

# Bridging Human and Machine Perception: Curvature Detection through Convolutional Neural Networks

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## Introduction

### Background:

- Curvature detection is critical in fields like robotics, virtual reality, and computer-aided design
- Humans exhibit a nuanced perception of curvature, integrating **multi-sensory cues**, such as touch and vision
- Machine learning models have made advancements but replicating the human-like **nuanced perception of curvature** still poses challenges

### Objective:

- To explore how **Convolutional Neural Networks (CNNs)** perceive different curvatures in images
- Examine the **unique behaviors** of different neural network architectures in interpreting curves
- Analyze connection between curvature discrimination by humans and by CNNs

## Methods

- Dataset of images with a **white line on black background**. Divided into 5 groups based on line curvature intensity: flat, high negative, high positive, low negative, low positive. Specific curvature value=inverse of radius
- Using transfer learning, trained both **GoogLeNet and AlexNet** to classify these images into their groups
- Analyzed **occlusion sensitivity heatmaps**, generated through the process of systematically occluding patches of an image in order to determine which areas are most critical to image classification
- Using matrices of the occlusion sensitivity heatmaps:
  - $((\max-\min)/n)+\min$  to find cutoff point for occlusion sensitivity. “n” can be calibrated to capture greater/less amounts of values in the matrix
  - Generate binary matrices, with values greater than cutoff as 1 and less than or equal as 0
  - Calculate number of columns in binary matrix with a 1. Divide by 227 (width of image) to get proportion of image width with occlusion sensitivity
- Occlusion sensitivity width was plotted along with respective curvature intensity value. Values over multiple model training iterations were averaged
- Curve fitted on dot plot with equation:  $b_1+b_2x+b_3x^2$

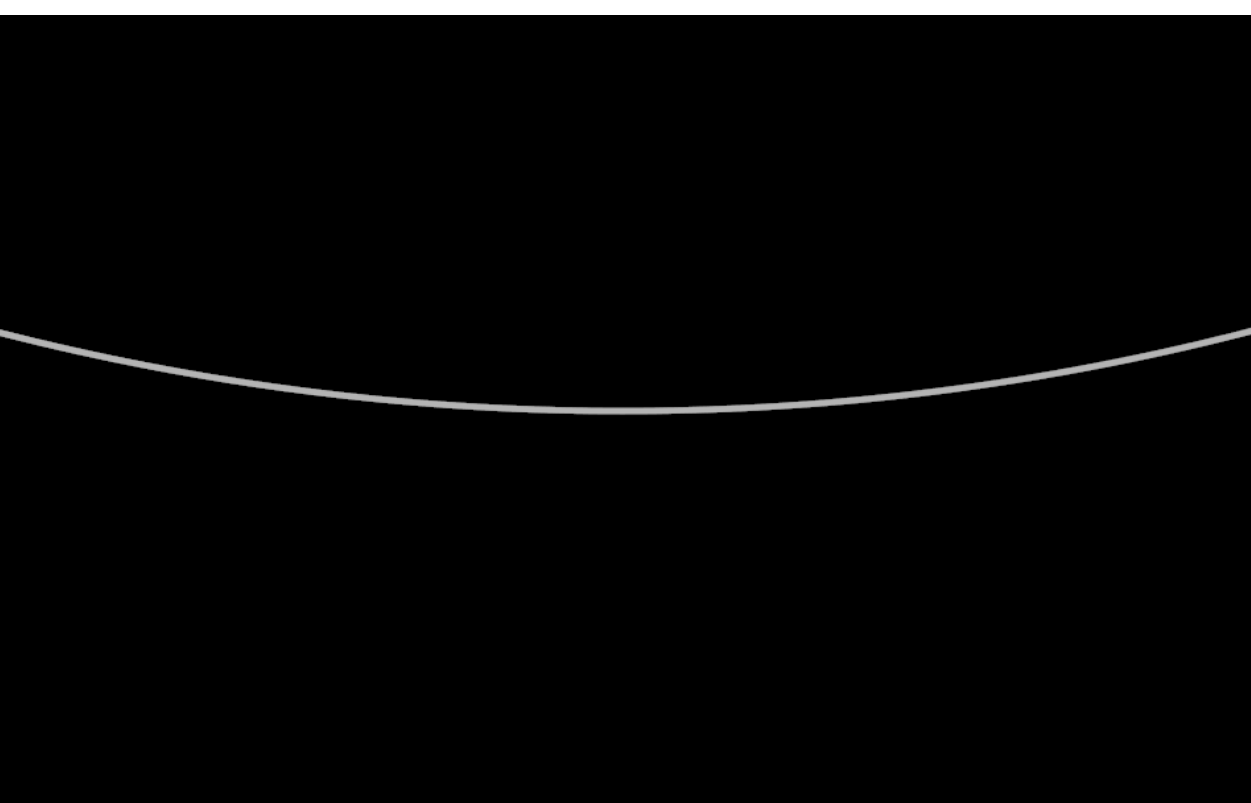


Figure 7: One of the curve pictures used for training, part of the “high negative” category. The curvature value was  $-5.99 \text{ m}^{-1}$ . All training and testing images used were generated in MATLAB

## Results

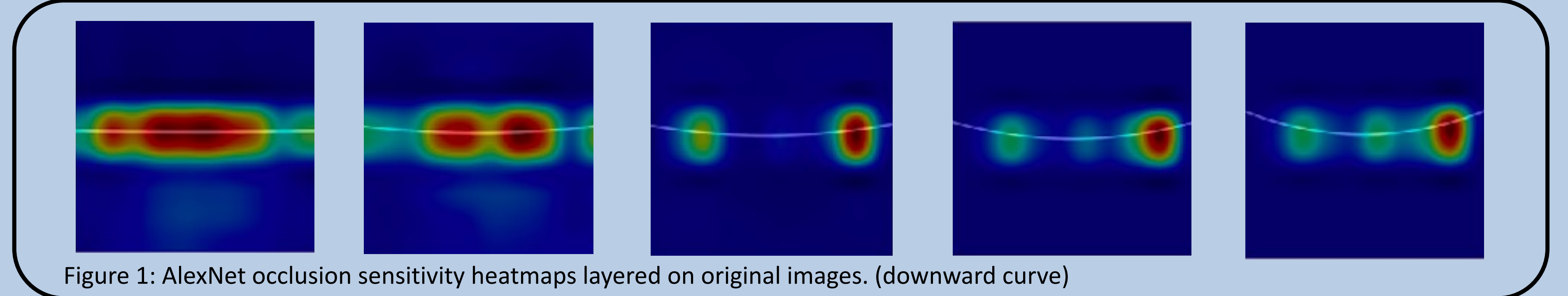


Figure 1: AlexNet occlusion sensitivity heatmaps layered on original images. (downward curve)

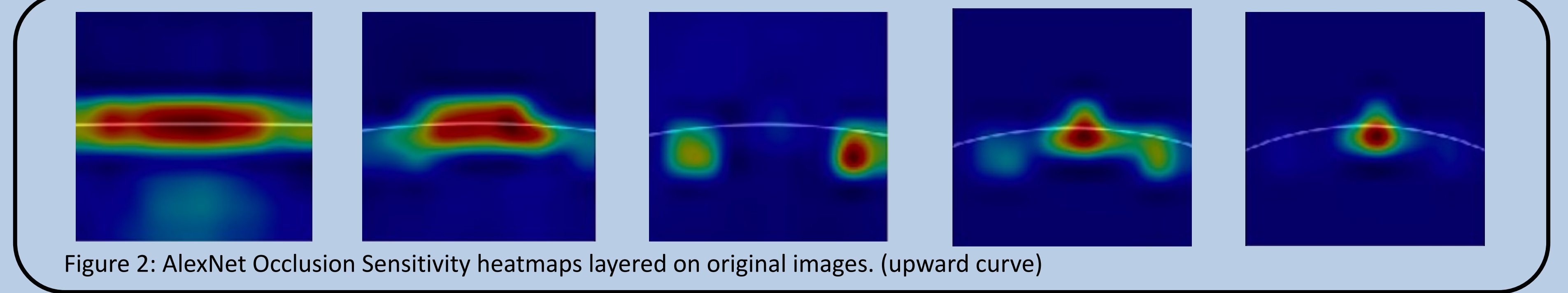


Figure 2: AlexNet Occlusion Sensitivity heatmaps layered on original images. (upward curve)

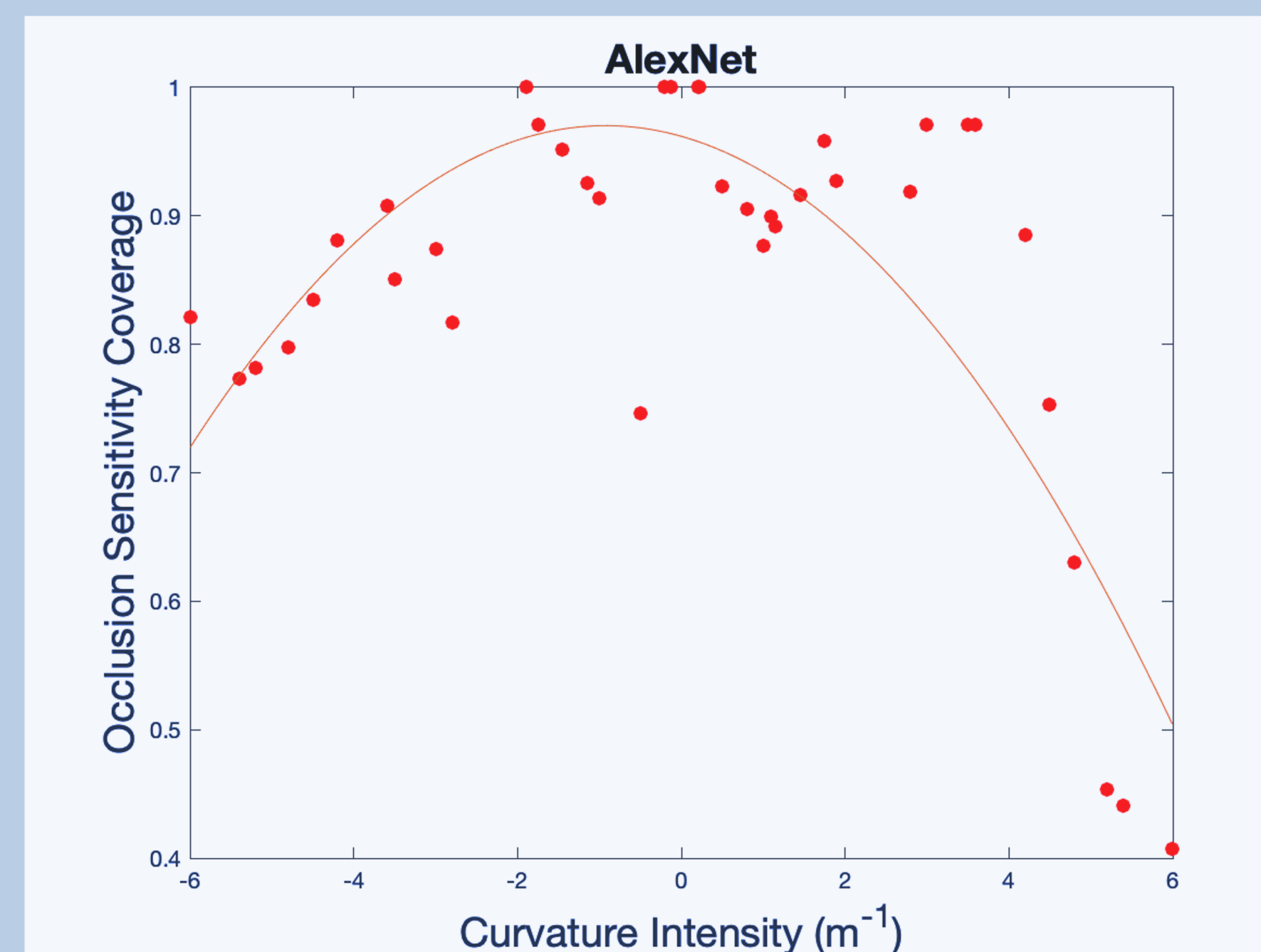


Figure 3: Curvature intensity vs occlusion sensitivity coverage with fitted curve for AlexNet.  $n=2$ ,  $R^2=0.69$ ,  $pval: b_1=7.86e-15 \ b_2=1.42e-08 \ b_3=7.23e-75$

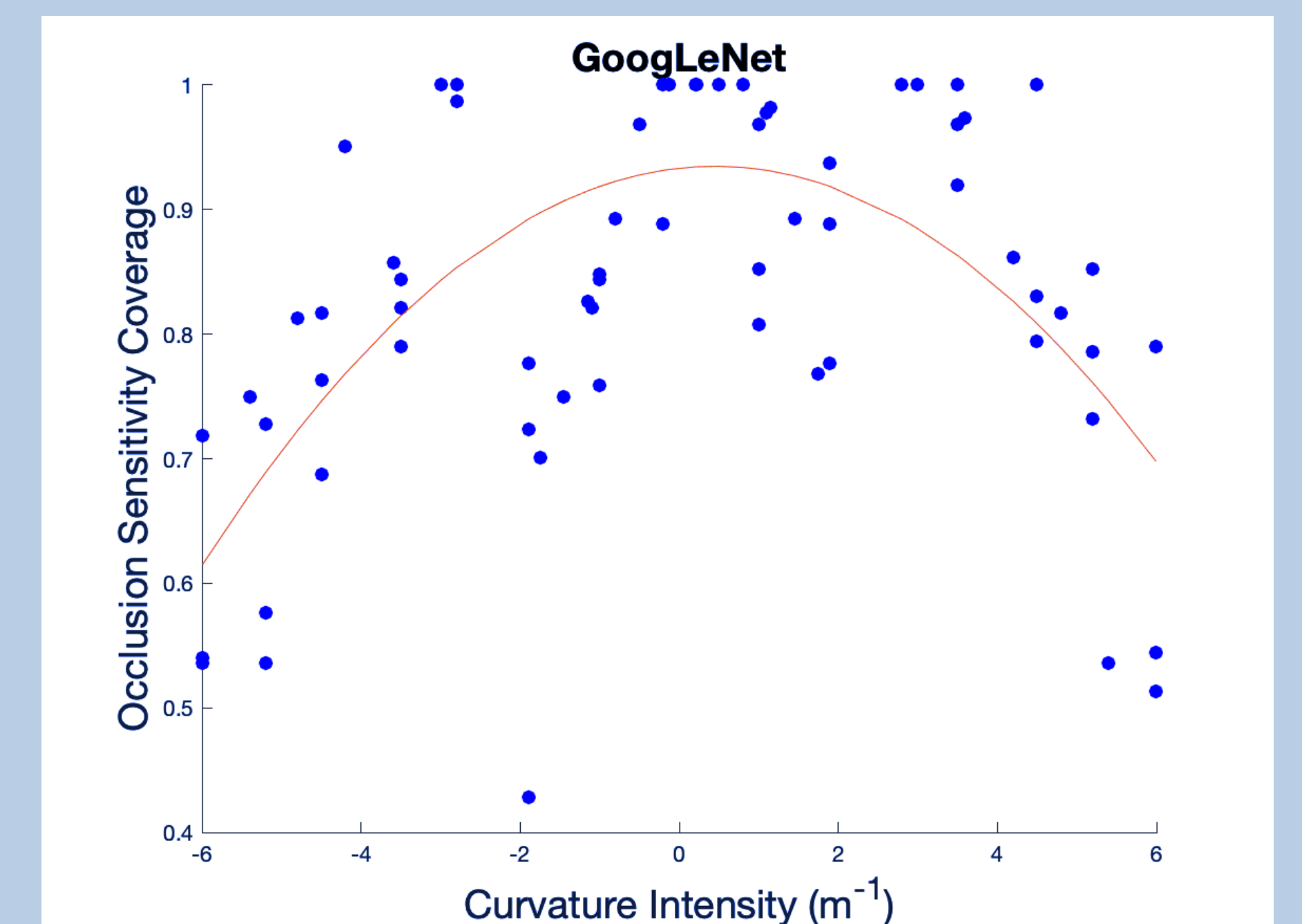


Figure 4: Curvature intensity vs occlusion sensitivity coverage with fitted curve for GoogLeNet.  $n=4.5$ ,  $R^2=0.41$ ,  $pval: b_1=1.12e-55 \ b_2=0.079 \ b_3=2.19e-09$

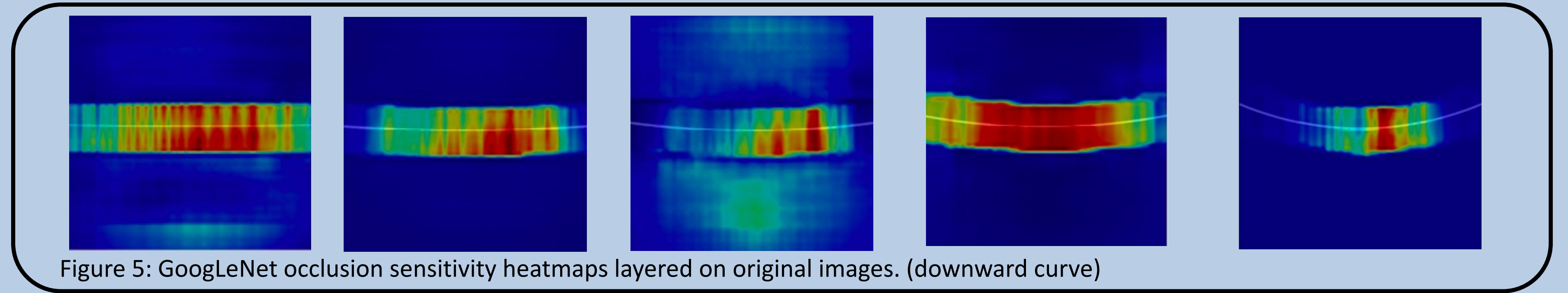


Figure 5: GoogLeNet occlusion sensitivity heatmaps layered on original images. (downward curve)

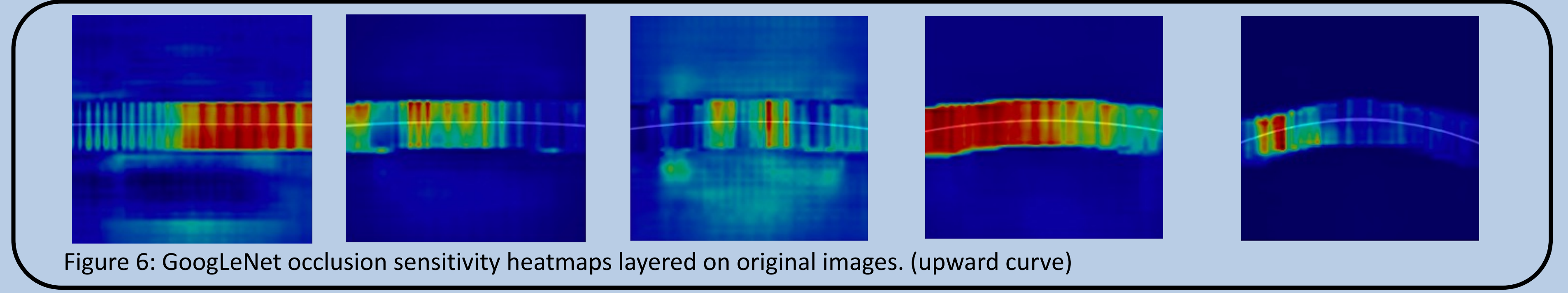


Figure 6: GoogLeNet occlusion sensitivity heatmaps layered on original images. (upward curve)

## Discussion/Conclusions

- It was found that generally, **occlusion sensitivity becomes more concentrated for intense curves and more spread out for less intense curves**.
- Findings were similar to those done previously on **haptic** curvature detection, where the more surface was in contact with the curve, the less the threshold for the curve was to be detectable by humans<sup>[1,3]</sup>
- This trend was consistent for both GoogLeNet and AlexNet
- These insights provide a more nuanced understanding of how CNNs perceive curvature
- However, it was found that AlexNet had a unique **asymmetry between upwards and downwards curves**
  - For upwards curves, as curvature intensity increased, occlusion sensitivity first concentrated into two areas, but then the two concentrated areas merged together in the center of the curve
  - For downwards curves, as curvature intensity increased, occlusion sensitivity concentrated into two separate areas and stayed that way
  - Could be due to the **natural images used to train the model**, where it has learned to find different optimized ways to look at upward curves in nature vs downward curves. Similar to how humans may look at the top of a building to identify a domed roof<sup>[4]</sup>
    - Examining the occlusion sensitivity maps for natural images classified by AlexNet, it can be seen that sharp angles or prominent curvature are most crucial to image classification, as these points usually provide the most information
- These insights provide a more nuanced understanding of how CNNs perceive curvature
- A step towards a more intuitive understanding of physical properties through artificial systems, with potential applications in areas requiring precise curvature detection

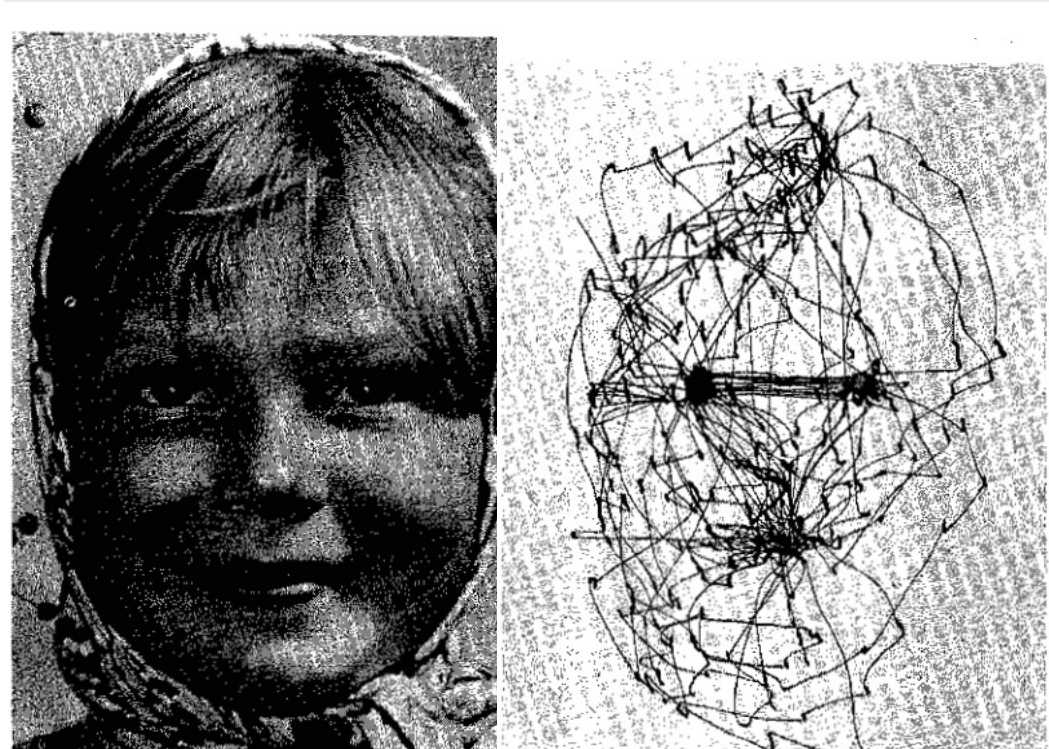


Figure 8: Research from Alfred Yarbus indicates that humans tend to look closely at where they predict to find the most information. <sup>[4]</sup> In a face, those points are usually the eyes and mouth. In a curve, looking at the vertex could provide most information.



Figure 9: Image was classified as “triumphal arch”. Occlusion sensitivity overlayed reveals how it is concentrated at the tip of the curve.

## References

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