Estimating Flood Depths of Submerged Vehicles with cNN

Lydia Kajeckas, Nikhil Lonberg, Tony Lucci
Erik Lindberg, James Pecore

Lydia Kajeckas

Agenda

I. Problem Statement
II. Flood Prediction
III. Image Preprocessing
IV. Depth Prediction
V. Conclusions

Lydia Kajeckas

I. Problem Statement

- Floods are the most common natural disaster in the US
- Vehicles are particularly vulnerable to flood damages
- Critical to both insurance companies and owners to be able to quickly access damage
- Our goal is to predict the depth of flood waters based on an image of a flooded car

June 2019 Mississippi River Floods

II. Executive Summary

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Create Dataset of Flooded Cars

Google Cloud Cloud Vision API

Label & Object Detection

= True

AND

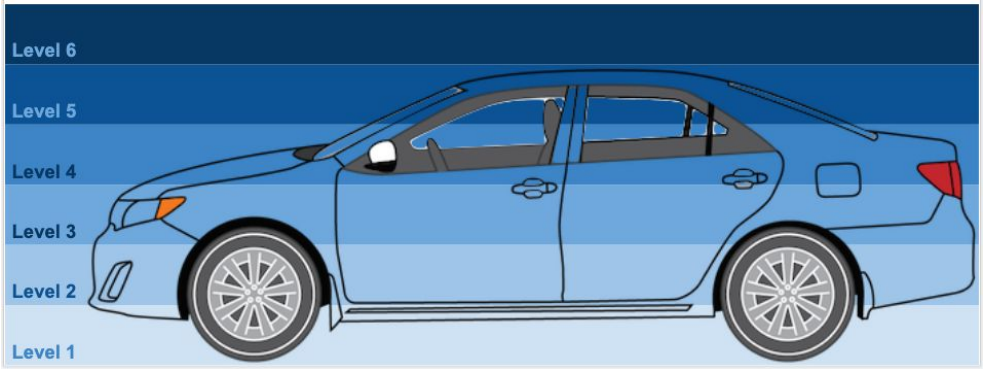
= True

PyTorch

Convolutional Neural Network

Estimated Flood Level

Labeling Training Data



James Pecore

III. Dataset Creation

FLOOD

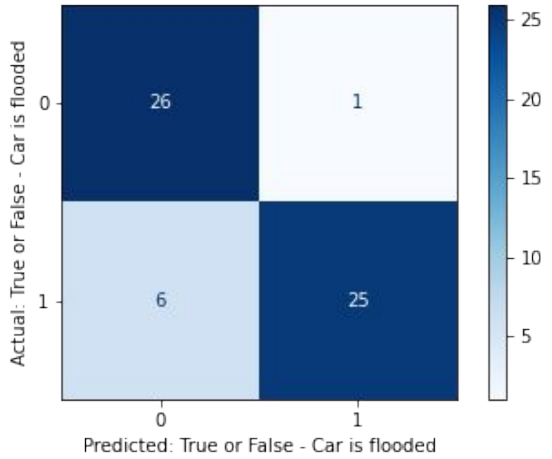
NO FLOOD

- Humans have the ability to detect “object continuity.”
  - This lets us differentiate a flooded car as a different object than the water surrounding it.
- We want to train a computer to also be able to recognize “object continuity.”

Tony Lucci

IV. Label Detection

- Scans and labels images with up to 10 key words (232 images)
- Count Vectorize
- Classification Models
  - Logistic Regression
  - Linear Support Vector Classification
  - **Multinomial Naive Bayes**



Baseline
54.15%

Accuracy
87.93%

Specificity ↓FP ↑%
96.30%

Sensitivity ↓FN ↑%
80.65%

NO FLOOD

Tony Lucci

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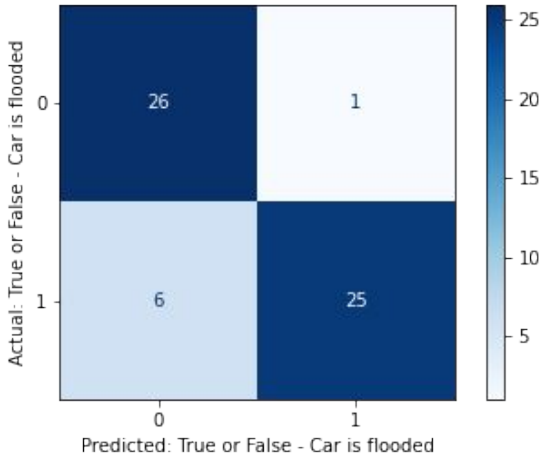

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FLOOD

Erik

V. Object Detection (Google Vision Image Annotator)

- API detects and labels objects, bounding objects with boxes
  - If images contained vehicles, we created a cropping function to grab those objects

Erik Lindberg

VI. Image Augmentation (Visual Bootstrapping)

- To increase image sample size for the model each cropped vehicle had three additional images created
- We did not create flipped images facing upside down, because that would impede our ability to estimate depth

Original Image

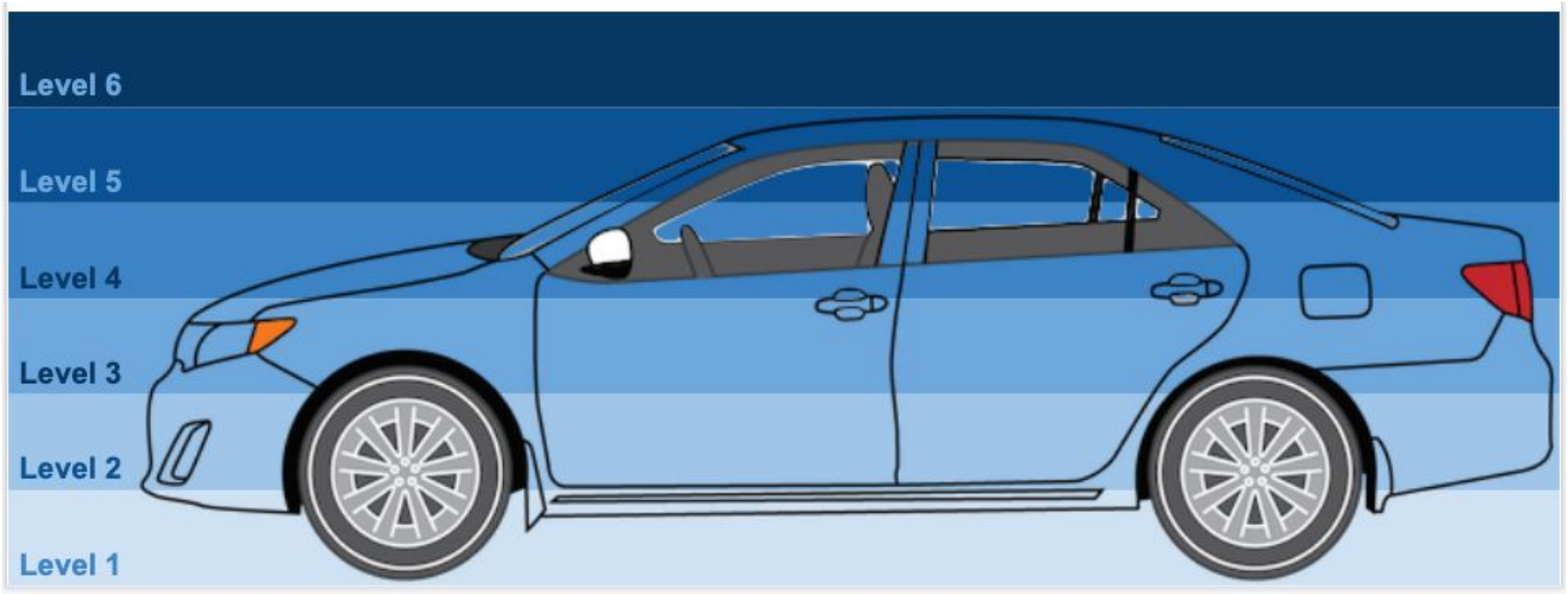
Brightened Image

Flipped Image

Inverted Image

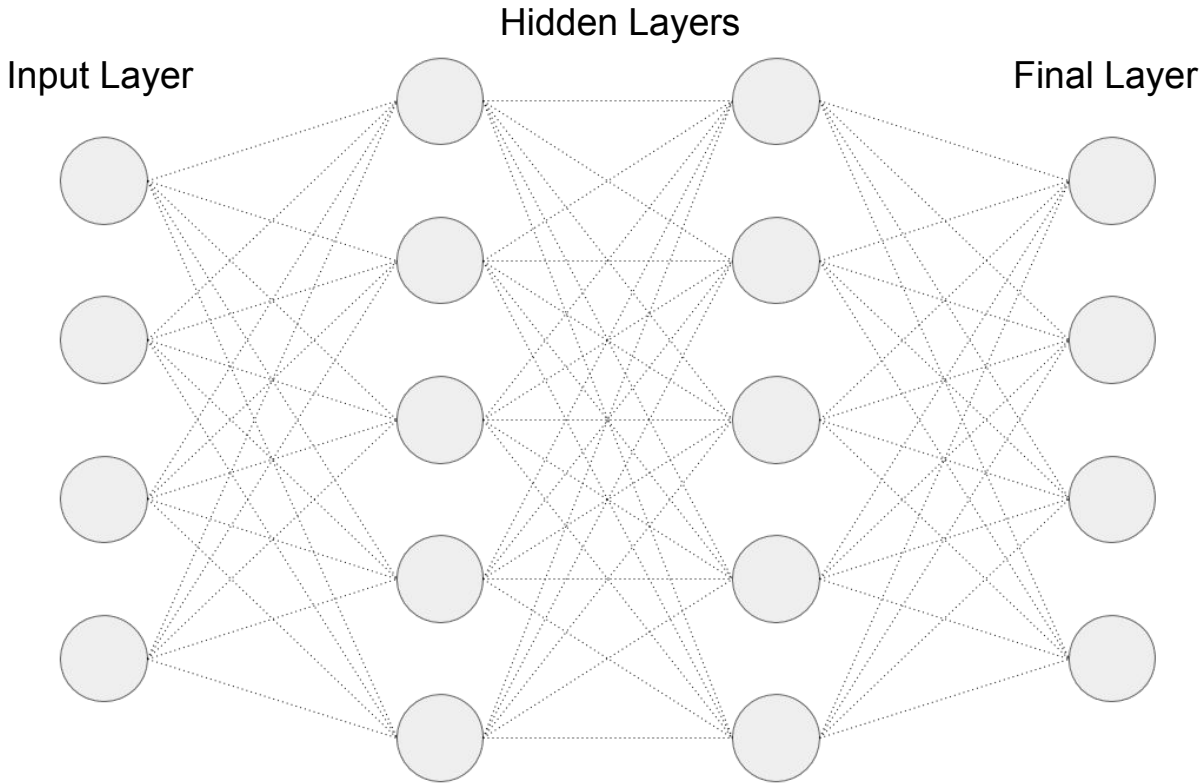
Lydia Kajeckas

VII. Assigning Flood Height to Images



Nikhil Lonberg

VIII. Modeling Flood Depth with a Neural Network



Nikhil Lonberg

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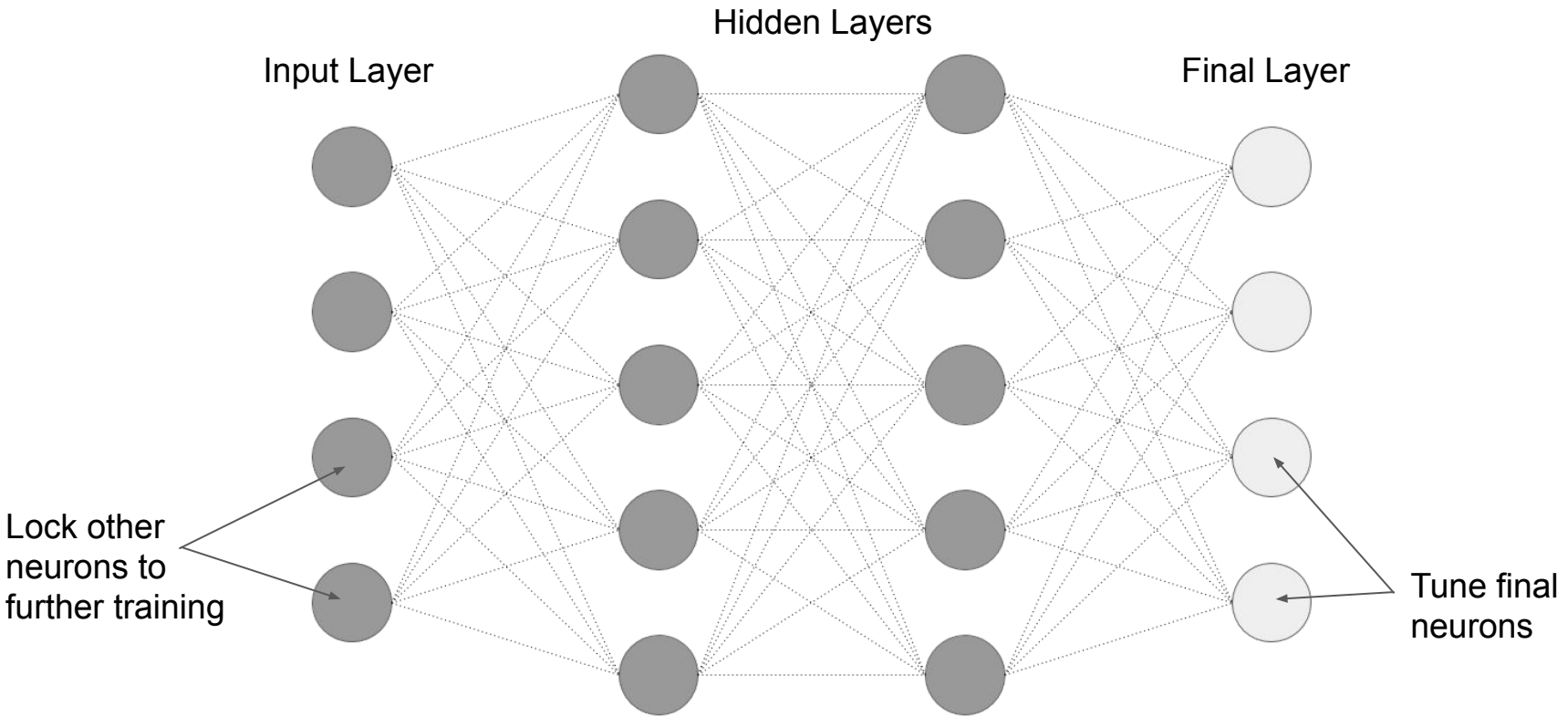


James Pecore

IX. Uses of Flood Depth Analysis

1. Insurance Companies
    a. Verifying insurance claims for flooded cars
    b. Estimating damages more quickly and with objective fairness
2. Citizen Flood Alerting
    a. An app could be created to upload images of flooded cars to the local authorities
    b. Allowing citizens to notify the news/authorities where flooding occurs
3. Climate Change Monitoring
    a. Allowing climate scientists to compare flood depths with previous years

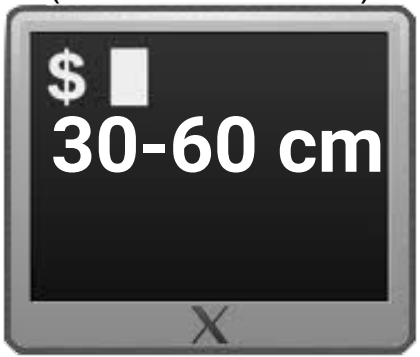
X. Conclusions

1. Using the Google Vision API, we can train a computer to detect cars as flooded/not-flooded almost 90% of the time.
2. We can use object and label detection to differentiate cars from their surrounding floods.
3. Using Image Augmentation, we can generate a much larger dataset from a relatively small database of flooded car images.
4. We can use a Convolutional Neural Network to estimate flood depth accurately 60% of the time
    a. The baseline flood accuracy is only 20%!
    b. This means we've made a huge improvement on this model!
    c. For a problem that has produced multiple Ph.D theses in Comp. Sci, these results are great!

James Pecore

XI. Our Product

Flood Depth:
Level Two
(30-60 cm of water)



XII. Further Research

1. Creating an app for estimating flood depths directly
2. Collect geotag data from images to utilize with google maps to provide which river has flooded and the height over its bank
3. Develop a better neural net / flood detector for predicting floods far OVER 90% of the time

XIII. References

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Questions?