Introduction

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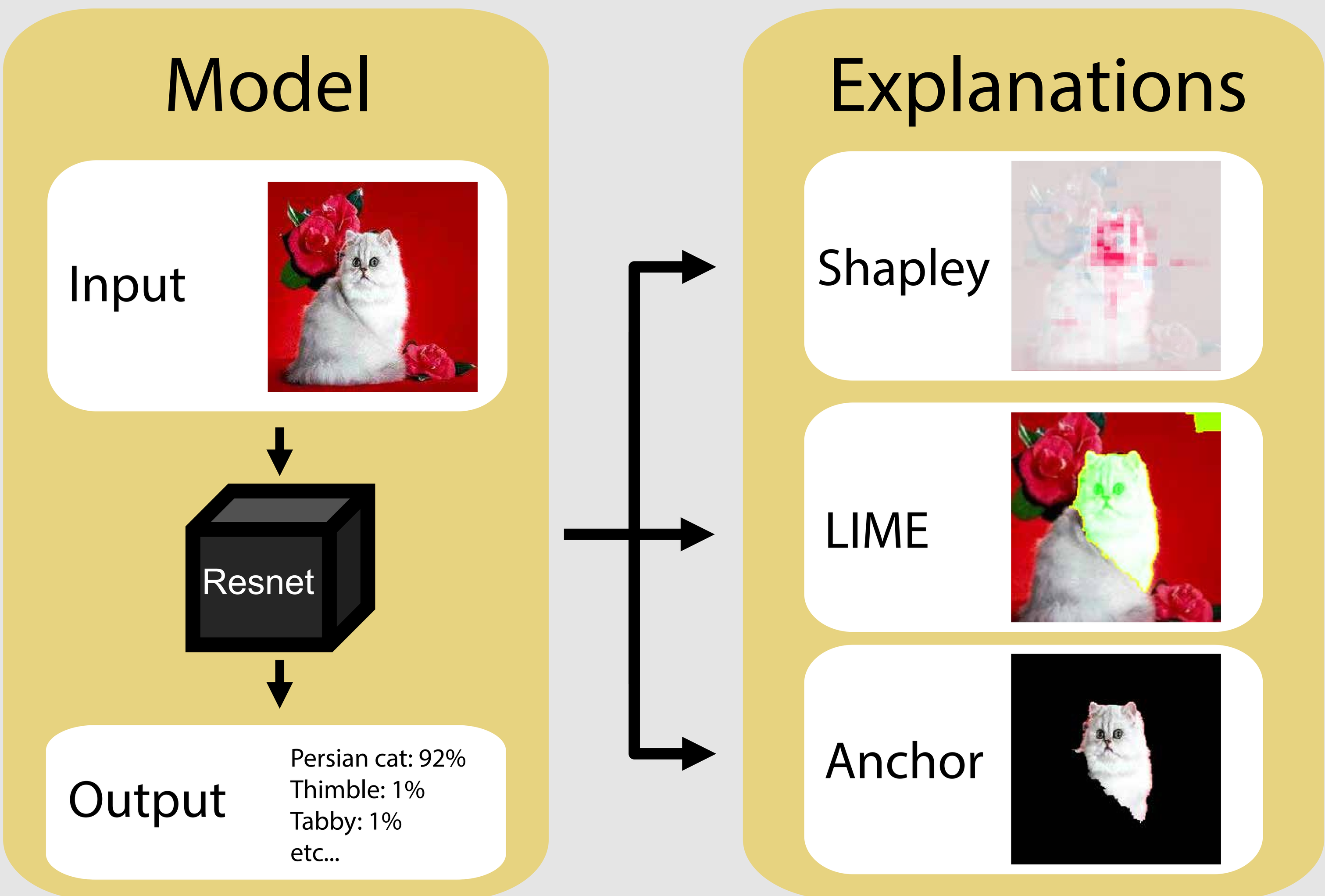

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Explainable AI: Breaking Down the Black Box

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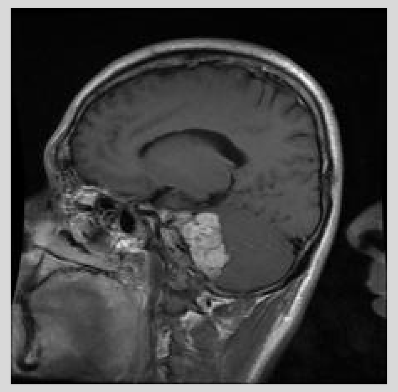
This is a German shorthaired pointer

(True)

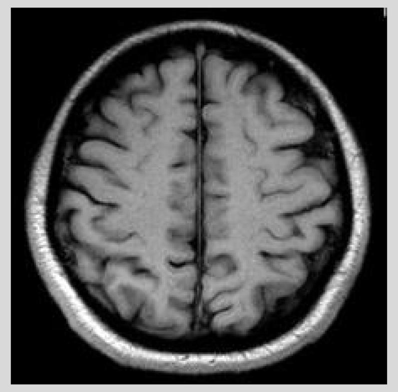


This person has a meningioma tumor

(True)

This is a horned viper

(False)



This person has a meningioma tumor

(False)

This is a polar bear

(False)

This is a tennis ball

(Arguably)

References & Acknowledgements

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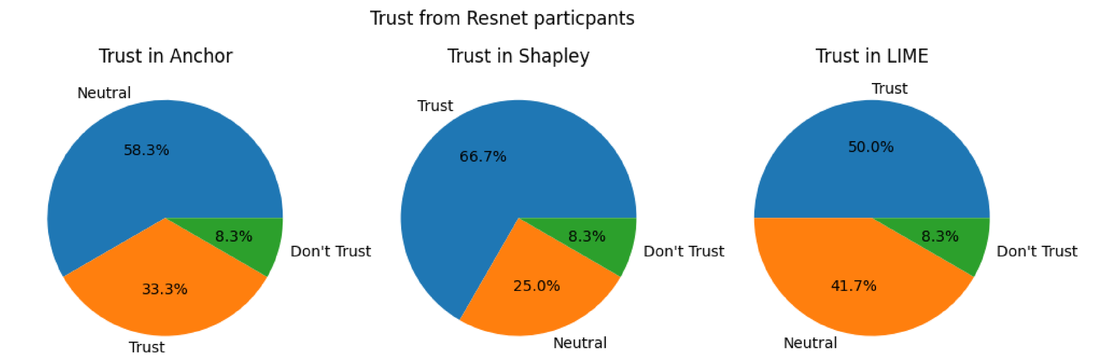

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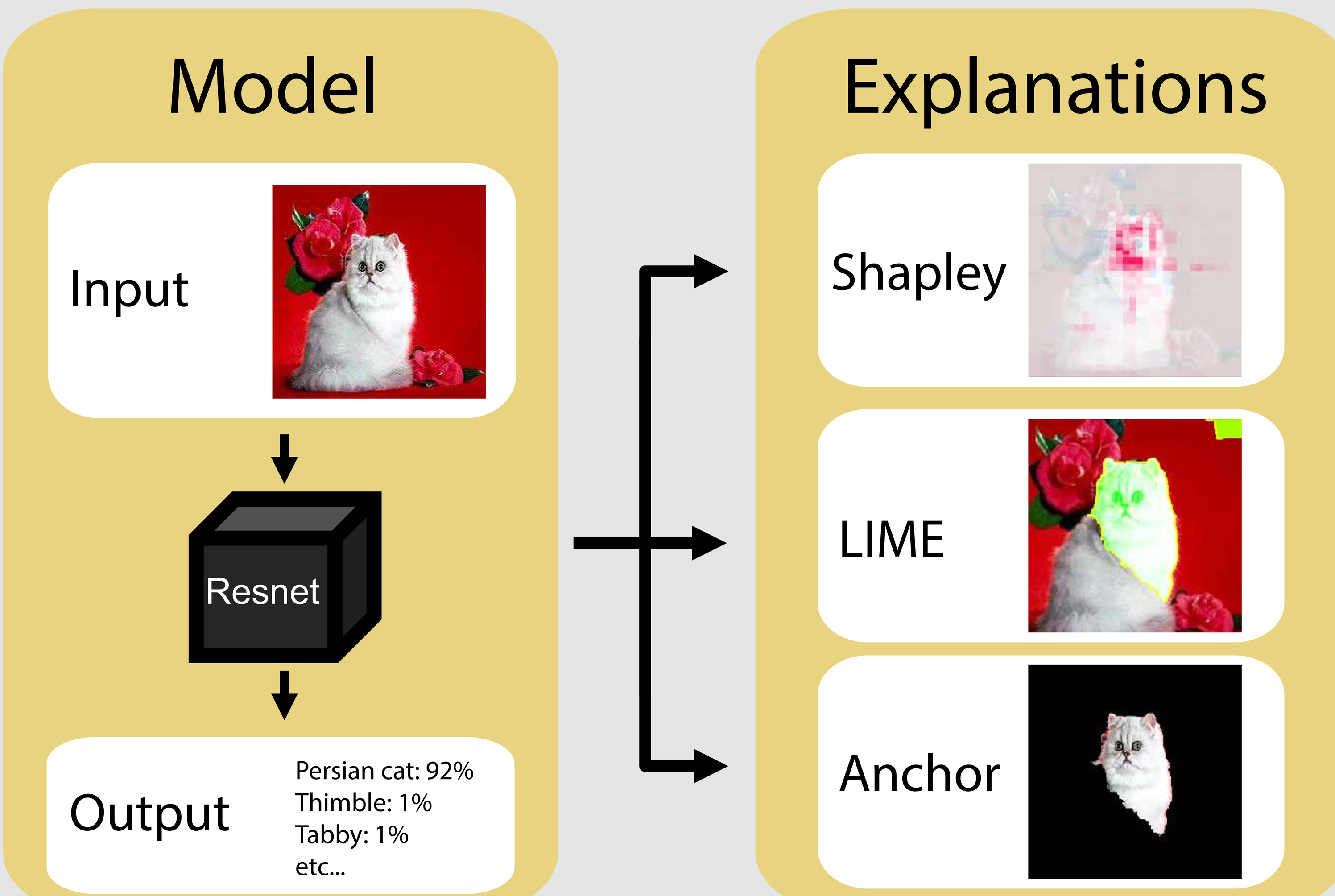

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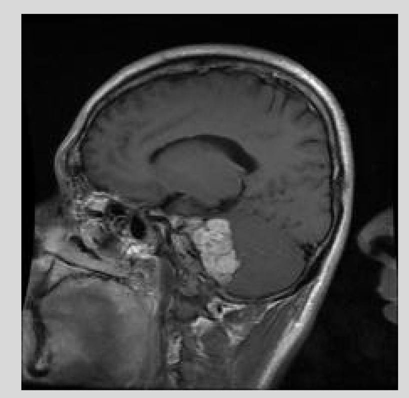
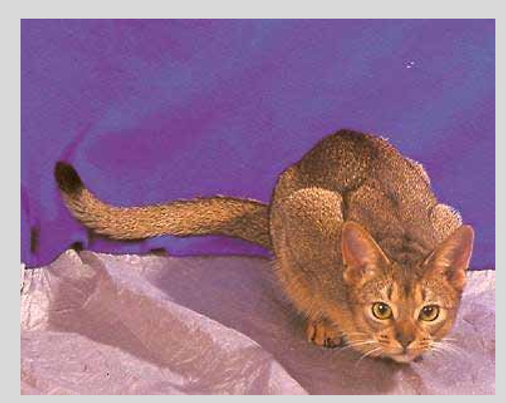
Model Confidences
German Shorthaired Pointer: 0.94
Chesapeake Bay Retriever: 0.03
Weimaraner: 0.01
...

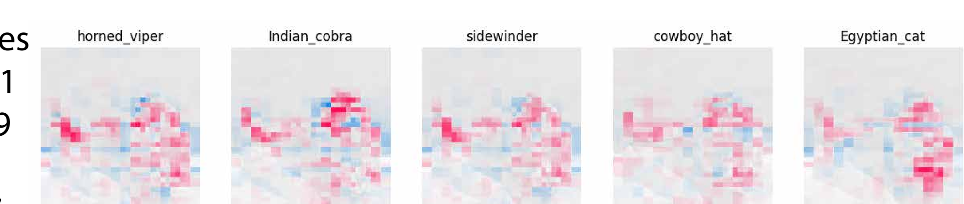
Model is correct and explanations agree why



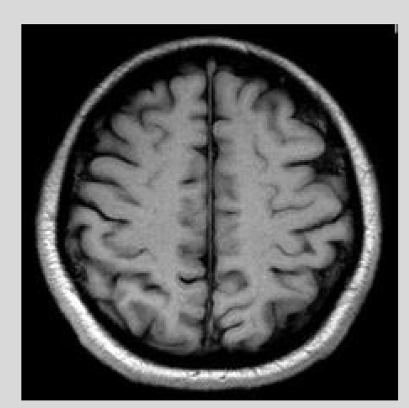
Model is correct, but explanations differ

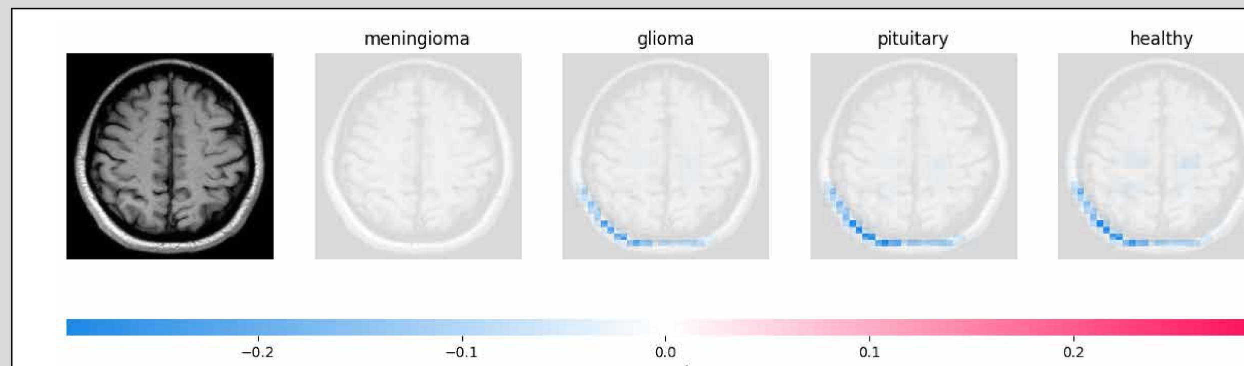


Model Confidences
Horned Viper: 0.21
Indian Cobra: 0.09
Sidewinder: 0.08
Cowboy Hat: 0.07
Egyptian cat: 0.06
...



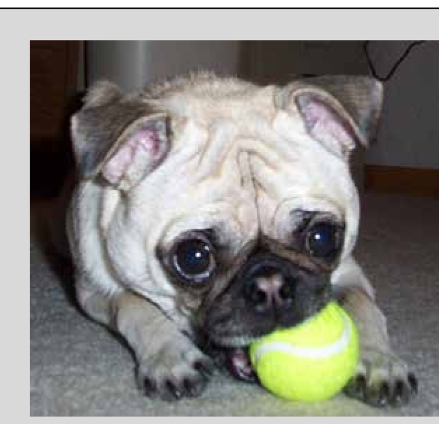
Cannot explain confidences





Model Confidences
Polar Bear: 0.56
Golden Retriever: 0.17
...

Sometimes the explanations of the same prediction disagree greatly



Model Confidences
Tennis Ball: 0.59
Pug: 0.37
...

Different explanations may be due to human-set values, like confidence thresholds

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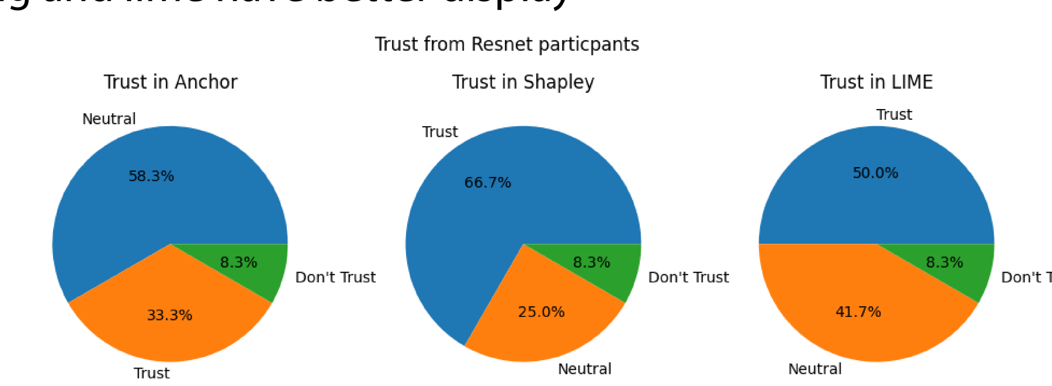

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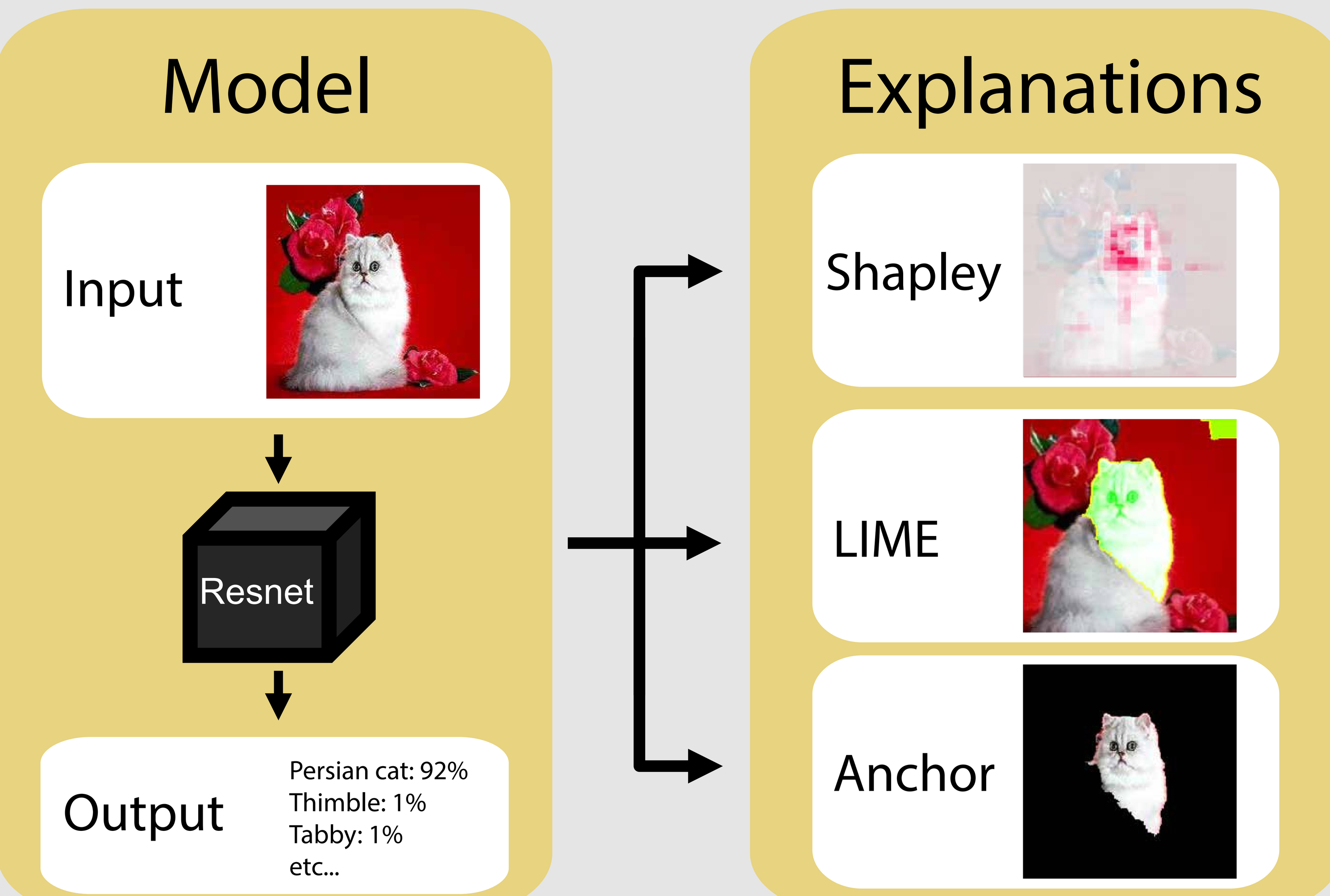

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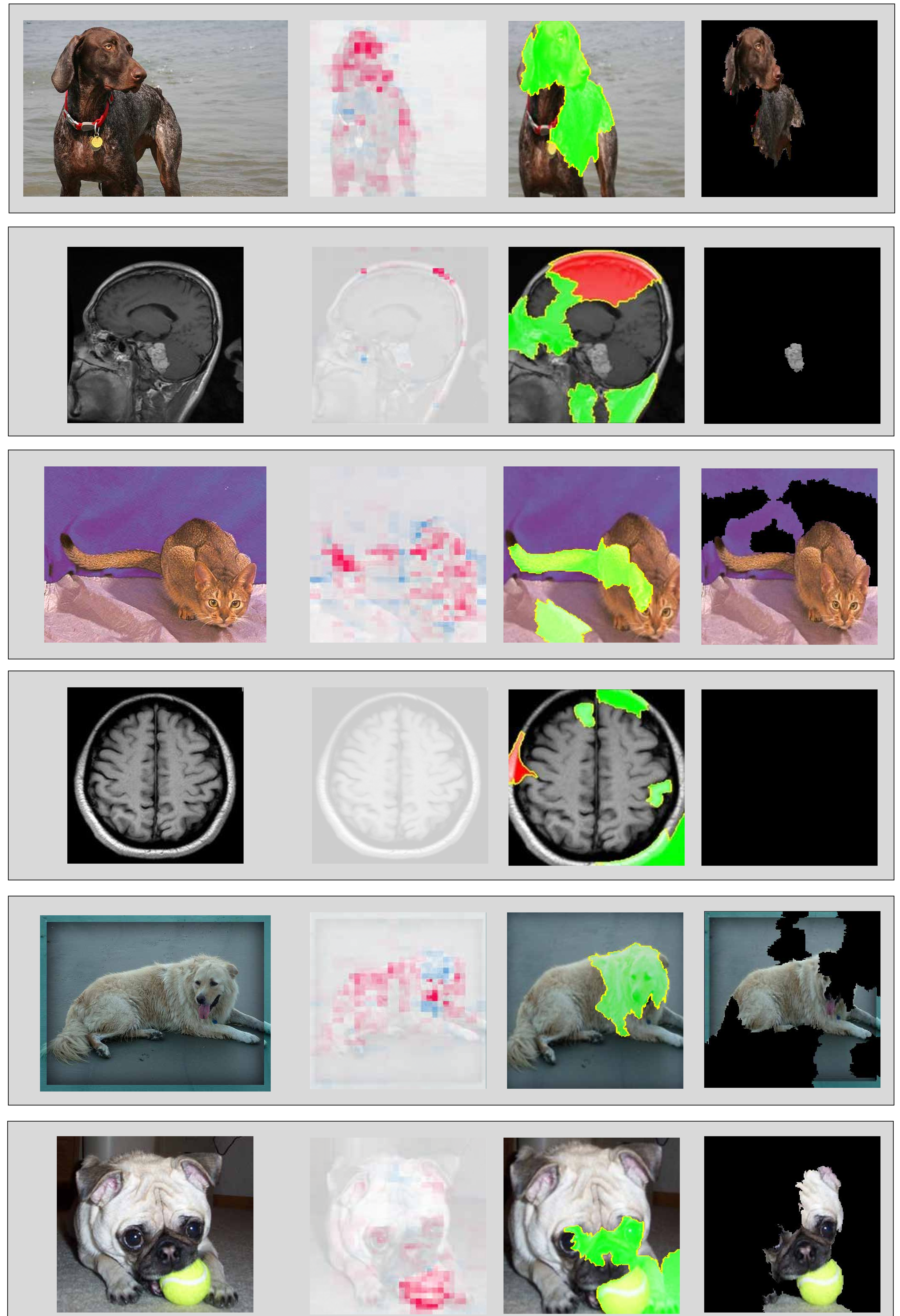

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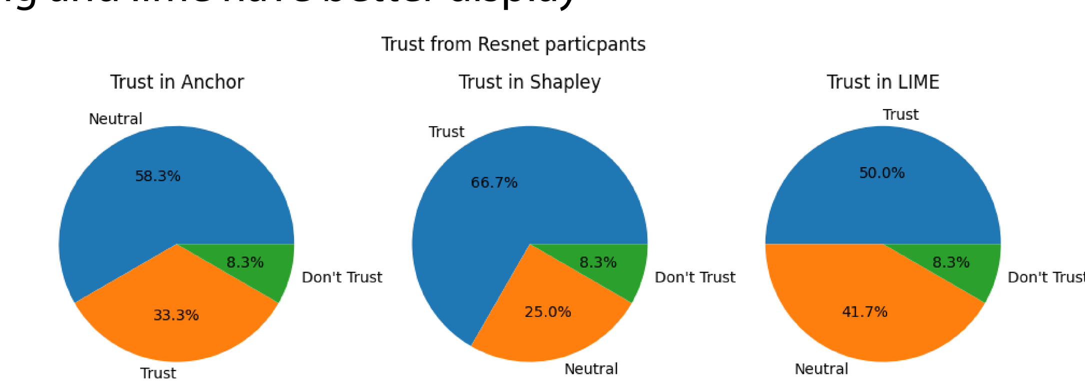

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