Bar Graph illustrating Percentage of United States Women in the Labor Force. The plot is between Percentage of Women on y-axis over Year on the x-axis. The Percentage of Women has an overall increasing trend from 1956 to 2012.

The plot depicts a Histogram with the bins ranging from 3 to 43 with 4.87 bin width. The mode of a histogram is 23 with a frequency of 397. The frequency distribution of histogram is the norm with following parameters loc=0.00, scale=1.00.

Figure 6: Examples of bar chart images that give erroneous results in BarChartAnalyzer. The errors in the chart reconstruction are indicated using red translucent boxes in row D.



(a) Textured grouped bar (b) Hollow bars with text inside (c) Bar chart with graphics (d) Hand drawn bar chart

Figure 7: Bar charts generated in different design spaces, which are known to not work with our chart analysis workflow, BarChartAnalyzer.

Evaluation: The premise of our work is to extract data from images of charts that do not have accompanying data tables, *i.e.,* the ground truth. Hence, to compare the extracted data with source information, we run our algorithm on images of charts generated using the plotting library, *e.g.,* `matplotlib`, from known data tables. While our algorithm works well with such synthetically generated images owing to their high resolution and fidelity, they are useful in computing exact numerical errors in the extracted data table. The extracted data achieved by mapping pixel location of cluster center of degenerate points and text location extracted using OCR. We observe that the extracted values have numerical precision errors predominantly. Hence, to compare the difference between the extracted values, we compute the normalized Mean Absolute Error (nMAE), and the Mean Absolute Percentage Error (MAPE) for the synthetic images (Figure 5), which are bounded in [0,1]. MAPE is commonly reported in a percentage format. We observe that nMAE captures our performance better than MAPE, as it does not augment numerical precision errors as much as MAPE. MAPE is augmented in the case of missing extracted data in grouped bar charts (Figure 5(ii)) and stacked bar charts (Figure 5(iii)) owing to relatively short bars or bar segments. For N data items with source data value x_i and its corresponding extracted value $x_i^{(e)}$,

$$\text{nMAE}=\frac{\sum_{i=1}^{N}|x_i-x_i^e|}{\sum_{i=1}^{N}x_i}\text{; and } MAPE = \frac{1}{N}\cdot\sum_{i=1}^{N}\left|\frac{x_i-x_i^{(e)}}{x}\right|.$$

In our representative examples in Figure 5, we observe relatively low nMAE values. Histograms are not included in this analysis as the source, and extracted data in its case is a frequency table, different from a data table in the case of bar charts.

BarChartAnalyzer achieves near-perfect accuracy for high-resolution bar chart images, created with standard or minimal formatting available commonly across all plotting libraries. The morphological methods for image preprocessing in C3 in BarChartAnalyzer improve data extraction accuracy from low-fidelity images. The aggregated accuracy for PlotQA [1] for CQA is 22%, and STL-CQA [12] achieves near-perfect accuracy, but with synthetic datasets. However, comparing our work with the CQA algorithms is not a fair comparison, as the goals are different, even though there are overlapping outcomes. Accuracy-based comparison is not a complete exercise in itself.

Limitations: In a limited number of cases, our system suffers from errors in detection, specifically when DBSCAN clustering does not distinguish small/insignificant height differences between bars/bins [4]. We have identified two such cases. The first case is of false negatives when bars are close to the baseline, which is the x-axis and y-axis for column and bar orientations, respectively (Figure 6(D, ii)). The second case is when heights of adjacent bins in a histogram have relatively small height differences, and the extracted data does not capture the differences (Figure 6(D, iv)). This error is also manifested as missing values in grouped and stacked bar charts when the bars or bar segments are relatively short (Figure 5(ii),(iii)).

The text recognition model [29] identifies text with F1 score of 0.93 on ICDAR 2013 dataset. This recognition model misidentifies and confuses the alphabet 'O' or 'o', irrespective of the case, as the numeral '0' and vice versa in chart images. Also, the model has gaps in handling special characters, such as $,%,£, sign(-), and cannot handle superscript symbols, *e.g.,* degrees, and exponents (Figure 6(C, iii)). These shortcomings affect the accuracy of extracted data scale (Figure 6(C, i)). The inaccurate results in text recognition also manifest as errors in the textual summary of the source image. Some of these errors in text detection are shown in the reconstructed chart in Figures 6(D, i) and (D, iii).

Thus, the key drawback in our BarChartAnalyzer is in the false positives for corner detection in relatively low-fidelity images, owing to aliasing and subsequent pixelation. Also, our classification model cannot handle variants of bar charts with textures in the bars or hollow bars. Our workflow fails for chart canvas extraction for such special test cases, *e.g.,* images shown in Figure 7. Even though not considered a best practice, bars may be created with text or bar value written inside each bar, as shown in Figure 7(b). BarChartAnalyzer also fails for another test case where the data extraction process cannot identify negative bars, as shown in Figure 7(c). The text recognition model fails to identify text written in the hand-drawn chart shown in Figure 7(d). One of the drawbacks in our methodology, just as is the case with the state-of-the-art, lies in human-guided canvas extraction and interactive hyperparameter setting for DBSCAN for clustering corner points.

5 Conclusions

As a next step, such a subtype-based analysis can be extended to other chart types, such as scatter plots. Our workflow requires user interaction for tasks such as image annotation for canvas extraction and setting hyperparameters of DBSCAN. We are considering methods to make the workflow more automated. We currently use tensor field computation on the chart images, which can be made more robust to separate chart objects from the source image. As VGGNet has been widely used for object detection tasks, our goal is to improve our classifier to automate the canvas extraction step to reduce user dependency. Super-resolution algorithms may be explored as an additional component in our algorithm to improve the accuracy of both OCR and object detection, especially for severely aliased images.

In summary, we propose a workflow BarChartAnalyzer using standard image processing techniques and deep learning models to perform the critical task of chart image digitization and summarization for bar charts. BarChartAnalyzer is novel in handling seven different bar chart subtypes. Our contributions include the mapping between pixel space data and the data space using the text detection model. We introduce the chart type- and structure-based templatized text summarization for the data extracted from the chart image. The summarization achieved from our system has the potential of being used in a language processing module, such as `gtts` in Python, to generate an audio summary of the given chart image for the visually impaired audience. As discussed, our workflow has limitations of the dependency of workflow on the image fidelity, object size, training dataset, a variety of chart images, etc. Overall, our work is a step towards chart image digitization.

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