2

working paper series: street level imagery

Street Level Imagery
for Machine Learning

2.1 Introduction

In early recovery, local responders operate under pressures from residential communities facing damage and destruction, as well as federal organizations and aid programs demanding damage reports. While one lever asks for help, the other demands information about damage through reporting. The two stand at odds with one another until damage is captured, documented, and processed. Typically, damage assessments are lengthy processes that require immense coordination and support. Assessors and emergency responders who conduct damage assessments travel to each household in a community to assess damage in person. The amount of time it takes to conduct door-to-door assessment is exhaustive, and the practice of locally administered damage assessments is unclear, nonuniform, and frequently biased.

Prolonged damage assessments not only prevent aid or support from timely distribution to residents in need, they also neglect to capture crucial data on damage. The inaccessibility of damage data is known as perishability. Perishable data is the loss of information, and its value, over time. For damage assessment practices, damage information is invaluable because it expresses the severity of harm and destruction. When people work quickly to repair their homes, information about a broken window or concave roof is lost. Altogether, manual damage assessment practices create data collection and resource distribution problems. These problems stall aid and resource allocation but inevitably provide insight about structural damage. In this light, damage assessments can assist and hinder recovery efforts.

New techniques are being developed to streamline damage assessment processes through data-driven tools. Researchers at the National Disaster Preparedness Training Center (NDPTC) are developing a new non-invasive tool known as the Rapid Integrated Damage Assessment (RIDA). The goal of this tool is to alleviate the tension between time, damage data, and local recovery needs through innovative machine learning applications. To do so, the RIDA model integrates whole image classification through machine learning algorithms to efficiently analyze household or building level damage. In this application, the use of machine learning helps (1) promote the rapid capture of perishable street-level data, (2) analyze damage severity quickly, and (3) reduce local burdens for assessment.

2.2 The NDPTC Model

As it stands, the NDPTC RIDA model currently uses the latest version in a series of object detection models known as YOLOv5. YOLOv5 is a machine learning algorithm that reviews data such as street level imagery to detect objects within the data. The purpose of integrating any machine learning algorithm into damage assessments is to preserve and capture on-the-ground data of damage and to assess severity levels. Further, the specific purpose of YOLOv5 is to capture. and store street level imagery while detecting damaged structures.

YOLOv5 balances fast processing speeds and high accuracy. The YOLOv5 model analyzes the data to detect damage on a scale from no damage,moderate damage, and severe damage. Researchers at the NDPTC use these three categories to train the machine learning algorithm without defining or describing classification categories. Each image is labeled according to perceived damage level based on information from the entire photo. The YOLOv5 model learns how to detect damage based on inconsistent whole image classification. After the model assesses damage severity levels based on annotated, whole images, the results can be communicated with local communities, disaster response professionals, and federal organizations more quickly than manual assessment.

2.3 Alternative Models

Although YOLOv5 is the machine learning model currently being employed in RIDA, it is not the only algorithm that can be leveraged. Other popular machine learning algorithms include Grad-CAM, Mask R-CNN, and Lobe.ai. Each algorithm relies on different learning techniques than whole image classification.

Grad Cam *(Image 2.1)*
Grad-CAM, also known as Gradient-weighted Class Activation Mapping, uses pixelated color gradients of objects or regions to detect their location and/or classification. While Grad-CAM has been deployed in many instances for localization and classification, there are no accessible instances of its application for street-level type detection. Grad-CAM appears to be used most frequently with small objects such as medical x-rays and animals.

Image 2.1: Example of Grad-CAM:: Application of pixel gradient maps on houses. Credits to Georgia Institute of Technology and Facebook AI Research.

Mask R-CNN *(Image 2.2)*
The Mask R-CNN model is one of the most robust machine learning algorithms for instance segmentation, as well as classification and localization. Mask R-CNN has extended the usability of other popular networks for "predicting an object mask in parallel with the existing branch for bounding box recognition." The Mask R-CNN model can be trained to detect damage through retailoring introductory tutorials and sample algorithms. For example, one Mask R-CNN algorithm detects and masks street-level data such as cars and houses through videos.

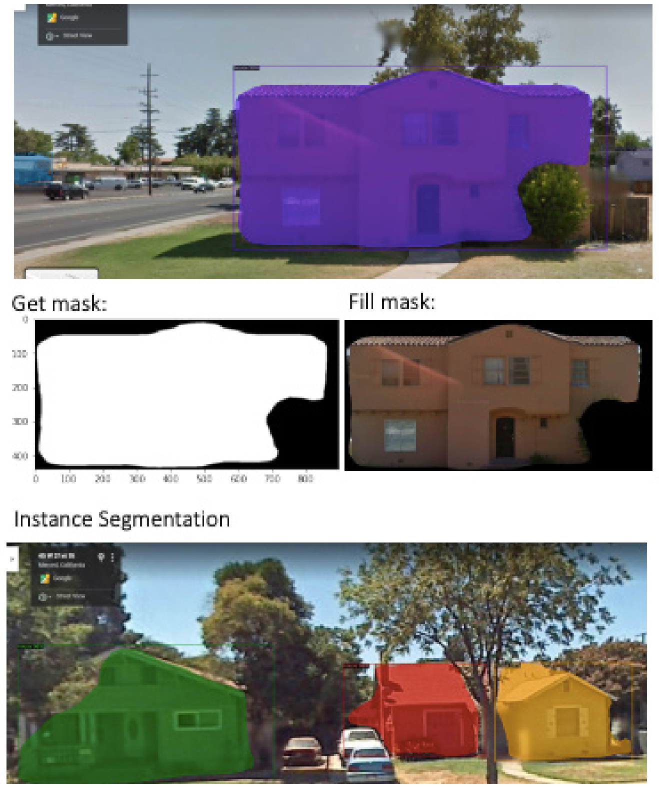


Image 2.2: Example of Mask-R CNN:: Segmentation of Historic Buildings of the City of Merced. Credits to Alberto Valle, Anais Guillem, David Torres-Rouff, PhD.

While many Mask R-CNN applications use binary classification and multi-classification to detect distinctly different objects from an image, there are no current models that replicate the nuances for disaster damage detection. To build a scalable model that incorporates the intricacies of damage detection is resource dependent and timely.

There are also developmental setbacks including annotation and training speeds that hinder the application of Mask R-CNN. Mask R-CNN online annotation platforms are moderately time consuming, taking roughly two hours to properly annotate, label, and download a dataset of only 100 images. The training speeds for Mask R-CNN tend to be much longer, averaging 5 frames per second (fps). For reference, YOLOv5 learns at a rate of 140 fps, which means it processes nearly 30 times more data per second than Mask R-CNN. Despite low fps rates, Mask R-CNN can be pre-trained for future application. Researchers at the NDPTC can prepare a model's algorithm beforehand to share in the future. Therefore, more exploration of testing speeds rather than training speeds on a pretrained Mask R-CNN model is necessary. Instance segmentation overall can increase data capture and generate faster insights on damage severity given a robust pre-trained model. However, for rapid training, deployment, or development, there are notable barriers compared to more basic, simplified models.

Lobe.ai

One last platform worth noting is Lobe.ai, an application that utilizes two machine learning algorithms simultaneously to improve the model's speed and accuracy (MobileNetV2 and Resnet-50V2, respectively). Developing a model on Lobe.ai begins with uploading a training dataset and labeling images via image classification. Lobe.ai continuously runs and updates the model throughout the annotation process. Image augmentation includes adjustments to brightness, contrast, saturation, hue, rotation, zoom, and noise of images. Since training data sets can contain hundreds or thousands of images, mistakes by humans during the classification of images may occur. Lobe.ai's user interface allows for easy review and analysis of those mistakes, and users can easily assess misclassified images even during model training. Machine learning models can be exported to no-code apps from Lobe.ai, such as Microsoft's Power Platform, or as Python-based notebooks. Lobe.ai is currently in beta development and only includes image classification but will release object detection models in the future.

2.4 Further Considerations

For other researchers interested in developing a machine learning damage assessment model, there are a few overarching considerations that contribute to the utilization of YOLOv5 over other described platforms. The key takeaways for a scalable model include the ability to adapt an algorithm, platform(s) accessibility and collaboration, and customization/replication. Video and written tutorials bridged the gap on machine learning coding, as well.

Whole Image Classification

The YOLOv5 model analyzes entire images and labels data using whole image classification. However, images contain much more data than what is being represented through a single label. If an algorithm is trained on whole images, then each pixel in the photo contributes to the algorithm's learning. This means that a YOLOv5 algorithm trained on whole images will detect damage severity levels based on all of the contents of an image. Street level images in particular capture data beyond the building, including other objects such as nearby forestry, shrubs, front yards, the sky, and vehicles. Therefore, machine learning decision making via whole image classification may inflate or deflate key data points outside the scope of structural damage. In the case of Hurricane Ida, the YOLOv5 model was unable to accurately detect damage levels of stilted houses due to potential influences of training data.

Bounding Box *(Image 2.3)*

The YOLOv5 algorithm is adaptable and can also learn to detect objects within a photo based on the bound box method. This method localizes the data inputs through user drawn and labeled boxes. The algorithm's training inputs are no longer an entire image when the bounding box method extracts only specified portions of the image for inputting. In this instance, the ability to detect structural damage to buildings and homes can be exclusively extracted and input into a model given a bounding box around the object. In Image 2.3, YOLOv5 detected a moderate level of damage to the structure. This determination was made because a machine learning algorithm only uses the data inside the bounding box for detection and classification.

Platforms

In addition, free, online platforms aided the process of developing and deploying YOLOv5 by enhancing the reliability of our methods

Image 2.3: Example of Bounding Box:: Implementation of the bounding box method comapred to whole image classification

and ability to test hypotheses. Since there are a few platforms available, the ones that were highly accessible aided the machine learning process through either collaborative annotation methods, succinct storage of data and images, and/or browser-based coding. Platforms like Roboflow allow cohesive annotation and dataset creation with potential extrapolation to different algorithms. Robodlow is a browser-based platform that encourages collaboration to rapidly assemble data sets for machine learning. Google Colaboratory is a platform that hosts many coding languages, and can be run on a web browser rather than a downloadable application. The user interface provides seamless access to strong computational power (GPU's) without any downloads. Altogether, accessible platforms with strong user interfaces increased the overall operating and testing speeds, all while increasing replicability of our methods. There are drawbacks to strictly relying on browser-based platforms such as the interconnected nature of coding. Each platform must grow and develop in tandem with one another, as each piece is essential to the overall machine learning pipeline. When one node changes, the process stops working. Therefore, we also caution that open, public platforms may adapt much faster than implementation of these tools.

2.5 In Application and Practice

FEMA's PDA as Annotation Framework *(Image 2.4)*

The levels of damage assessment outlined by FEMA's Preliminary Damage Assessment Guide *(see Image 2.5)* provide the foundation for street-level machine learning annotations in two primary ways. Firstly, the severity level of damage (i.e., affected, minor, major, destroyed) includes clear instructions on categorizing assessment of both manufactured homes and conventionally built homes. Secondly, the terminology of damage assessment classification in the PDA is the primary source of communicating incident impacts contributing to Presidential disaster declarations decisions. One example of classifying a house as having "minor" damage in the event of a non-flood event is "nonstructural damage to roof components over essential living spaces (e.g., shingles, roof covering, fascia board, soffit, flashing, and skylight)." Incorporating strict guidelines for classifying and annotating images helps reduce the number of cognitive biases introduced to a dataset. In the event of a Presidential disaster declaration, more resources are made available through Federal funding to assist in recovery efforts.

Collecting Imagery from Multiple Sources and Events

Collecting natural disaster damage assessment imagery from multiple sources equalizes the

Image 2.4: FEMA PDA Catergories:: There are four catergories that classify severity of damage. Credit to Federal Emergency Management Agency.

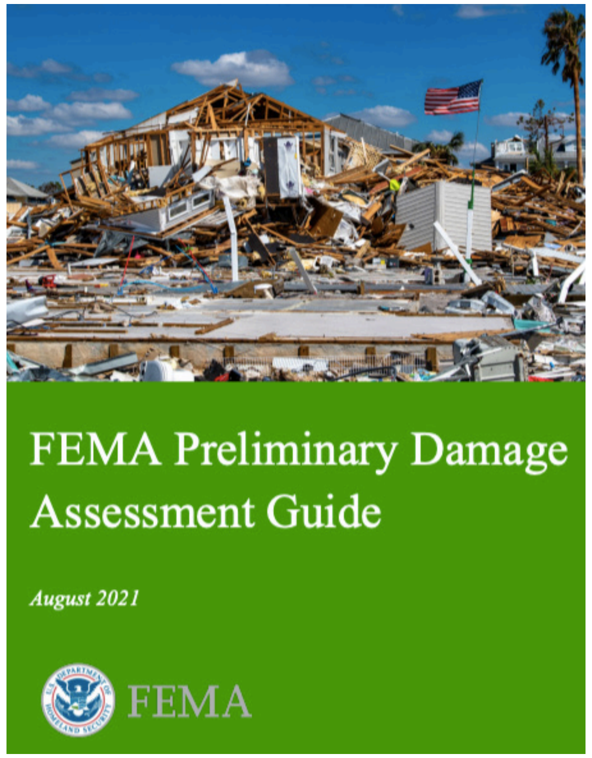


Image 2.5: The federal emergency response agencies damage assessment guidleines. Credit to Federal Emergency Management Agency.

frequency of damage assessment classifications in machine learning training datasets. Images obtained from a single source, such as conventional new media outlets, are designed to tell a compelling story of a natural disaster event. In this case, the likelihood of overrepresentation of more severe damage assessment categories is higher because the most compelling story is where the most damage occurs. In the article *Damage Assessment from Social Media Imagery Data During Disasters*, the authors provide evidence of increasing machine learning accuracy, precision, and recall by combining images from Google searches and multiple events of the same type (Nepal 2015, Ecuador 2016 Earthquakes). To increase machine learning model metrics and create a dataset with equal representation of damage assessment categories, the collection of images for this exploratory research model include:

- Social media platforms (Twitter)
- Open-source databases (Crisis NLP)
- Google images
- Stock photography websites
- NDPTC field visits *(see Image 2.6)*
- University of Michigan field visit
- Conventional local and national media sources for natural disaster reporting

Inspired by the research paper Damage Assessment from Social Media Imagery Data During Disasters and a research inquiry by the National Disaster Preparedness Training Center, this research dataset also includes imagery from different disaster events. This training dataset includes images from multiple hurricanes, earthquakes, and tornados both internationally and within the United States. Damage assessment photos from wildfires are excluded from the dataset due to the overrepresentation of images with live fires present and available through internet-based sources. Including more types and quantity of events in a dataset increases the chances the training images will have an equal representation of classifications. A machine learning model trained only on a Category 5 hurricane will have high precision for categorizing homes with severe damage but will not perform well at identifying lower levels of damage seen in weaker storms. Additionally, a model trained on images from a natural disaster in Louisiana will likely underperform if the model is tested on images from another country because the difference is building architecture is not represented in the training dataset.

Image 2.6: Data from St Charles Parish, Louisana. Credits to NDPTC.

Model Testing on Hurricane Ida

The adaptation of a pre-trained YOLOv5 model designed for damage detection in early recovery was tested on a recent natural disaster. If the goal of machine learning for damage detection is to be deployed post-disaster in early recovery, then incorporating and testing a model on recent natural disaster imagery is one way to observe its utility.

Hurricane Ida, a Category 4 hurricane, made landfall in Louisiana on August 26th, 2021. Data collection and capacity research was conducted to observe the effects of early recovery on communities and how to make improvements to the RIDA model's deployment. Just five months after the disaster, organizations and residents in the area were focused on recovery— rebuilding and repairing homes, finding more permanent solutions, and restarting local economies. In this recovery phase, the RIDA model could have enabled people through the FEMA aid process or insurance claims. Visiting the region at this point allowed researchers to take advantage of hindsight, asking the question, "how can we improve recovery?" At the same time, the event is still fresh in the minds of community members.

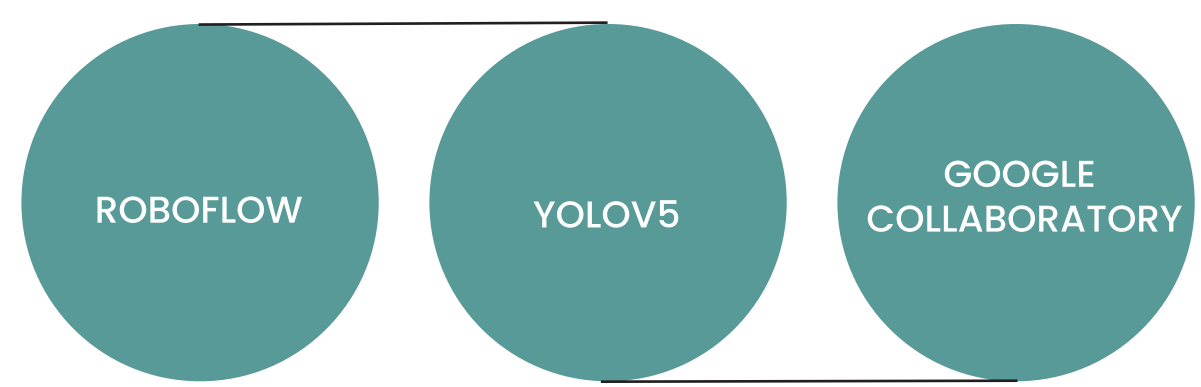
2.5 Programs, Processing, and Platforms

To make the tool accessible, the NDPTC should leverage pre-existing data platforms. These platforms should be highly accessible to any local planning or emergency management office. Platforms that are free of cost, user friendly, and browser/interest accessible are notable ways to ensure receptiveness. Listed below are some entry level platforms that could easily be used during training of machine learning processes.

ROBOFLOW

Collaboration and Configurations

Researchers or planners must label images according to what is being detected or classified for machine learning algorithms to understand data. Roboflow is an online annotation platform that is free and browser based *(See 2.7)*. The platform allows multiple collaborators to upload individually collected photos regardless of format (.jpg, .png, etc). The Roboflow processes will take in a variety of data and produce a downloadable or accessible dataset in a variety of formats. The ability to produce different formats allows the dataset to be integrated into different algorithms, especially YOLOv5. Additionally, the pooled imagery can be divided among collaborators and researchers for annotation purposes, allowing cross collaboration on dataset creation. With the ability to upload multiple imagery sources, different natural disaster dataset configurations of considerable size can also be created and hosted on Roboflow. New imagery can be integrated into pre-existing datasets when a natural disaster occurs. Multiple events can be combined in different ways to test if certain elements of disaster damage from events mimic other natural disasters. More importantly, testing multiple natural disaster imagery configurations can help experiment to identify the most precise



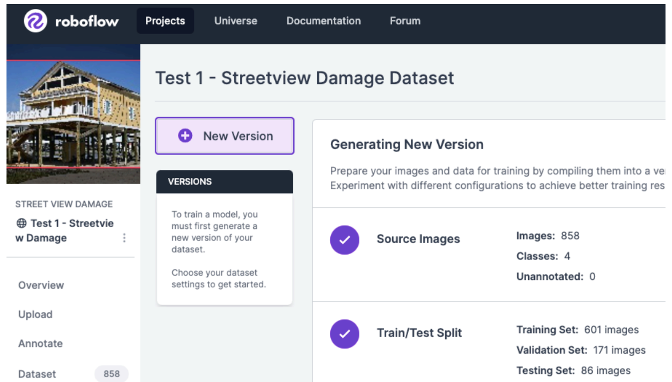


Image 2.7: Overacrching view of the Roboflow API for dataset creation website. Credit from Roboflow.com.

model for street level damage detection. The combination of multiple disaster event imagery enhances precision and recall for street level machine learning algorithms. For implementation purposes, we recommend entry entry level machine learners, such as local emergency responders, planners, and others leverage Roboflow to enable various configurations of model scaling for increased precision. Roboflow also allows a multitude of local recovery professionals the ability to create and contribute to datasets, access or utilize dataset configurations, and train and test on algorithms with ease.

Integration with YOLOv5

In further support of Roboflow utilization for damage detection, the designers of the YOLOv5 model have strategically aligned their coding processes with Roboflow's Application Programming Interface (API), for seamless transition from dataset annotation to training. Other annotation programs such as VGG Image Annotator (VIA) or Labelme are applicable to object detection with bounding box methods. However, Roboflow directly integrates into YOLOv5 notebooks and prevents minor coding errors such as file misstructuring (.json, .csv, .text). Lastly, cloud-based notebooks allow for use without the need to download datasets to local drives and reduces the risk of error.

Preprocessing and Augmentation

Roboflow enables image pre-processing and augmentation, in other words imagery alterations. Annotation platforms offer limited levels of alterations, whereas Roboflow offers a wide variety. Pre-processing and augmentation assist with what and how machine learning algorithms should understand data. Steps that Roboflow offers include resizing which either shrinks or expands an image's size. This step is both helpful for training speeds, but also for datasets with a variety of image sizes. Resizing can skew images and data, potentially to such extremes that it impacts the outcomes detrimentally.. While there are a myriad of image alterations, the field asserts these steps increase algorithmic precision, however there are unclear standards for best practices. This is due to how the model learns and what processing enhances detection, so pre-processing or augmentation changes based on the application of machine learning. For the purposes of damage assessment from street level machine learning models, there are a few imagery alterations that may align with damage detection goals.

PREPROCESSING AND AUGMENTATIONS

Horizontal flip: This step flips or inverts the image. A machine learning algorithm can be trained on images of houses and structures with different orientations for better detection and classification.

Auto-contrast: This step enhances pixel contrast. A damage detection algorithm, or other imagery algorithms, use contrasting to increase the algorithm's ability to understand boundaries and lines.

Image Resize: This step alters image size. Damage detection images can vary in size, from phone cameras to social media to on the ground cameras, so the variability allows the machine learning algorithm to understand all of the data in a consistent manner while also making the training and testing faster.

Shearing (+/- 15°): This step distorts the image horizontally to mimic real world data capture. street level cameras used by organizations such as Mapillary or Google tend to have a warped or distorted view that mimics the shearing feature. This step enhances the model's algorithm by understanding different types of imagery.

YOLOv5

These augmentations and preprocessing techniques can reduce model accuracy and precision. These steps should be constantly evaluated for best model performance. Since Roboflow allows multiple enhancements, researchers can generate multiple datasets and train or test based on alterations.

The decision to operate and experiment with the YOLOv5 framework is not an easy determination. As discussed previously, there are opportunities for other algorithms to not only detect damage, but detect, classify, and mask other pertinent indications of damage. With street level damage imagery being captured, other algorithms could produce insight into not only the severity of damage but variety. YOLOv5 is fast and accessible, while also producing strong results through accuracy and precision metrics such as Recall. Instance segmentation annotations are new features in Roboflow and if paired with a tutorial or custom notebook could allow NDPTC to develop targeted damage detection. This includes the ability to observe roof vs structural damage, or even the ability to detect debris, property, and landscaping damage. Segmentation could identify damage through the capture of other data points such as materiality of structure, height or level(s) of structure, and elevation from sea level. Perhaps machine learning can supplement that data collection and enhance damage detection simultaneously.
Altogether, YOLOv5 is a stand out machine learning algorithm that can adequately adapt to local capacities post-disaster to produce accurate, fast results. YOLOv5 is accessible and integrates annotation into its notebooks for customization and accessibility.

GOOGLE COLABORATORY

A recommended platform for YOLOv5 implementation is Google Colaboratory notebooks. Google Colaboratory is a browser based, free platform that allows users to execute code with rich text in a single space. The integration of code and text allows for template notebooks to be organized pre-coding. Organizing a notebook allows multiple users access to code, while also understanding what each execution entails. For example, in the customizable notebook for YOLOv5, there were rich text, images, and gifs that explained the annotation processes all the way to training deployment.

Not only does Google Colaboratory notebooks allow collaboration for customization of notebooks, the platform ran code of Google's cloud servers. This means that the operation speed to run code is remotely managed, allowing users to utilize faster graphics processing units (GPU's).

With customization and processing speed, Google Colaboratory takes coding machine learning algorithms a step further. Machine learning developers create and share Google Colaboratory specific notebooks for replication of methods. This means that users can essentially copy and paste entire pre-built guidelines, minimally changing or altering just a few lines of code. This is the case for YOLOv5, which has a series of extremely digestible pre-built notebooks that run without error and consistently perform at fast rates.

The burden to organize machine learning algorithms and their corresponding code is significantly reduced due to formatted and organized Google Colaboratory notebooks, cloud-based processing, and pre-built guidelines. The integration of YOLOv5 and Roboflow into Google Colaboratory notebooks streamlines machine learning processes for faster, more robust experiments and applications.

2.6 Recommendations

If RIDA becomes a tool deployed at the local scale to be monitored by local emergency managers and disaster response professionals, the tool must be adaptable, accessible, and equitable. As it stands, RIDA has the potential to bridge the gap between the data science and planning fields. To bring that potential to light, the following steps should be taken to ensure proper use of the tool during the machine learning steps of the process.

Pool and Share Data
The ability to share and leverage pre-existing resources makes the production and training of machine learning processes faster, and more importantly, more accurate. From research articles or actual applications of machine learning, the integration of data that represents and documents various disaster related damage, housing typologies, level of damage, and in general a variety of imagery, enhances the models accuracy. To achieve data sharing, organizations can provide a host of open-sourced and public materials. These materials can include:

(1) a continuously growing dataset on general infrastructural damage
(2) annotation protocols designed for federal agencies (FEMA, HUD, etc)
(3) a pre-built machine learning algorithm
(4) annotated datasets for each natural disaster
(5) open source platforms for contributions of disaster damage and images

Those interested in damage assessment assistance through machine learning, such as the NDPTC, should recognize its position as a liaison between the local and federal actors. Large scale organizations or locally embedded recovery professionals can act as the host for materials, tools, processes, and data. Disaster recovery and preparedness organizations benefit from the data pooling and storage because it increases the damage assessment model accuracy and transferability. Altogether, sharing and pooling data helps eradicate the noted barriers of perishable data by directly sourcing disaster data throughout local networks and beyond.

Alternative Algorithms and Continuous Training
The YOLOv5's model accuracy and efficiency are two great assets for a street level machine learning model that detects severity of damage. The creators of the YOLOv5 algorithm are continually transparent with their improvements, modifications, and methods. The algorithm can be run using cloud based processing speeds which eradicates the requirement for individual users to operate or download multiple softwares and platforms. Google Colaboratory also has tutorials that are easily navigable for an entry-level practitioner. However, as mentioned previously, while the YOLOv5 algorithm is reliable for the NDPTC project, we strongly recommend continued exploration of more precise machine learning algorithms for street level damage assessment such as Mask R-CNN and Lobe.ai.

In the field, there are a few available solutions to continuous training. The first potential solution is utilizing a machine learning designed end-to-end platform. An end-to-end platform starts with processing multiple datasets using pre-existing or custom data parsers. Then within the same process, the code can run various algorithms including YOLOv5 or Mask R-CNN, to train images in one succinct process. The inspiration for an end-to-end machine learning platform was driven by the need to instill continuous learning and experimentation protocols, but also due to the need to organize each machine learning step into one coding narrative.

Audit and Monitor
To train and deploy models for testing, there are several qualitative metrics that determine model performance to review. It is important to include a coherent method for review to audit the model's performance both in training and in application. There are important metrics that should be evaluated for both steps to machine learning. The metrics related to training a model are mean average precision (mAP) and recall. Even training data can be monitored using Roboflows health check. Checking these metrics ensures

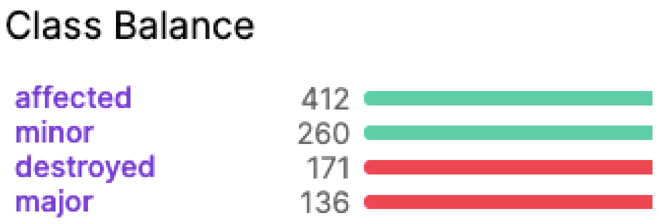


Image 2.8: Roboflow Health Check: Totoal raining images per classification catergory. Credit from Roboflow.com.

data representation at each step is balanced. In Image 2.8, our dataset has notable variations of classification sizes which is less than preferable as described above in Section 2.5. With the curation of a widespread disaster damage dataset, these categories can be evened out over time.

2.7 Conclusions

The Case for Iterative Model Design
The ability to iterate on model design allows machine learning researchers to better adapt to changing conditions of natural disasters and reflect upon model performance and community representation. As this is an academic project in understanding how artificial intelligence can aid disaster recovery, the initial exploratory analysis of data collection, annotation methods, and machine learning model selection mimicked the process of thoughtful and iterative model design. Through experimentation on machine learning model development, findings suggest collecting images with the intention of the model's primary objective. If the imagery intended for model training and validation does not aid in the damage assessment of buildings, it should be excluded from the dataset. FEMA's Preliminary Damage Assessment Guide helps researchers select relevant images and provide a framework for annotations.

Selecting preprocessing edits and augmentations to allow for more robust training datasets should be chosen based on the model's deployment phase. As discussed, preprocessing alters images by rotating, flipping, adding contrast, or cropping to provide more training data inputs in a model. A model with three preprocessing modifications can learn from three times the images, providing a catalyst to model performance while cutting down on time spent on data collection. The RIDA model ultimately collects images for preliminary damage assessment from a car-mounted 360-degree camera, including a modification for "shearing" images or rotating them +/- 15°, which is selected to mimic real-world conditions.

Lowering the Barriers to Machine Learning
The growth of programming-less machine learning programs, such as Lobe.ai, can also lower the barriers to entry into machine learning to the point that rapid adoption and progression of application techniques for artificial intelligence in disaster relief can become commonplace. In a brief experiment, annotation and training of a machine learning model capable of categorizing damage assessment following FEMA's PDA took a fraction of the time to develop compared to YOLOv5. Lobe.ai's damage assessment model's observed accuracy is 93%, while the highest accuracy of a YOLOv5 model observed through this research is 70%.

Based on research and experimentation, damage assessment as conducted through machine learning practices must continue to iterate on

Image 2.9: Shearing Example: This picture is from the 360 imaging company NCTech's vehicle-mounted iSTAR Pulsar camera. The photo demonstrates potential distorted images for machine learning unless trained on these distortations know as shearing. Credit to GIS Lounge https://www.gislounge.com/next-generation-asset-management-with-istar-pulsar/

its methods, while decreasing the barriers to the data-driven tool. For now, general findings identify the YOLOv5 model as the most accessible in terms of the availability of tutorials and supporting software, such as Roboflow. Though pre-coded notebooks are freely available for running YOLOv5, some programming experience is required to understand the complexities of operating machine learning algorithms.

For emergency managers, community organization directors, and other recovery personnel, the barriers to entry into machine learning models for damage assessment are much too high for practical adoption. At this stage in the development of artificial intelligence for disaster recovery, the benefits of integrating machine learning into preliminary damage assessments for rapid deployment are not yet visible. When a disaster strikes a community, it is often too late to learn and implement new tools into an overly complex recovery process. Machine learning tools for disaster recovery must be developed in anticipation of deployment.

Going Forward

Altogether, street level machine learning stands as a growing data-driven tool that reduces assessment delays through improved data collection and imagery analysis. This paper is far from comprehensive in regard to machine learning development, however it comments on the general industry trends from annotation platforms and protocols to useful machine learning algorithms. These considerations directly contribute to the design and development of damage assessment models in early recovery, including potential environments for bias. To learn more about machine learning bias, see "Social Bias in Machine Learning and Early Recovery." Nevertheless, for local disaster response professionals who are interested in the reduction of assessment bias or local capacity burdens, machine learning using accessible interfaces can streamline those processes and offer enhanced insight on damage.

To access more information on how to build your own model, there is a customized YOLOv5 template notebook in Google Colaboratory with Roboflow integrations. To assist with knowledge transfer, data sharing, and tools going forward, there are supplementary videos and the "Basics of Machine Learning Paper" that assist in the development. All of the work is hosted on the University of Michigan Capstone website and corresponding GitHub repository.

ENDNOTES

1. Selvaraju, R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., and Batra, D. (2019) Grad-{CAM}: Visual Explanations from Deep Networks via Gradient-Based Localization. International Journal of Computer Vision, 128(2). 336-359. https://doi.org/10.1007%2Fs11263-019-01228-7

2. Xray Pasa, F ; Golkov, V ; Pfeiffer, F ; Cremers, D ; Pfeiffer, D. (n.d.). Efficient Deep Network Architectures for Fast Chest X-Ray Tuberculosis Screening and Visualization. Scientific Reports. 9(1), 6268–6268. doi:10.1038/s41598-019-42557-4.
Animals

3. He, K., Gkioxari, G., Dollár, P., and Girshick R. (2017) Mask R-CNN. IEEE International Conference on Computer Vision (ICCV), 2980-2988. hhttps://doi: 10.1109/ICCV.2017.322

4. Metallo, N., (2017) Using Mask R-CNN in the streets of Buenos Aires. Medium. Accessed on April 24, 2022. https://medium.com/@nicolas.metallo/using-mask-r-cnn-in-the-streets-of-buenos-aires-a6cb6509ca75

5. Labelme2. MIT, Computer Science and Artificial Intelligence Laboratory. labelme.csail.mit.edu/Release3.0/ https://www.robots.ox.ac.uk/~vgg/software/via/via_demo.html

6. Zhang, Q., Chang, X., and Bian, S. (2020). Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN. IEEE Access. Doi: 10.1109/ACCESS.2020.2964055.

7. Nelson, J. (2020) YOLOv5 is Here: State-of-the-Art Object Detection at 140 FPS. Roboflow. Accessed on May 1, 2022.

8. FEMA. (2020). Preliminary Damage Assessment Guide (p. 127).

9. FEMA. (2020). Preliminary Damage Assessment Guide (p. 127).

10. FEMA. (2020). Preliminary Damage Assessment Guide (p. 127).

11. Cherry, K. (2020, July 19). What Is Cognitive Bias? [Psychology]. Very Well Mind. https://www.verywellmind.com/what-is-a-cognitive-bias-2794963

12. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017) Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109

13. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017) Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109

14. Dutta, A., Gupta, A., and Zisserman, A. (2019) The VIA Annotation Software for Images, Audio and Video. In Proceedings of the 27th ACM International Conference on Multimedia. https://doi.org/10.1145/3343032.3350535

15. Labelme2. MIT, Computer Science and Artificial Intelligence Laboratory. labelme.csail.mit.edu/Release3.0/

RISING ABOVE THE DELUGE

STREET LEVEL IMAGERY FOR MACHINE LEARNING

about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, valuing local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN