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Protecting Blind Screen-Reader Users From Deceptive Content

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Motivation

- Blind users are dependent on Screen Readers
- Visual cues are not usable
- One dimensional method of navigation
- Leads to
    - Sketchy sites
    - Unsafe downloads
- Nothing currently available to help

Existing Works

Existing works are mainly focused on visual accessibility like alt text using automatically created image captions as described in the first article below

Many articles did not look into something for the user to use, rather running many different experiments to find what is inaccessible, and then depending on website developers to make the changes for a site to be accessible as shown in other 2 articles

Auto-Parsing Network for Image Captioning and Visual Question Answering Xu Yang, Chongyang Gao, Hanwang Zhang, Jianfei Cai; Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2021, pp. 2197-2207

Moving toward a universally accessible web: Web accessibility and education Serhat Kurt , PhD
https://doi.org/10.1080/10400435.2017.1414086

Alnfiai, Mrim, and Wajdi Alhakami. "The Accessibility of Taif University Blackboard for Visually Impaired Students." International Journal of Computer Science & Network Security 21.6 (2021): 258-268.

Solution

Built an intelligent browser extension to help users identify deceptive items (unintentional or intentional)

Tasks

- Data set construction
- Machine learning classifiers
- Refine ML Algorithms and classifiers
- Future: Integration into browser extension

Methodology

1. Navigated websites using the NVDA screen reader
2. Marked in the website where items are not entirely clear when read by the screen reader
3. Built a dataset
    1. Gathered a variety of 62 websites - news, stores, articles, blogs, travel
    2. Tagged 574 total data points with 286 “data-attribute=’deceptive’” and 288 “data-attribute=’nondeceptive’”
4. Using the data-attributes, BeautifulSoup, and strings, wrote code to export features to a csv

	pAlt	pKeyword	lengthAlt	pVideoTa	code
0	1	0	268	1	0
1	1	0	97	0	0
2	1	0	143	0	0
3	1	0	167	0	0
4	1	0	71	0	0
5	1	0	60	0	0
6	1	0	68	0	0
7	1	0	49	0	0
8	0	0	0	0	0
9	0	0	0	0	1
10	0	0	0	0	1
568	0	0	0	0	1
569	0	0	0	0	1
570	0	0	0	0	1
571	0	0	0	0	1
572	0	0	0	0	1
573	0	0	0	0	1
574	0	0	0	0	1

Feature Engineering

Features for classifiers were handcrafted based on manual analysis of deceptive content

Presence of alt text

Presence of keywords

Length of alt text

Presence of video tag if video graphic

Presence of close(x) ad button with no alt text

Redirect url to different page/domain

Text length in picture

If text is present in the picture

Keywords in image text

Presence of the blue > ad symbol

Size/dimensions of image

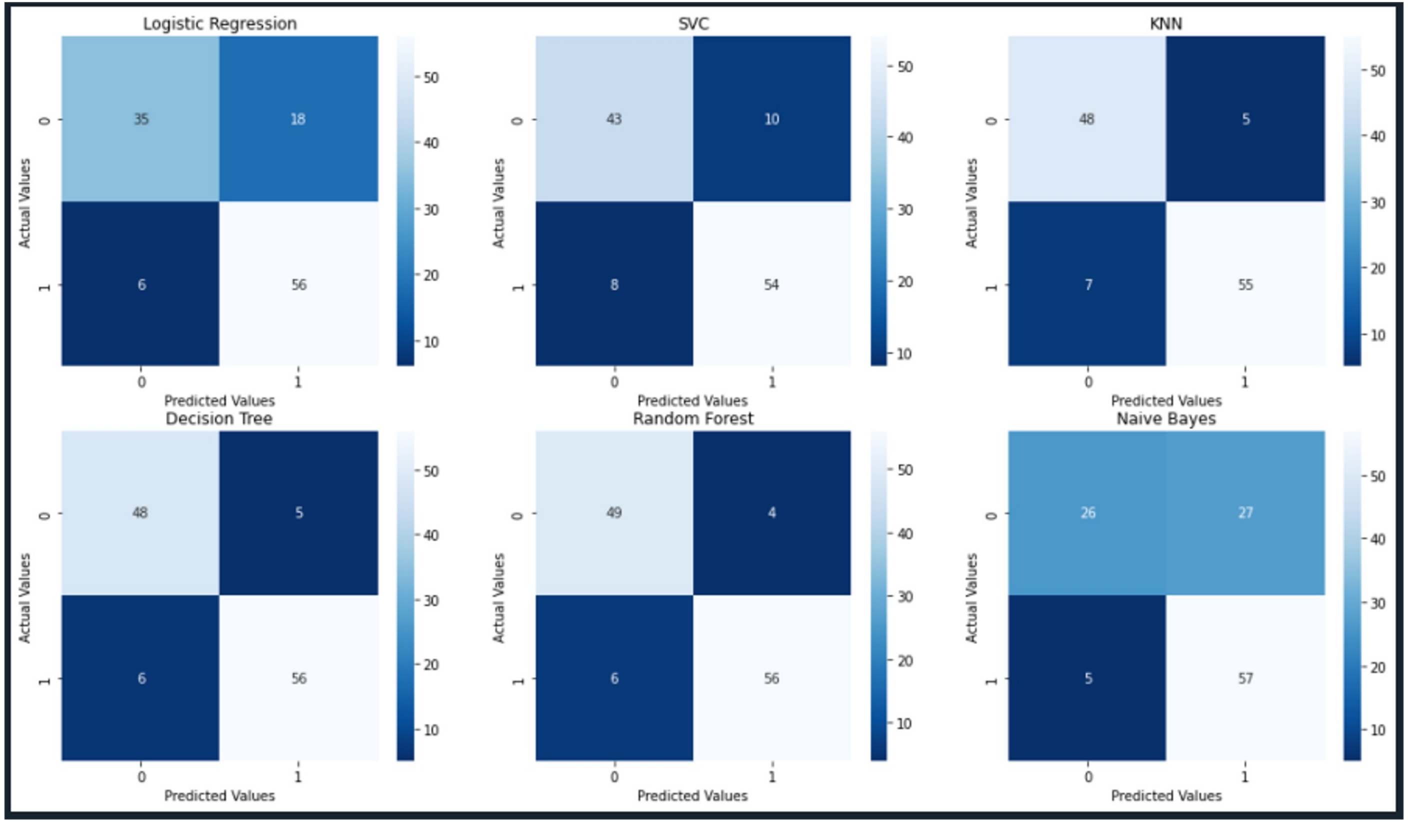
Machine Learning algorithm

- Used sklearn to split the full dataset into training and testing
- Using 6 different algorithms from the Scikit-Learn Python Machine Learning Library to evaluate the dataset
  - Logistic Regression, SVC, KNN, Decision Tree, Random Forest, Naive Bayes
- Use classification_report for each to get precision, regression, and f1
- Create confusion matrices to visualize which algorithm is best for this dataset
- Output a table of the accuracy and AUC for each algorithm

	Model	Accuracy	AUC
0	Logistic Regression	0.791304	0.78
1	SVC	0.843478	0.84
2	KNN	0.895652	0.90
3	Decision Tree	0.904348	0.90
4	Random Forest	0.913043	0.91
5	Naive Bayes	0.721739	0.70

ML results

Training and Testing sets



Classification Report for Logistic Regression

	precision	recall	f1-score	support
0	0.85	0.66	0.74	53
1	0.76	0.90	0.82	62
accuracy			0.79	115
macro avg	0.81	0.78	0.78	115
weighted avg	0.80	0.79	0.79	115

Classification Report for SVC

	precision	recall	f1-score	support
0	0.84	0.81	0.83	53
1	0.84	0.87	0.86	62
accuracy			0.84	115
macro avg	0.84	0.84	0.84	115
weighted avg	0.84	0.84	0.84	115

Classification Report for KNN

	precision	recall	f1-score	support
0	0.87	0.91	0.89	53
1	0.92	0.89	0.90	62
accuracy			0.90	115
macro avg	0.89	0.90	0.90	115
weighted avg	0.90	0.90	0.90	115

Classification Report for Decision Tree

	precision	recall	f1-score	support
0	0.89	0.91	0.90	53
1	0.92	0.90	0.91	62
accuracy			0.90	115
macro avg	0.90	0.90	0.90	115
weighted avg	0.90	0.90	0.90	115

Classification Report for Random Forest

	precision	recall	f1-score	support
0	0.89	0.92	0.91	53
1	0.93	0.90	0.92	62
accuracy			0.91	115
macro avg	0.91	0.91	0.91	115
weighted avg	0.91	0.91	0.91	115

Classification Report for Naive Bayes

	precision	recall	f1-score	support
0	0.84	0.49	0.62	53
1	0.68	0.92	0.78	62
accuracy			0.72	115
macro avg	0.76	0.70	0.70	115
weighted avg	0.75	0.72	0.71	115

ML - Current Focus

Hyperparameter Tuning

```
0.9217391304347826
{'n_estimators': 1600, 'min_samples_split': 10, 'min_samples_leaf': 1, 'max_features': 'auto', 'max_depth':
80, 'bootstrap': True}
              precision    recall  f1-score   support

           0       0.92      0.91      0.91        53
           1       0.92      0.94      0.93        62

    accuracy                           0.92       115
   macro avg       0.92      0.92      0.92       115
weighted avg       0.92      0.92      0.92       115
```

Analysis

Common reasons why it was incorrectly classified:

- Data point is row of only 0
  - Nondeceptive because of additional features not used due to time constraints
- Deceptive data point with one of the other features having a value other than 0
  - Deceptive even with that feature as a lack of another feature or description makes it unclear
- Non-exhaustive list of keywords

Additional hyperparameter tuning would be needed to truly see the best model

Future Work

- Add computer vision and deep learning to deal with other features such as redirect urls and image processing
- Expand the features to increase the accuracy and scope of the model
- Expand the dataset
- Create a chrome extension to mark deceptive content for screen readers
- Evaluate extension in a user study
- Prepare a manuscript for submission to a conference