Intelligently Identifying and Locating Electronic Components in Power System Circuit Diagrams

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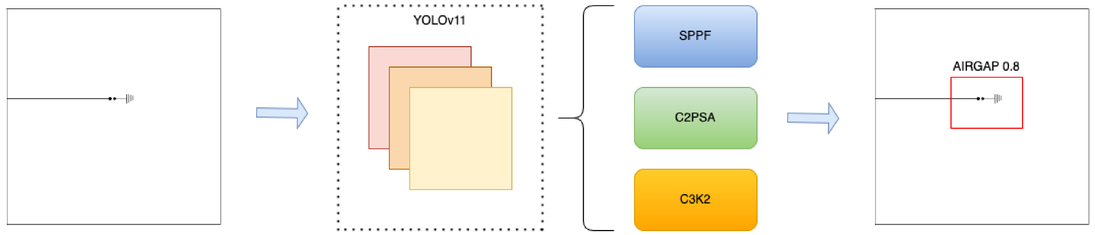
Problem Statement

- Given the large volume of diagrams handled by power companies, manual analysis is often inefficient and error-prone.
- Existing software tools:
  - Prone to human error
  - Contract driven services
  - Reliance on trained staff
- By leveraging artificial intelligence and image processing techniques, this project seeks to build a machine learning model to detect various components within these diagrams. This approach will enhance efficiency in power system design, planning, analysis, and troubleshooting.

Project Method

- The SPPF layer detects components at various scales, ensuring accurate identification of both small and large objects.
- The C2PSA layer focuses on the most important details of the image, while filtering out irrelevant areas to improve precision.
- The C3K2 layer accelerates the processing time without compromising accuracy, enabling real-time performance.
- The model outputs a label for the detected component, assigns a confidence score, and draws a precise bounding box around it.



Future Work

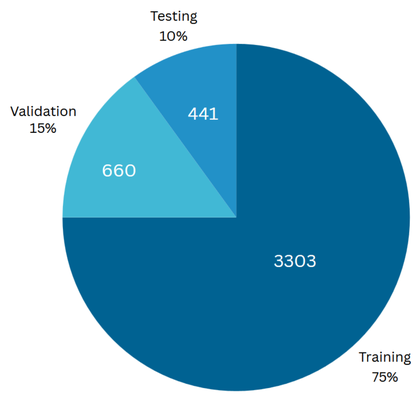
- Expand the model to gather information from the diagrams regarding location
- Further increase the size of the training dataset in number of images
- Provide information on multiple components within a complete diagram

Challenges and Limitations

- Computational power: Model training is resource-intensive, typically taking 30 minutes on a GPU within our scope.
- Dataset size: More data could be collected for training on other standards of component design styles.

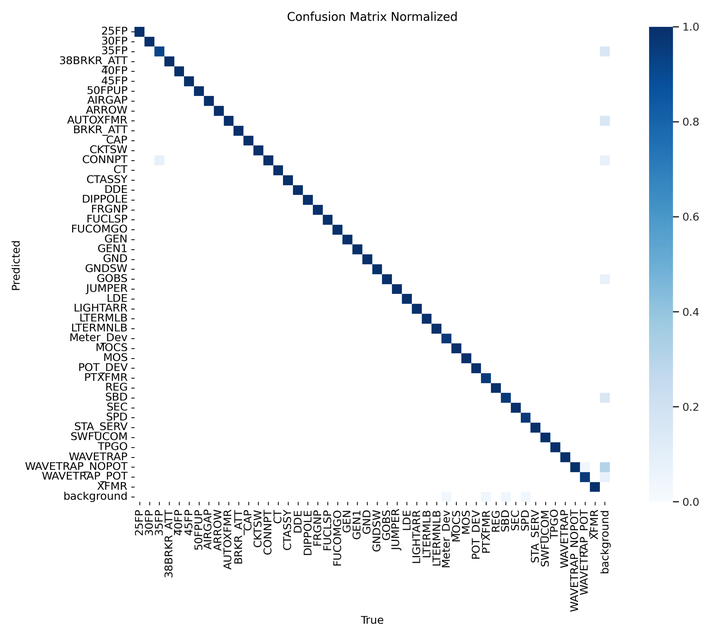
Data

- The dataset was split into test, train, and validate sets with 47 unique components.



Model Output

Class	Images	Instances	Box(P	R	mAP50	mAP50-95):
all	660	660	0.959	0.983	0.991	0.695
25FP	5	5	1	0.87	0.995	0.735
30FP	8	8	0.953	1	0.995	0.672
35FP	4	4	0.45	1	0.995	0.73
38BRKR_ATT	10	10	0.963	1	0.995	0.76
40FP	6	6	0.945	1	0.995	0.824
45FP	7	7	0.954	1	0.995	0.774
50FPUP	12	12	0.969	1	0.995	0.841
AIRGAP	7	7	0.992	1	0.995	0.792
ARROW	20	20	0.921	0.95	0.946	0.615
AUTOXFMR	18	18	0.981	1	0.995	0.804
BRKR_ATT	27	27	0.988	1	0.995	0.666
CAP	15	15	0.978	1	0.995	0.637
CKTSW	15	15	0.976	1	0.995	0.725
CONNPT	17	17	1	0.734	0.995	0.666
CT	20	20	0.984	1	0.995	0.671
CTASSY	12	12	0.952	1	0.995	0.767
DDE	19	19	0.977	1	0.995	0.666
DIPPOLE	16	16	0.982	1	0.995	0.71
FRGNP	9	9	0.969	1	0.995	0.699
FUCLSP	13	13	0.974	1	0.995	0.726
FUCOMGO	11	11	0.979	1	0.995	0.616
GEN	8	8	0.949	1	0.995	0.74
GEN1	18	18	0.977	1	0.995	0.78
GND	17	17	0.982	1	0.995	0.541
WAVETRAP_POT	17	17	0.897	1	0.995	0.902
XFMR	16	16	0.98	1	0.995	0.773



Technology Stack

python™

PyTorch

ultralytics YOLO

AutoCAD

VCU College of Engineering