Parcel Package Classifier for Automated Conveyor System

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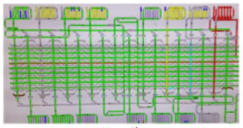
https://www.youtube.com/watch?v=kyb9ANNf7V4&feature=youtu.be&hd=1

Introduction

- Everyday, logistics companies like UPS and FedEx lose millions of dollars as a result of damaged packages
- As packages flow through distribution centers with miles of conveyor belts, they are at risk of becoming crushed, breached with holes, or opened
- These packages might contain vital medicines or hazardous materials
- Currently the system is monitored manually increasing the possibility for errors and limits scope
  - Humans make mistakes, can't see everywhere and everything
- We propose:
  - Build a neural network classification system that can detect whether a package is damaged
  - Connect camera to neural network (future work)
  - Place cameras strategically throughout the system (future work)



.75 miles

- *Conveyor system comprised of many miles of conveyor belts*
- *Packages can become damaged at any point*
- *Place cameras connected to neural network to detect damaged packages*

Dataset and Preprocessing

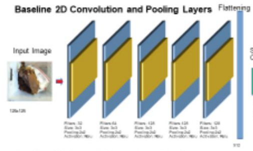
- Baseline images: 128x128 RGB images of parcel boxes.
- Data set collected from various sources, including google search and photos from UPS distribution facility
- 2000 RGB normalized training images
- 200 RGB normalized validation images
- 200 RGB normalized test images

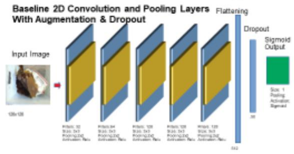
Examples of damaged packaging

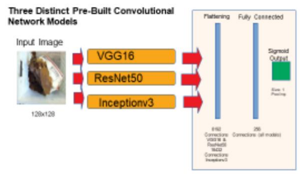
Examples of un-damaged packaging

Deep Learning Methods

- Five neural network architectures were trained and tested on the data
- Loss Function: $J = -\sum_{i=1}^{N} y_i \log(h_\theta(x_i)) + (1-y_i)\log(1-h_\theta(x_i))$
- Employed visualization on baseline models to gain insight on activations of the layers







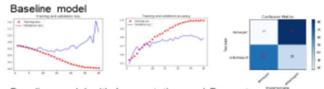
- Hyperparameters explored include:
  - Epochs
  - Learning Rate
  - Dropout
  - Augmentation
  - Transfer Learning

Results & Discussion

Model	Learn Rate	Epochs	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy	Test Accuracy	Transfer Learning
Baseline Model	0.0001	30	.015	1.02	99.5%	80.5%	25%	No
Baseline plus Augmentation and Dropout	0.0001	30	0.28	0.42	87%	83%	35%	No
VGG16	0.0001	30	0.36	0.37	84%	88%	48%	Yes
ResNet50	0.0001	60	0.25	2.17	89%	50%	50%	Yes
Inceptionv3	0.0001	30	0.50	2.98	77%	67%	50%	Yes

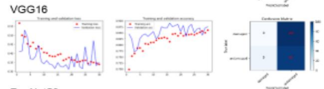
Increasing Test Accuracy

Baseline model

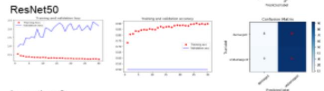


Baseline model with Augmentation and Dropout

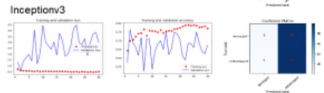
VGG16



ResNet50



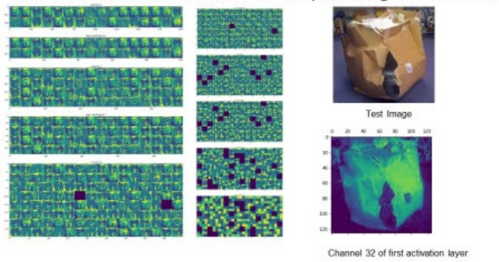
Inceptionv3



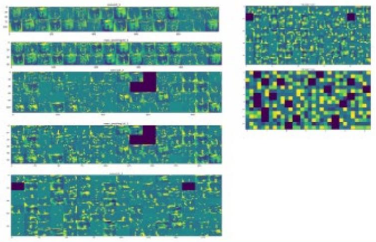
- *Most models performed well on training and validation but not so well on test data*
- *VGG16 performed better than other models*
- *Models had high bias*

Visualization of Layers

Baseline model visualization shows no specific region activations



Baseline model visualization with augmentation and dropout



Conclusions and Future Work

Conclusions

- Models perform well and training and validation but not on test images.
- Models showed high variance between validation and test data
- Dropout seemed to help prevent overfitting
- Need more data and better preprocessing
- There is much room for improvement of performance of models on the type of data that was tested. This was expected.
- Using bounding boxes around specific regions of damage might help with activations.

Future Work

- More preprocessing of images by putting bounding boxes around zones of damage and labeling them.
- Collect much more data.
- Explore applications to other practical areas such as food quality.

References

1. Mattew D. Zeiler, Rob Fergus, 2013, Visualizing and Understanding Convolutional Networks
2. Martin Rajchl, Matthew C. H. Lee, Ozan Oktay et al., 2016, DeepCut: Object Segmentation from Bounding Box Annotations using Convolutional Neural Networks