Towards Better Semantic Understanding of Mobile Interfaces

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Abstract

Improving the accessibility and automation capabilities of mobile devices can have a significant positive impact on the daily lives of countless users. To stimulate research in this direction, we release a human-annotated dataset with approximately 500k unique annotations aimed at increasing the understanding of the functionality of UI elements. This dataset augments images and view hierarchies from RICO, a large dataset of mobile UIs, with annotations for icons based on their shapes and semantics, and associations between different elements and their corresponding text labels, resulting in a significant increase in the number of UI elements and the categories assigned to them. We also release models using image-only and multimodal inputs; we experiment with various architectures and study the benefits of using multimodal inputs on the new dataset. Our models demonstrate strong performance on an evaluation set of unseen apps, indicating their generalizability to newer screens. These models, combined with the new dataset, can enable innovative functionalities like referring to UI elements by their labels, improved coverage and better semantics for icons etc., which would go a long way in making UIs more usable for everyone.

1 Introduction

Mobile devices like phones and tablets have become ubiquitous and indispensable to carry out our daily activities. It is not an exaggeration to say that usage of mobile devices is becoming a requirement for full participation in society. Recent reports from the WHO and others (Organization, 2021; Peter Ackland and Bourne, 2017) estimate that around 2.2 billion people across the world have some form of vision impairment, out of which 36 million people are blind. Accessibility of mobile devices is necessary for these visually impaired users to carry out their daily tasks and is an important tool for their social integration (Ladner, 2015).

Accessibility of mobile apps has improved significantly over the past few years aided by developments on two main fronts: Firstly, the development of screen readers, like VoiceOver (Apple, 2021c) on iOS and TalkBack (Accessibility, 2021e) on Android, enable visually impaired users to control their phone in an eyes-free manner. Secondly, development tools and standards to enhance accessibility, such as the Accessibility guidelines for iOS and Android (Accessibility, 2021a; Apple, 2021b), Android Accessibility Scanner (Accessibility, 2021b), and iOS Accessibility Inspector (Apple, 2021a), have helped developers identify and fix accessibility issues for applications. Among most of these utilities, the main source of accessibility data is the accessibility labels (Accessibility, 2021d) provided by app developers. These labels are specified as attributes on a structured representation such as View Hierarchy, for the different UI elements on the screen and are available to screen readers (Accessibility, 2021c; Apple, 2018). Despite the growth in accessibility tools, recent studies (Ross et al., 2020, 2017; Chen et al., 2020a) have found that even the most widely used apps have large gaps in accessibility. For instance, a study by Chen et al. (2020a) of more than 7k apps and 279k screens revealed that around 77% of the apps and 60% of the screens had at least one element without explicit labels. Similarly, Ross et al. (2020) found that, in a population of 10k apps, 53% of the Image Button elements were missing labels.

In this paper, we attempt to encourage further research into improving mobile device accessibility and increasing device automation by releasing an enhanced version of the RICO dataset (Deka et al., 2017) with high-quality human annotations aimed at semantic understanding of various UI elements. Firstly, following a study by Ross et al.

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(2020) where missing labels for Image Button instances was found to be the primary accessibility barrier, we focus on creating annotations useful for identifying icons. In particular, we annotated the most frequent 77 classes of icons based on their appearance. We refer to this task as the *Icon Shape* task. Secondly, we identified icon shapes which can have multiple semantic meanings and annotated each such icon with its semantic label. This task is called *Icon Semantics*. Some examples of such icons can be seen in Figure 1b. Finally, we annotate UI elements, like icons, text inputs, checkboxes etc., and associate them with their text labels. These associations can help us identify meaningful labels for the long tail of icons and UI elements not present in our schema, but having a textual label associated with them. We refer to this task as the *Label Association* task. The main contributions of this paper are as follows:

- A large scale dataset[1] of human annotations for 1) Icon Shape 2) Icon Semantics and 3) selected general UI Elements (icons, form fields, radio buttons, text fields) and their associated text labels on the RICO dataset.

- Strong benchmark models[2] based on state of the art models (He et al., 2016; Carion et al., 2020; Vaswani et al., 2017) using image-only and multimodal inputs with different architectures. We present an analysis of these models evaluating the benefits of using View Hierarchy attributes and optical character recognition (OCR) along with the image pixels.

2 Related Work

2.1 Datasets

Large scale datasets like ImageNet (Deng et al., 2009) played a crucial part in the development of Deep Learning models (Krizhevsky et al., 2012; He et al., 2016) for Image Understanding. Similarly, the release of the RICO dataset (Deka et al., 2017) enabled data driven modeling for understanding user interfaces of mobile apps. RICO is, to the best of our knowledge, the largest public repository of mobile app data, containing 72k UI screenshots and their View Hierarchies from 9.7k Android apps spanning 27 categories. Apart from RICO, other datasets include ERICA (Deka et al., 2016) with sequences of user interactions with mobile UIs and LabelDROID (Chen et al., 2020a) which contains 13.1k mobile UI screenshots and View Hierarchies.

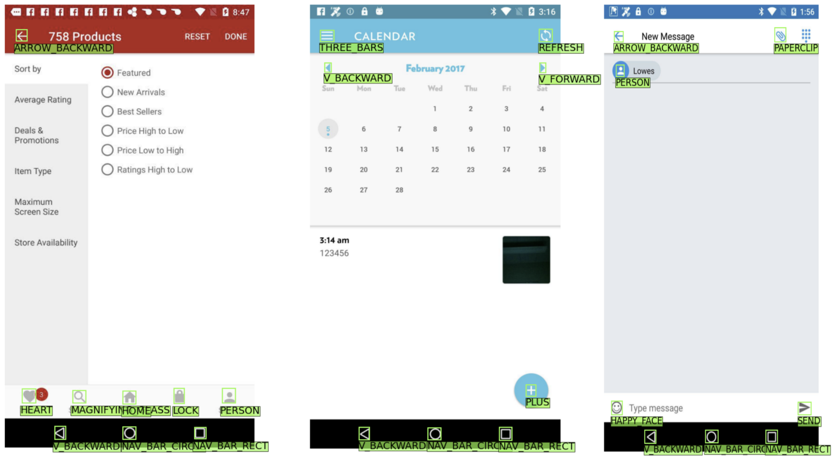
There have been a few efforts to provide additional annotations on RICO. SWIRE (Huang et al., 2019) and VINS (Bunian et al., 2021) added annotations for UI retrieval, Enrico (Leiva et al., 2020) added annotations for 20 design topics. Liu et al. (2018) automatically generated semantic annotations for UI elements using a convolutional neural network trained on a subset of the data. Recently Li et al. (2022) released UI element labels on view hierarchy boxes including identifying boxes which do not match to any elements in the UI. Even though some of these works are similar in spirit to the dataset presented in this paper, there are two major differences: 1) The icon and UI element labels are *inferred* on the boxes extracted from the View Hierarchy, whereas, in our work, we add *human annotated* bounding boxes directly on the image. Due to noise in the view hierarchies like missing and misaligned bounding boxes for UI elements (Li et al., 2020a, 2022), we observe that human annotation increases the number of icons labelled by 47%. 2) The semantic icon labels in Liu et al. (2018) conflate appearance and functionality. For example "close" and "delete," "undo" and "back," "add" and "expand" are mapped to the same class, even though they represent different functionalities. The *Icon Semantics* annotations in our dataset specifically try to distinguish between icons with the same appearance but differences in functionality.

2.2 Models

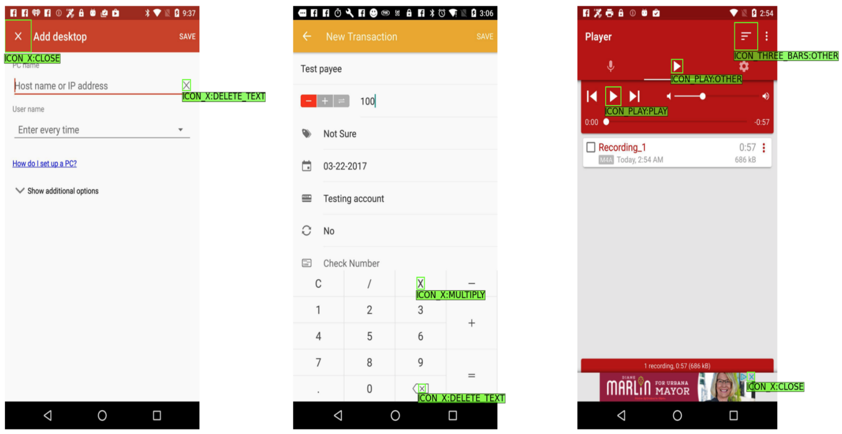
Pixel based methods for UI understanding have been studied for a long time. They have been used for a variety of applications like GUI testing (Yeh et al., 2009; Chang et al., 2010), identifying similar products across screens (Bell and Bala, 2015), finding similar designs and UIs (Behrang et al., 2018; Bunian et al., 2021), detecting issues in UIs (Liu, 2020), generating accessibility metadata (Zhang et al., 2021) and generating descriptions of elements (Chen et al., 2020a). A recent study by Chen et al. (2020b) compares traditional image processing methods and Deep Learning methods to identify different UI elements. The image-only baseline models studied in this paper are based on Object Detection methods presented in Chen et al.

[1]The datasets are released at https://github.com/google-research-datasets/rico-semantics.

[2]Benchmark models and code are released at https://https://github.com/google-research/google-research/tree/master/rico-semantics



(a) Examples of 76 *icon shape* annotations. We include classes that reflect the social aspects of app usage, e.g., "person" for profile and community, share via popular apps such as Facebook and Twitter, etc.



(b) Examples of 38 *icon semantics* annotations, in the format of <shape>:<semantics>. Note that a single shape may represent multiple semantics, depending on the context. E.g., "X" shape may mean "close", "delete text", or "multiply". We use an umbrella semantic class "OTHER" to cover the semantics not covered in our proposed set of classes

Figure 1: In this paper, we annotated the RICO dataset with both **icon shapes** and their **semantics**, to encourage further research on app automation and accessibility. The existing icon annotations from Liu et al. (2018) were algorithmically generated with 10% of them verified. However, we observed $\sim$ 32% were missing labels compared to our full human annotations. We release our annotations in the hope to contribute back to the community.

(2020b), Zhang et al. (2021), Chen et al. (2020a), and Carion et al. (2020).

Extending to other modalities beyond pixels, Banovic et al. (2012) use video tutorials to understand UIs and annotate them with additional information. Li et al. (2021) use only the screen information for identifying embeddings of UI elements. Hurst et al. (2010) use both the screen and accessibility API information to identify interaction targets in UIs and Chang et al. (2011) use similar inputs to detect and identify certain UI elements and Nguyen et al. (2018) use it for identifying similar UI designs. Multimodal inputs have also been used for understanding screen contents like generating element descriptions (Li et al., 2020b), training UI embeddings for multiple downstream tasks (He et al., 2021; Bai et al., 2021) and, denoising data, predicting bounding box types (Li et al., 2022).

3 Datasets, taxonomy and annotation

To enable accessible hands-free experience for mobile users, it is necessary for the system to understand the functionality of the different screen UI elements. For learning data driven models to enable these functionalities, we use the RICO dataset (Deka et al., 2017). RICO spans >9K apps and >72K UIs, each with a screenshot and information regarding the structure of the UI in the form of a View Hierarchy (VH). Besides the bounding boxes of the different UI elements, the VH contains useful attributes like the *content description* and *resource id* which provide information regarding the functionality of the different UI elements. However, Li et al. (2020a) found that only 35% of the unique screens in RICO contain a matching View Hierarchy and screenshot. In the next few sections, we describe how we overcome the mismtach issue and describe the different type of annotations.

3.1 Icon Shape

As the study by Ross et al. (2020) found that one of the main accessibility barriers on mobile devices are missing labels for ImageButton elements, in the *icon shape* and *semantics* tasks we focus on creating annotations useful for identifying icons. Liu et al. (2018) attempted to provide semantic labels for the icons in the RICO dataset by identifying different concepts represented by the ImageButton elements on a subset of the data. Using these concepts and models trained on a subset of the data they identified semantic labels over the entire dataset. They inferred labels for more than 100 icons types, 25 UI element types and 197 text button types. However, due to the presence of view hierarchies with bounding boxes missing and misaligned for UI elements (Li et al., 2020a, 2022), these labels miss several UI elements. By comparing with manually labeled data, we found that the annotations in Liu et al. (2018) did not identify around 32% of all icon instances captured by manual labeling. For improving the coverage of icons, in our dataset we asked raters to manually annotate all the bounding boxes. We created a schema of the 77 most commonly used icon classes, reusing many of the classes identified in Liu et al. (2018). Examples of these icon classes and images are shown in Figure 1a.

3.2 Icon Semantics

To support voice driven usage of mobile devices, we identify icons not only based on their shape and appearance but also functionality and semantic meaning. For example, an "X" shaped icon can mean "close," "remove an option/entry," "delete/clear text," or "multiply." One way to enable users to refer to the various semantics is to map the multiple semantics to the same class in the *Icon Shape* schema. This approach has two limitations: 1) Mapping each icon shape to multiple semantics can lead to confusion for applications like Screen Readers. 2) We noticed that there are many instances of icons with different semantics but same shape occurring in the same screen. In particular 11% of all images with *ICON_PLAY*, 4.9% with *ICON_X* and 4.8% with *ICON_CHAT* have icons with multiple semantics.

We identified a list of common icons which have more than one semantic meaning associated with them by the following steps: 1) Manually inspect a variety of the icon annotations and list the functionality of each icon instance, 2) Use the plurality of words matching to the same icon shape in the RICO icon labels in (Liu et al., 2018) as an indicator of multiple semantics, and 3) Recognize confusing app logos. For example, the logo for WhatsApp contains a Phone icon but it is most natural for a user to say, "open WhatsApp".

After these steps, we arrived at a list of 12 shape icons which were further classified into 38 semantic shapes. For icons with semantic meanings not covered by our schema, we assign the semantic type *OTHER* as the default label. Out of the 101,625 annotated icons 15,640 (around 15%) are labeled as *OTHER*. We observed that it is difficult to cover all of the tail semantics classes with a schema. Thus, we also obtained annotations for the text labels associated with UI elements, described in the section below.

3.3 Label Association

Many UI elements have an associated text labels that best describes UI elements. Our data analysis showed that 24.6% of icons, form fields, check boxes and radio buttons have an associated label. However, we found that these labels are commonly neither syntactically associated within view hierarchies nor visually aligned in screenshot pixels. First, we attempted to identify labels associated with UI elements by using heuristics relying on the View Hierarchy, like searching the siblings and parent node's siblings for axis aligned text elements for each of the UI elements. We found that only 40% of UI elements with labels could be correctly associated using such heuristics with a significant number of false positive associations. Next, we attempted to match UI element bounding boxes with line boxes detected by OCR. We matched each UI element bounding box with the OCR text box nearest to the top left corner with a maximum distance threshold. This method achieved 29.5% accuracy. These empirical studies indicated that, like many machine perception tasks, this *L*abel Association task may in fact be non-trivial despite appearing straightforward to humans. Some examples can be seen in figure 2. We believe this novel task can help address the limitation of annotations with a fixed set of classes by making use of the text label information present in the UI.

3.4 Annotation Procedure

For the three tasks described above, we follow the annotation procedure below to collect annotated data. We used a team of 40 trained human raters with single replication to annotate the screenshots. The raters were initially provided with example image patches for each icon or UI element type similar to Figure 1a and then followed the annotation procedure below:

- Round 1: Each rater is presented with a screenshot and is asked to draw a bounding box around every icon and UI element on the screen. For each icon box, they can specify an icon shape class if it is included in the schema and otherwise they classify it as a general icon class. Once an icon shape class is identified, if there are multiple semantics associated with that shape, the raters choose one semantic class among the different options for that class. These options also include the *OTHER* class to capture semantics not in the icon semantics schema. For the label association task, we ask raters to identify the icons, form fields, radio buttons, and check boxes first, followed by the text labels, by drawing their bounding boxes and assigning the respective classes. Then the raters group the text labels with their associated UI element if it exists.

- Round 2: To improve the annotation quality, we send the datasets for a second round of cleaning where the raters can adjust the bounding box or the classes assigned.

- Round 3: After round 2, if we still find some classes are poorly labeled by manual inspection, we use trained models to identify potential incorrect labels. We train Object Detection models on the entire dataset, and use the model to predict labels for the train, validation and test sets. If there are any differences between the model predictions and the human annotations, we identify these instances as potentially error-prone and send these images back to the raters to re-annotate them.

Using the above procedure, we annotated all of the screenshots in RICO with icon shape, semantics and label association classes. The distribution of top labels for the icon tasks can be seen in figures 3, 4. The entire taxonomy and exact counts are in Appendix A.

4 Baseline Models

We conducted several experiments to investigate the effectiveness of various deep learning approaches for solving the tasks presented in Section 3. The overall goal of these experiments is to: 1) provide good baseline models to be used for image-only and image+VH settings 2) study the effect of using multi-modal inputs v/s only the screenshot for these tasks.

4.1 Problem Setup

For the three tasks, we distinguish two different approaches: 1) the Object Detection (OD) approach using only the image and, 2) the bounding box classification (BB-CLS) approach using image, OCR and view hierarchy. We describe these two approaches in the following sections. We split the data into 80% train, 10% validation and 10% test by package name to avoid data leakage and use the same split for all experiments.

4.1.1 Object Detection (OD)

In this setup, the models take the screenshot as input and output bounding box, class label and score for each object found. We used object detection models based on the widely used and better performing (Chen et al., 2020b) Faster R-CNN (Ren et al., 2015) and Centernet (Zhou et al., 2019) architectures. We train these models with various backbones (Szegedy et al., 2017; He et al., 2016; Lin et al., 2017; Newell et al., 2016) and report results for the best performing ones. Finally, we experimented with Object Detection models based on Transformer (Vaswani et al., 2017) architecture like DETR (Carion et al., 2020; Zhu et al., 2020) to verify the hypothesis that for the *Icon Semantics* and the *Label Association* tasks, the models need more information from their context compared to the *Icon Shape* task. We use standard Object Detection metrics like mAP@0.5IOU to compare the model performance.

4.1.2 Bounding box classification (BB-CLS)

For this setup, we train models to classify bounding boxes extracted from the view hierarchy (VH)

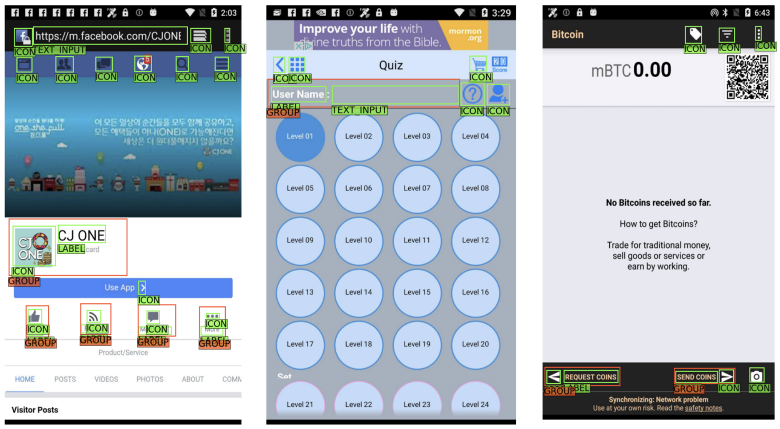


Figure 2: When an associated text label appears with a UI element, it is natural to refer to the icon using the text directly. 24.6% of icons, form fields, check boxes and radio buttons have an associated text label. *Label Association* examples are provided in the figure in red. However, rule-based approaches using view hierarchies or OCR can only achieve 40% and 29.5% accuracies respectively. These annotations enable us to identify the elements to interact with for voice commands like "Enter User Name as test user" or "Request Coins".

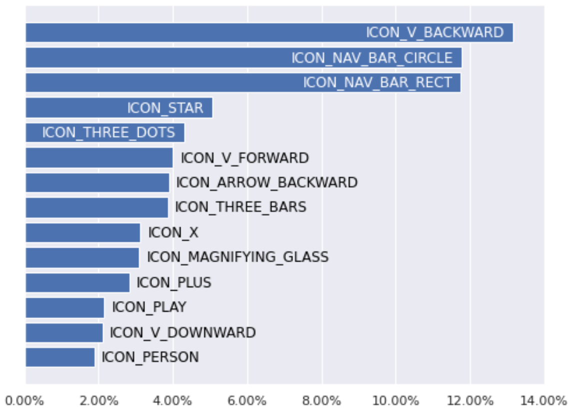


Figure 3: Distribution of the top 14 *icon shape* classes. These classes account for 72% of the total icons covered by the *icon shape* labels.

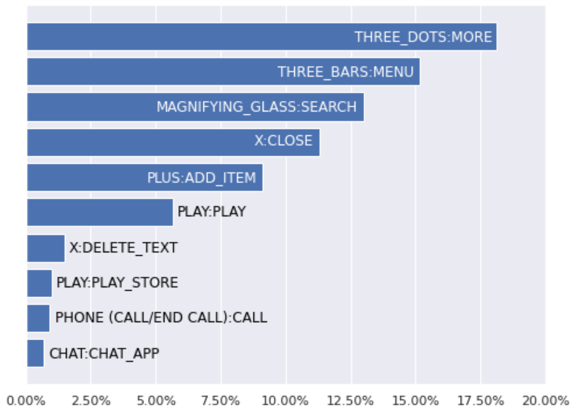


Figure 4: Distribution of the top 10 *icon semantics* classes. These classes account for 76% of the total icons covered by the *icon semantics* labels.

and assign them labels among the candidate classes. The groundtruth (GT) set contains boxes that have been created and labeled by crowd workers. These two sets of boxes are greedily matched as follows. 1) Each GT box is matched to at most one VH box and vice versa. 2) For every GT box, we find the VH box with maximum Intersection over Union (IoU). Only the matches for which the IoU value is greater than the threshold of *0.5* are kept. 3) Once a VH box is matched with a GT, it is not considered for future matches. After this matching procedure is complete, we assign a background class to the unmatched VH boxes. We use a Transformer (Vaswani et al., 2017) based network as described in UIBert (Bai et al., 2021) for the *Icon Shape*, *Semantics* tasks framed as a classification problem and compare models based on Macro F-1 score.

For the *Label Association* task, we compute an embedding of each UI element following Bai et al. (2021) and perform clustering on projected embeddings to identify UI elements which belong to a group. We use F-1 score of the associated elements as the metric of comparison. For every set of elements predicted to be a group, it is considered a True Positive if the same group is present in the groundtruth, and considered a False Positive if it is not. All groundtruth groups which are not in predictions count as False Negatives and the F-1 score is computed based on these counts.

Compared to OD models the BB-CLS models have an advantage as they do not need to predict the bounding boxes for UI elements. To enable a comparison between the two approaches, we add the unmatched GT boxes as inputs by setting all the other VH attributes to be empty values. To use this in a real-world setting, this procedure assumes the existence of a good VH without missing boxes. We study BB-CLS models here as it helps us validate the potential benefit of using VH attributes from the UI elements on the screen and consequently can motivate improving the view hierarchies for various apps and web-sites.

4.2 Model Configurations and Training Details

For the Centernet model, we used the hourglass-104 backbone (Zhou et al., 2019) with an input size of 1024×1024. For the DETR model (Carion et al., 2020), each image is proportionally resized and padded to the shape 1280×1280. We use a ResNet-50 (He et al., 2016) pretrained on ImageNet (Deng et al., 2009) as the backbone with frozen batch normalization layers for training stability. We add position embedding and object queries to each layer. The DETR models are trained on cloud TPUs with a batch size of 256 and reduce learning rate from 1×10^{-4} to 1×10^{-5} after 120k steps.

For classification and clustering models based on UIBert (Bai et al., 2021), we use an EfficientNet-B0 (Tan and Le, 2019) model for encoding the image patches and use ALBERT text encoder (Lan et al., 2019) for encoding OCR and VH attributes. We use a Transformer layer with 6 layers, 16 heads and a intermediate size of 512. We train these models on cloud TPUs with a batch size of 128 using the Adam optimizer (Kingma and Ba, 2014) with a warmup over 10k steps and reduce learning rate from 1×10^{-4} by a factor of 3 for every 50k steps . All the models were implemented using Tensorflow (Abadi et al., 2015) and converged within two days.

4.3 Results and Analysis

In this section, we report our model performance for each problem setup. For all model variants, we choose the model with the best performance on the validation set and report the numbers on the test set. Overall, we observe that for *BB-CLS* models using Image + VH + OCR perform better than models using Image + OCR and Image only. For *OD* models, we report the results from the best performing Faster R-CNN model, the best performing CenterNet model, and DETR, the overall best model for each task. We report both these results as it allows us to compare the performance of CNN based architectures with Transformer based ones. Also CenterNet models enable fast inference (Duan et al., 2019) on mobile phones compared to DETR models, making the baseline models directly usable on mobile phones. Results for all the different architectures we experimented with can be found in the Appendix A. For *BB-CLS* models, we estimate the 95% Confidence Intervals based on 5 model runs with the same configuration.

4.3.1 Icon Shape and Semantics

Among *OD* models, we observe that models based on DETR (Carion et al., 2020) which uses Transformers + Convolutions outperform CNN-based object detection models. DETR models achieve an mAP@0.5IOU of 77.94% on the test set vs 72.50% for CenterNet models on *Icon Shape* task and achieve an mAP@0.5IOU of 55.74% vs 54% for CenterNet models for *Icon Semantics* task. The performance of all of the models is weaker for *Icon Semantics* vs *Icon Shape* task. We believe this is due to *Icon Semantics* being a harder task as objects of similar shape can belong to different classes based on the rest of the screenshot or other assumptions. Additionally, since semantic labels are a sub-classification of shape labels, this dataset has fewer labeled examples per class.

For the *BB-CLS* models, we observe that models which take the VH as input outperform models without VH for both tasks. Models with Image + VH + OCR outperform models with Image + OCR by 0.63% and 2.6% for the *Shape* and *Semantics* tasks respectively. We believe this could be a result of information regarding the elements being present in VH attributes like content description. However, adding OCR does not seem to improve model performance significantly over using only the image as input. Detailed results for these tasks can be found in Tables 1, 2.

4.3.2 Label Association

For the *Label Association* task, DETR-based models also outperform CenterNet models in terms of F-1 score of 79.17% vs 75.65%. For BB-CLS models, we observe that models using VH attributes outperform models not using VH with an F-1 score of 87.23% vs 85.29%. Detailed results can be found in Table 3. We observe a significant gap in the F1-score achieved by BB-CLS models v/s OD models.

Model Type	mAP	mAP@0.5IOU
Faster R-CNN	34.60	70.24
CenterNet Hourglass	37.50	72.50
DETR	**39.28**	**77.94**

(a) Object Detection

Inputs	F-1 score	95% CI
Image + OCR + VH	**83.38**	[83.23 - 83.53]
Image + OCR	82.75	[82.54 - 82.95]
Image only	82.08	[81.71 - 82.44]

(b) Bounding box Classification

Table 1: Baseline model performance on *Icon Shape* task. For the object detection models, DETR outperforms CenterNet and Faster R-CNN architectures. For bounding box classification, models using the image OCR and view hierarchy outperform ones not using all modalities.

Model Type	mAP	mAP@0.5IOU
Faster R-CNN	25.33	53.59
CenterNet Hourglass	25.70	54.00
DETR	**26.69**	**55.74**

(a) Object Detection

Inputs	F-1 score	95% CI
Image + OCR + VH	**67.16**	[66.74 - 67.58]
Image + OCR	64.52	[63.98 - 65.05]
Image only	63.66	[63.15 - 64.16]

(b) Bounding box Classification

Table 2: Baseline model performance on *Icon Semantics* task. Similar to the For the *Icon Shape* task DETR is the best performing object detection model and models using image, OCR and view hierarchy perform the best. However, there is no statistically significant improvement between image only and image + OCR models.

Model Type	mAP	F-1 score
Faster R-CNN	36.90	75.75
CenterNet Hourglass	38.00	75.65
DETR	**40.71**	**79.17**

(a) Object Detection

Inputs	F-1 score	95% CI
Image + OCR + VH	**87.23**	[86.40 - 88.05]
Image + OCR	85.29	[84.78 - 85.79]
Image only	84.33	[83.30 - 85.36]

(b) Bounding box Classification

Table 3: Baseline model performance on *Label Association* task. The model performance characteristics are very similar to those observed for the *Icon Semantics* task.

5 Applications and Future Work

This dataset and models built on it to predict the icon and text association labels can be used to improve the label coverage for various accessibility applications like VoiceOver (Apple, 2021c), TalkBack (Accessibility, 2021e), Voice Access (Accessibility, 2022) etc. In addition, these labels can be used to improve the accessibility labels for various other platforms like web browsers and desktop applications. The models can also be used to automatically suggest accessibility labels for UI elements based on their appearance in various developer platforms (XCode, 2022; AndroidStudio, 2021) so that developers can improve the accessibility of their apps easily. Along with improving accessibility, we believe this dataset is a step towards enabling new features like voice control, screen summarization and others.

The baseline models presented in this paper can be improved in a number of ways like training multitask models for a single model to output the different labels, bridge the gap between the models which use only the image and models which use view hierarchy, improve the ability of multimodal models to handle missing view hierarchy elements and their attributes. Other directions of research include inferring labels for the long tail icon classes using the *ICON* class annotations from the *label association* task, inferring semantic labels for general UI elements. This supervised data can also be used to improve the performance of self-supervised methods for UI elements like ActionBert (He et al., 2021), UIBert (Bai et al., 2021) etc.

6 Conclusions

In this paper, we presented an enhanced version of the RICO dataset with three new sets of annotations aimed at improving the semantic understanding of mobile screens, namely *icon shape*, *icon semantics*, and *label association*. We outlined the benefits of human annotated data over automatically labeled data and released strong baseline models using image and view hierarchy for each of these tasks. Our dataset, benchmark models and experiments lay the groundwork for future research on building better models for semantic understanding of UIs. We observe that using pre-trained models and view hierarchy attributes is a promising direction for improving these models. These models can be combined with other techniques like heuristic rules to infer the multitude of labels useful for driving improvements in accessibility and automation of mobile devices.

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A Appendix: Data distribution and experiment results

This section contains more details on the datasets. Section A.1 contains the definitions used for attributing the detailed data distribution for each of the tasks. Table 4 contains the data distribution for the 76 *icon shape* classes. Table 5 contains the shape classes and their semantic classification along with counts for each class and table 6 contains the data distribution for the *label association* classes.

In addition Table 7 contains results for object detection models based on Faster R-CNN on the 3 tasks discussed in the paper.

A.1 Semantic class definitions

As mentioned in section 3.2 the shape icons are further sub-divided into various categories based on their functionality. The definitions of the various semantic types are given below. Each semantic icon name is prefixed by the corresponding shape name. We exclude the OTHER category for each icon shape as it is used to capture all other functionalities not covered by the mentioned semantics.

- ICON_X:CLOSE Close windows or tabs or exit a window.
- ICON_X:DELETE TEXT Delete entries, items, text, suggestions etc.
- ICON_X:MULTIPLY Mathematical operation of multiplication.
- ICON_ARROW_UPWARD:CAPITALIZE Caps Lock icon to toggle upper case and lower case letters in the keyboard.
- ICON_MAGNIFYING_GLASS:SEARCH Search in the current app or website.
- ICON_MAGNIFYING_GLASS:ZOOM IN Zoom-in to a picture, document etc.
- ICON_MAGNIFYING_GLASS:ZOOM OUT Zoom-out of a picture, document etc.
- ICON_UNDO:REPLY Reply to a message, mail etc.
- ICON_UNDO:UNDO Undo the previous action.
- ICON_UNDO:BACK Go back to the previous screen or state.
- ICON_REDO:SHARE Share this item.

- ICON_REDO:REDO Redo the previous action.
- ICON_THREE_BARS:MENU Icon to display menu options.
- ICON_PHONE:CALL Start a phone call.
- ICON_PHONE:CHAT APP Icon for a chat app.
- ICON_PHONE:PHONE APP Open the phone app.
- ICON_PHONE:END CALL End a phone or video call.
- ICON_PLAY:PLAY Playing video, audio, games, etc.
- ICON_PLAY:PLAY STORE Icon for the Google Play Store.
- ICON_PLAY:YOUTUBE Icon for the YouTube app.
- ICON_CHAT:CHAT Send a message to someone or view comments.
- ICON_CHAT:WHATSAPP Icon for the WhatsApp app.
- ICON_CHAT:FACEBOOK MESSENGER Icon for the Facebook Messenger app.
- ICON_TAKE_PHOTO:INSTAGRAM Icon for the Instagram app.
- ICON_THREE_DOTS:MORE For "more" options, contents, etc. It could also refer to menu.
- ICON_PLUS:ADD ITEM Add a new item to an existing list.
- ICON_PLUS:EXPAND Expand a UI element to show more details.

Shape Class	Count
ICON V BACKWARD	46,431
ICON NAV BAR CIRCLE	41,551
ICON NAV BAR RECT	41,449
ICON STAR	17,890
ICON THREE DOTS	15,194
ICON V FORWARD	14,131
ICON ARROW BACKWARD	13,767
ICON THREE BARS	13,659
ICON X	11,058
ICON MAGNIFYING GLASS	10,911
ICON PLUS	9,971
ICON PLAY	7,576
ICON V DOWNWARD	7,447
ICON PERSON	6,648
ICON CHECK	6,583
ICON HEART	6,274
ICON CHAT	5,483
ICON SETTINGS	4,909
ICON SHARE	4,871
ICON ARROW FORWARD	3,463
ICON LOCATION	3,398
ICON INFO	3,287
ICON HOME	3,172
ICON TIME	3,123
ICON REFRESH	2,987
ICON CLOUD	2,436
ICON EDIT	2,280
ICON QUESTION	2,263
ICON TAKE PHOTO	2,110
ICON SHOPPING CART	1,900
ICON CALENDAR	1,851
ICON NOTIFICATIONS	1,817
ICON CLOUD	2,436
ICON EDIT	2,280
ICON QUESTION	2,263
ICON TAKE PHOTO	2,110
ICON SHOPPING CART	1,900
ICON CALENDAR	1,851
ICON NOTIFICATIONS	1,817
ICON FACEBOOK	1,700
ICON ENVELOPE	1,659
ICON PEOPLE	1,658

Shape Class	Count
ICON LOCK	1,622
ICON GALLERY	1,535
ICON CALL	1,488
ICON V UPWARD	1,392
ICON VOLUME STATE	1,359
ICON LIST	1,346
ICON DOWNLOAD	1,344
ICON THUMBS UP	1,335
ICON SUN	1,327
ICON ARROW DOWNWARD	1,317
ICON LAUNCH APPS	1,136
ICON ARROW UPWARD	1,094
ICON MIC	1,016
ICON HAPPY FACE	955
ICON PAUSE	864
ICON TWITTER	860
ICON SHOPPING BAG	776
ICON MOON	719
ICON SEND	711
ICON COMPASS	691
ICON DELETE	665
ICON REDO	546
ICON VIDEOCAM	521
ICON HISTORY	447
ICON UNDO	441
ICON HEADSET	412
ICON THUMBS DOWN	382
ICON EXPAND	356
ICON GOOGLE	334
ICON UPLOAD	328
ICON SAD FACE	239
ICON STOP	204
ICON CAST	150
ICON PAPERCLIP	139
ICON VOLUME MUTE	77
ICON END CALL	65
ICON VOLUME DOWN	21
ICON CONTRACT	19
ICON VOLUME UP	14
ICON MIC MUTE	13
ICON ASSISTANT	4
TOTAL	**353,171**

Table 4: Number of instances for each icon class for the *Icon Shape* annotations.

Shape Class	Semantic Class	Count
ICON X	CLOSE	8,899
	DELETE TEXT	1,163
	MULTIPLY	50
	OTHER	840
ICON ARROW UPWARD	CAPITALIZE	154
	OTHER	915
ICON MAGNIFYING GLASS	SEARCH	10,243
	ZOOM IN	142
	ZOOM OUT	92
	OTHER	331
ICON UNDO	REPLY	113
	UNDO	109
	BACK	101
	OTHER	115
ICON REDO	SHARE	354
	REDO	63
	OTHER	117
ICON THREE BARS	MENU	11,929
	OTHER	1,329
ICON PHONE	CALL	729
	CHAT APP	530
	PHONE APP	89
	END CALL	12
	OTHER	571
ICON CHAT	CHAT APP	530
	WHATSAPP	120
	FACEBOOK MESSENGER	61
	OTHER	4,663
ICON CAMERA	INSTAGRAM	192
	OTHER	1,884
ICON PLAY	PLAY	4,452
	PLAY STORE	782
	YOUTUBE	356
	OTHER	1,846
ICON THREE DOTS	MORE	14,285
	OTHER	785
ICON PLUS	ADD ITEM	7,170
	EXPAND	396
	OTHER	2,244
TOTAL	**-**	**78,756**

Table 5: Classification of *Icon Shape* classes into semantic classes.

Class name	**Count**	**# with text labels**	**% with text labels**
Icon	252,342	57,716	22.87%
Text Field	16,131	3,292	20.41%
Check Box	5,958	3,723	62.49%
Radio Button	2,558	1,659	64.86%
Total	**276,989**	**66,390**	**23.96%**

Table 6: *Label Association* task statistics indicating the overall counts of the different classes and the frequency with which text labels are associated with them.

	Icon Shape		Icon Semantics		Label Association	
Backbone	mAP	mAP@0.5IOU	mAP	mAP@0.5IOU	mAP	mAP@0.5IOU
ResNet-101	32.07	65.72	**25.33**	**53.59**	34.70	73.37
Inception ResNet	31.61	70.14	25.17	53.36	36.63	75.19
ResNet-101 with FPN	**34.60**	**70.24**	25.34	53.17	**36.90**	**75.75**

Table 7: Object Detection model performance for Faster R-CNN based models with different backbone networks. The numbers in bold indicate the backbone with the best mAP@0.5IOU for the task.