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Reducing Appliance E-waste by Generating Repair Schematics Directly from Photos With CNN-GCN

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ABSTRACT: The repair of electronic appliances is often hindered by the lack of available circuit schematics, leading to unnecessary waste and environmental harm. While right-to-repair legislation has improved access to repair services, circuit-level diagnostics remain challenging, contributing significantly to electronic waste (e-waste). This paper hypothesizes that circuit schematics can be generated from PCB images to assist in repair and introduces *Appliance X-ray*, an AI-driven system designed for this purpose. Inspired by medical X-rays that help doctors diagnose patients, *Appliance X-ray* extracts and reconstructs schematics from PCB images, making circuit structures more interpretable. The system employs a YOLOv5 convolutional neural network (CNN) to detect circuit components, followed by k-nearest neighbors regression to predict missing elements based on inferred circuit functionality. A novel graph convolutional network (GCN) is then used to analyze component relationships to reconstruct the schematic. Additionally, human-in-the-loop feedback refines model predictions, enhancing future iterations. Experimental results demonstrate the effectiveness of this dual CNN-GCN model in identifying components and inferring connections, while also contributing a novel, scalable dataset of circuit schematic graphs derived from both real and synthetic data to support future research in circuit analysis and repair automation.

KEYWORDS: Robotics and Intelligent Machines, Machine Learning, Inference Model, Regression, Graph Convolutional Network.

Introduction

Initial Problem:

Around 62 million metric tons of e-waste are generated globally each year, of which small appliances contribute significantly. Such e-waste contains toxic substances like mercury, lead, and cadmium, which can leach into the environment and pose serious risks to human health, including neurological damage and cancer.[1] Small appliances could be repaired or refurbished rather than discarded, especially after the implementation of right-to-repair legislation such as California SB-244. This bill grants consumers the right to service-related literature and parts by mandating appliance producers design appliances with repairable features and release appliance-level designs.[2] However, waste trends continue as many appliances remain in landfills. Previous attempts at containing waste (landfills) will eventually fail due to the finite space on a finite planet where humanity resides. Extrapolating the status quo of appliance waste leads to worrying thoughts about the dwindling space of humanity's only home.

Partial Solution:

Appliance repair is a promising avenue in reducing appliance waste. This method not only directly reduces waste in landfills but also provides valuable vocational training opportunities and lowers appliance costs.[1] In finding the motivations behind choosing repair for consumers and professionals, Torca-Adell *et al.* found that while appliance failure was common for appliances in domestic and professional use, habits among this base trended towards replacement instead of repair as an alternative. Torca-Adell *et al.* identify that the economic nonviability of repair is a significant factor in consumers not choosing repair over replacement.[3] Such nonviability can be attributed to the complex structures within the circuitry of appliances, increasing the difficulty of repair and thereby indirectly increasing time spent and costs. Failing to gauge the complexity of a circuit can also result in bodily harm to repair technicians due to the presence of high-voltage components. Without a proper avenue for determining the composition of a circuit and its connections, the opportunity cost of purchasing another device often outweighs a lengthy, dangerous, and potentially impossible repair.

Companies such as iFixIt have identified this lack of accessible repair as a potential market. This company specifically has released a multitude of appliance-level schematics and their corresponding repair guides, improving the probability of repair and efficiency of fixing an appliance.

Further Problem:

However, main control board failure and various other circuit-related breakages within appliances, while common, are unable to be fixed with appliance-level repairs due to the difficulty in managing the complex connections within a circuit without knowledge of its interior. Even in appliances documented by the iFixIt platform, where circuits are available, the common recommendation for circuit-level failures is the abandonment of repair – a situation that becomes more inevitable when the model of the appliance is unknown as well.

Past attempts have been made at improving the quality and efficiency of circuit-level repair based on technological solutions with text input. Notable examples of such AI-based circuit design assistants include Flux AI, which focuses on assisting circuit design through large language model (LLM) features.[4] As the focus of such tools is primarily oriented towards circuit defect identification, the scale of their work is confined to manufacturing quality assessment and not the schematic generation used for repair. However, current programs rely solely on text input to generate circuits and cannot accept visual input, limiting their utility in the generation of desired circuit schematics from a photo. This input structure prevents large benefits in appliance repair when visual and not text data is available to the technician. Existing technologies for recreating circuit schematics from Gunay and Koseoglu that utilized a CNN (R-CNN) to determine circuit components from an image were able to do so, yet did not determine PCB top-layer and discrete connections.[5] The presence of discrete connections in PCB boards causes purely visual methods to be unable to reconstruct a circuit diagram from an image, due to connections being hidden under multiple layers of opaque material. Therefore, the creation of a system with the capability of improving the quality and likelihood of circuit-level repairs by providing repair schematics fills a useful niche, continuing successful trends in appliance repair.

Goal:

It is hypothesized that the most direct implementation of this goal would involve the creation of a circuit schematic to identify possible points of failure unknown in previous systems. Creating a circuit's schematic from a photo, the most likely available information is a step towards the final goal of eliminating appliance waste by resolving circuit-level repairs previously untouchable with traditional technology. The success of this program will be gauged by the accuracy and precision of identifying circuit components and whether or not it is able to identify circuit-level connections.

Methods

Proposed Method:

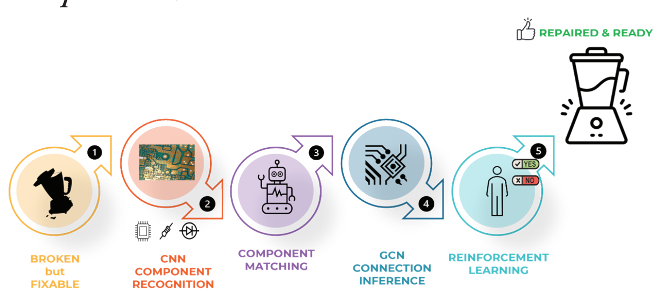

Figure 1: The general workflow of the CNN-GCN system, which takes in an image to output it as a schematic for repair. A photo of an appliance circuit is taken, where the components are individually identified with a CNN and used to infer the general purpose of the circuit. Afterward, "missing" components based on the circuit's purpose are added to the list of circuits, with the likely connections between components identified with a GCN system and sent to the user for a final evaluation. The user identifies the components and connections considered correct, which can then be reinput into the component and connection inference models for future training. Icons from PowerPoint, Author, and Flaticon.

The finalized method, demonstrated in Figure 1, aimed at creating a circuit schematic as an output to an input of a circuit image revolved around a three-step process of circuit component identification, inferring circuit purpose, and inferring component connections. The program accepts an input of a circuit image, which is then processed by a YOLOv5 CNN model to identify circuit components. The component type and position are identified, with its centroid indicated on a coordinate plot using the Matplotlib and Networkx libraries. With this plot completed, a matching algorithm finds the closest matching circuit in a dataset of circuit schematics to the plot of components identified. The purpose (e.g., toaster) of the closest matching circuit is attached to the current plot of components as its inferred purpose, with key missing components inserted into the existing patchwork of component nodes. A human-in-the-loop now has the option to confirm or deny insertions by the matching algorithm. Afterward, a GCN trained on various circuit connections infers the connections between individual circuit components based on their type and proximity. The finalized schematic is then output to a human-in-the-loop, who selects the connections amongst the list of inferred connections.

CNN:

For this project, Thoma *et al.*'s ground truth CGHD circuit schematic dataset and Nayak's PCB component dataset were consulted.[6,7] Thoma *et al.*'s dataset consisted of 1152 schematics of 144 circuits, with individual electrical components as well as important connections like junction points indicated with a bounding box to represent their size and position. This dataset was used to train CNN models to identify circuit components among the forty-five given classes. Similarly, Nayak's dataset of circuit images was also used to train CNNs in the identification of circuit components, albeit using real circuit images. Nayak's dataset has more direct utility in the identification of circuit components and was used as the training dataset during the CNN model creation.

The results of the YOLOv5 CNN circuit detection model were produced after training with the Nayak circuit dataset. The confusion matrix, F1 score, precision and other metrics are shown below.

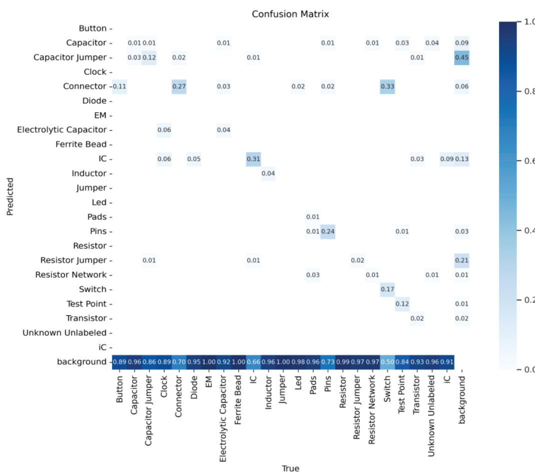

Figure 2: The confusion matrix of the YOLOv5 circuit component identification model. True positives are shown in the left top-to-bottom diagonal, and all others on the sides. The number in each box represents the proportion of tests that fit the above description. While a false negative rate is high for nearly all components, these false negatives are not the result of systematic bias but components being misclassified as the circuit background. This enables future work focused on inference models and matching to infer the existence of these “missing” components to be done. Information created from a train/valid/test split of 106/35/10 images. From the author.

The confusion matrix, Figure 2, shows that out of all components, the highest probability of its classification is as part of the background. Out of all components, the IC has the highest probability of being classified correctly, at 31%. The most common misclassification for each component is being identified as a portion of the background (not being classified).

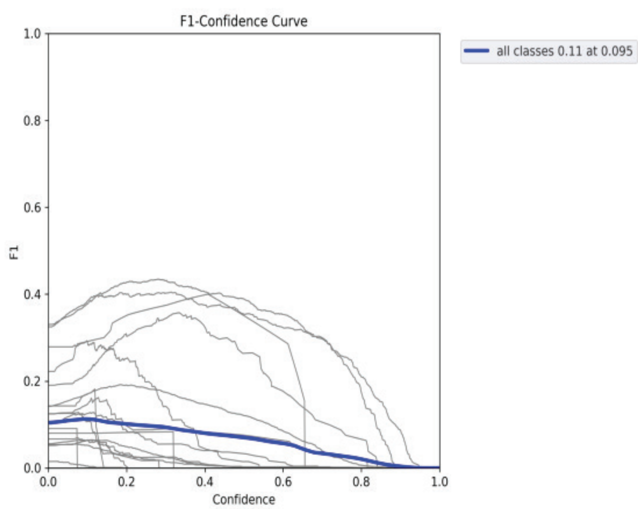

Figure 3: The F1-confidence of the YOLOv5 network after training, a measure of predictive performance. Trends in the F1-confidence curve show an acceptable rate of predictive performance, especially considering how misclassifications are mostly due to classifying components as part of the background. Each individual line shows the F1 score (how well data is classified, with a higher score being better) at a certain confidence level (how confident the model is in what a component is). Each individual line represents an individual component, while the blue line represents the aggregate F1 confidence of all components. The F1 staying consistently under 0.4 mirrors the information acquired from Figure 3’s confusion matrix. From the author.

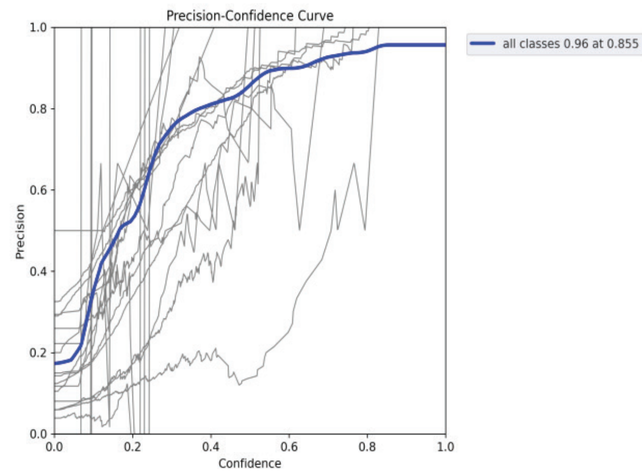

Figure 4: The precision-confidence curve of the YOLOv5 component identification network during training, used to measure true positive rate. The precision stabilizes at around 0.95 after 0.8 confidence, showing a high rate of stability in the model’s predictions. Precision is a measure of variation, with a higher precision meaning less variation. Each individual line represents how precisely a component is classified with set confidence, with the blue line representing the aggregate of all components. Source: author.

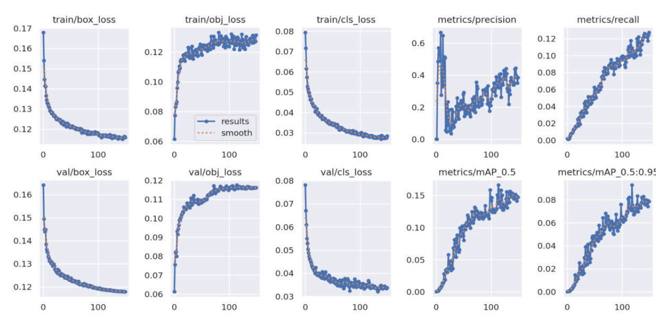

Figure 5: A list of metrics regarding the usability of the YOLOv5 component identification model. The x-axis is the number of epochs. Train/box_loss, train/obj_loss, and train/cls_loss describe the loss function of the model during training and are measures of the model’s difference between predictions and the ground truth. Val/box_loss, obj_loss, and cls_loss describe the validation model’s loss and the results produced by the model when used on the validation dataset split from the training data. Lastly, the metric parameters precision and recall describe ratios of true positives to total predictions or relevant items. mAP is the mean average precision, or the average precision of the model when identifying all classes of components. With more training, it is expected that loss decreases and mean average precision increases, with the box (position) loss, classification loss, and mean average precision all following the set pattern. However, object loss increases with training, going against the expected pattern. More research is required when examining object loss.

Overall, Figure 3 demonstrates a negative linear relationship with the mean aggregate F1 score of the model and confidence, while Figure 4 demonstrates a logarithmic relationship of the mean aggregate model precision and confidence. Figure 5 demonstrates that the YOLOv5 model can stabilize the precision of its predictions at around 0.4 and reduce the loss to around 0.1.

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GCN:

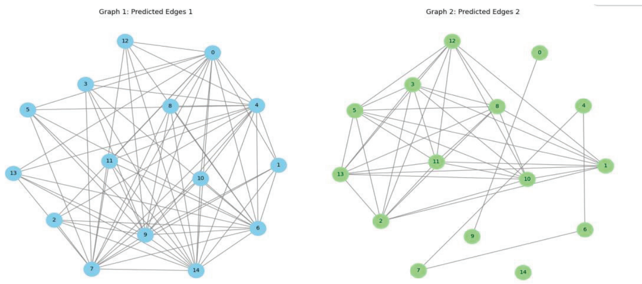

Figure 6: An example output of the GCN algorithm after an input of a list of components. Each node represents a component, while each line represents a likely connection between them. The set of blue connections on the left is inferred from a standard GCN, while the predicted edges on the right are inferred after a cosine similarity filtering algorithm. Such a list of nodes and connections can be input into a computer-aided design tool to output the list in human-readable schematic form. There are significantly fewer connections inferred after the cosine similarity filtering algorithm, showing potential in its usage in terms of saving time while maintaining accurate predictions. From the author.

The node maps displayed in Figure 6 are the outputs of the GCN model after an input of a list of nodes. Each node represents an identified component, while each line represents a connection between two components. The map on the left is the result of a standard GCN inference, while the map on the right is the result of a filtered set of connections after a cosine similarity function. The cosine similarity filtering significantly reduced the total number of inferred connections, with the raised threshold removing many extraneous connections from certain nodes (e.g., 14). Specifically, components like node 14 vary greatly in connections due to it being a misclassified IC, confusing the GCN model. After the usage of a cosine similarity filtering model, the low confidence of all connections with node 14, due to its misclassified nature, leads to no expected connections. The lack of connections that should not exist is an indication that the model is functioning properly. These example maps point to the trade-off between inference count and precision when setting thresholds for confident connection inference.

■ Result and Discussion

Component Identification:

The usage of a CNN model in identifying circuit components was viewed as the most direct alternative to combined identification models reliant on stable diffusion or GAN, due to its prevalence in similar alternative identification processes (e.g., facial recognition), as well as Gunay and Koseoglu's work in proving the efficiency of identifying circuit components with an R-CNN.[5] For this reason, the mature YOLO series of CNN models, specifically YOLOv5, was chosen to identify circuit components in the final iteration of this project for its versatility and accuracy. The Nayak dataset of circuit images was fed into the YOLOv5 model via the Roboflow platform and showed acceptable accuracy. However, one disadvantage of using the Nayak dataset for training appliance circuit recognition is its composition. While the Nayak dataset is composed primarily of circuits with surface-mount devices (SMDs) and ICs with multiple layers (discrete components), common appliance circuits are usually single-layered PCBs with few/no discrete components. This leads to a difference in the training dataset and the type of circuit the system is supposed to identify.

Preliminary testing has shown that this composition has a slight negative impact on the identification of components in appliance circuits and could be a point of future research.

A k-nearest-neighbors (kNN) regression algorithm would be able to identify potential missing components in the predicted position of the input circuit, based on an inferred purpose of the component list. Past research by Goyal *et al.* has proven that such kNN methods are effective in similar use cases.[9] The kNN method is currently a successful example of inserting missing components, although alternative methods, including a direct component list comparison as well as alternative weighting within the kNN, are being assessed. The matching program works as a complement to the connection inference system, as a minor difference in circuit component composition could mean deviations from a general template in terms of connections, despite having the same general purpose. This leads to a potential for confusion in the matching algorithm if it is responsible for inferring a circuit's purpose, missing components, and potential connections at once. A human-in-the-loop system could increase the accuracy of the matching program. Users will confirm or deny the inferred circuit's purpose and missing components, and send them back to the matching program for training in future iterations. Synthetic data of circuits could also be generated to increase the amount of training data available to both the component and connection determination programs.

Connection Inference:

Circuit boards often have discrete connections due to their multilayered structure, making visual detection of connections impossible. The workaround to this limitation found in pure-visual systems proposed is a novel GCN-based approach, a research first (to the best of the author's knowledge). This system would be trained with datasets of circuits involving the types of nodes and their corresponding connections. Unlike previous approaches, GCN systems can deliver probabilistic calculations of each circuit's component-level connections due to the usage of a probabilistic neural circuit (PNC). Following normalization by a leaky ReLU algorithm, components with sufficiently high confidence levels are sent to the user for final inspection. This final human-in-the-loop phase reduces the impact of misidentified connections by leaving final decision choices to the user. The use of a human-in-the-loop system could also allow for negative inferences (least likely connections) to be identified and fed back into the model to improve future iterations, while also allowing for decision responsibilities to be left to the user as an independent agent.

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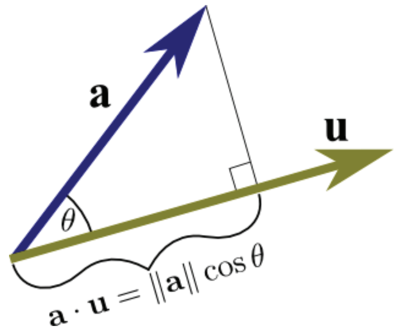

Figure 7: The vector dot product formula. This gives a score that can measure the likelihood of circuit connections when the GCN represents each component and its connections to other components as a vector. Source: Math Insight.[11]

Representing each component as a multi-dimensional vector, displayed in Figure 7, is the operating principle behind the GCN. The GCN is first trained using data, including the connections between each component. After the training, the GCN accepts an input of a list of circuit components, embedding the vector representation of connections for each node. Out of the n choose two connections possible in n components, and the dot-product of each component is calculated. If the dot product of the connection is over a set threshold of 0.5 (1 is most likely, 0 is least likely), the connection is inferred as a possible connection by the GCN. By utilizing this dot-product threshold algorithm, a mathematical model of gauging uncertainty is developed, forming a quantitative gauge of an inference's probability. This operating principle is the same for many other AI use cases, including Retrieval-Augmented Generative (RAG) models,[12] for the improvement of overall accuracy. The GCN used for this project operates with a nine-dimensional vector initially, reducing the complexity of the multi-dimensional vectors required if no component pre-processing is done.

The creation of a "net" component prevents the concentration of multiple disconnected power sources or alternative signals connected to different pins on the same component from converging on the same point, increasing the accuracy of the inference model. Lastly, the presence of a human-in-the-loop not only prevents a significant impact of erroneous identifications and connections but also provides the potential to increase the limited training data of this model to improve future iterations. Every time a user uses the system, an input of novel circuit data, as well as a schematic, made from the user's selections of connections from a list of suggestions, will be generated. Such data could be added to the training dataset for the sake of reinforcement learning.

This design implements a variety of methods to increase the accuracy of the inference model. Firstly, the implementation of the similarity matching model is done to make up for inevitable misidentification by CNN. The complex structure of circuits, coupled with the substantial number of components present, makes the perfect identification of all components difficult. The similarity matching model makes up for this imperfection by ensuring that key components are inserted properly into the circuit schematic, even if not properly identified by the CNN. A human-in-the-loop can also prevent erroneous insertions from being made.

Despite the capabilities of the GCN system, the wide range of connections provides a wide range of confidence for each one. This required all connection confidences to be normalized using the sigmoid function, with a threshold for determining a connection either set manually or as the mean confidence of all confidence values. The sigmoid function can remove most variances in confidence values; however, the data produced has a strong left skew and results in high confidence for all expected connections. This skew may be the result of the vector representation of connections only having nine dimensions, while previous implementations had thousands of dimensions, leading to unnaturally high levels of confidence. Such a distribution makes the true confidence threshold hard to set, with the current manual confidence of 0.99999 being chosen as a heuristic value. Human-in-the-loop corrections are likely to improve the current model by lowering variances through more training data; however, the sigmoid function is the current necessary stopgap before then. Future work will likely involve changing the sigmoid function to another for the sake of more normalized confidence values.

Conclusion

This CNN-GCN system shows potential in both the identification of circuit components and circuit connections as a probing study. The model can identify circuit components, with missing key components filled in through inference by a similarity matching algorithm. The inference-based GCN system used to infer component-level connections is also promising in detecting erroneous and unlikely connections. Lastly, this project creates a novel method in the uncommon practice of PCB to schematic translation as circuits are usually created from schematics.

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