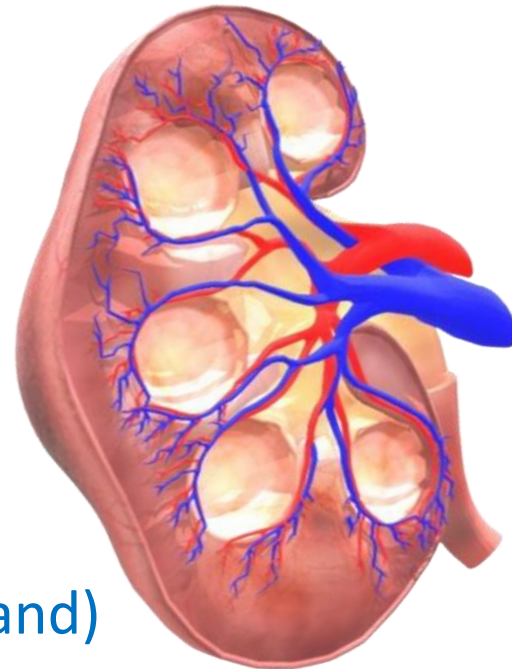


Explainable AI and It's Use in Medical Imaging



MOHAN BHANDARI

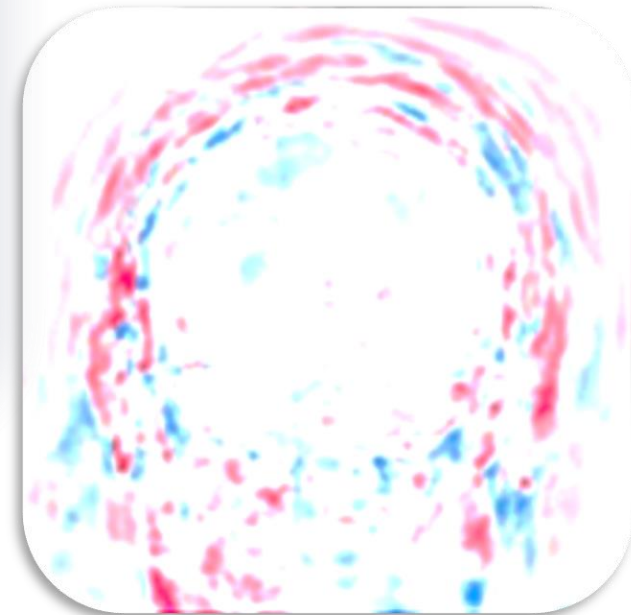
(PhD Student, SIIT, Thammasat University, Thailand)





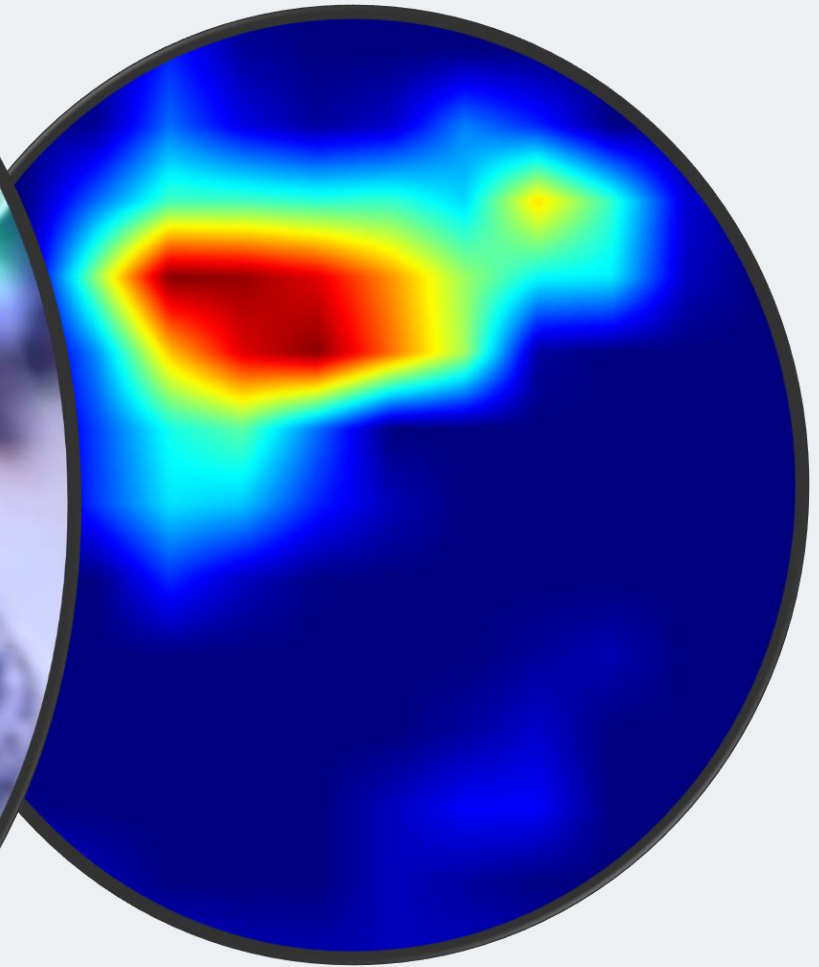
Outlines

- ☐ Introduction
- ☐ Essence
- ☐ XAI Frameworks
- ☐ Implementations
- ☐ Limitations
- ☐ Discussion





Normal Image



Heatmap

Artificial Intelligence

- ❑ Simulation of human intelligence processes by machines, especially computer systems.
- ❑ Includes learning (acquiring knowledge and skills), reasoning (using logic to make decisions), and self-correction.
- ❑ Algorithms

Machine Learning, Deep Learning and Reinforcement Learning

Why many AI algorithms are black box?

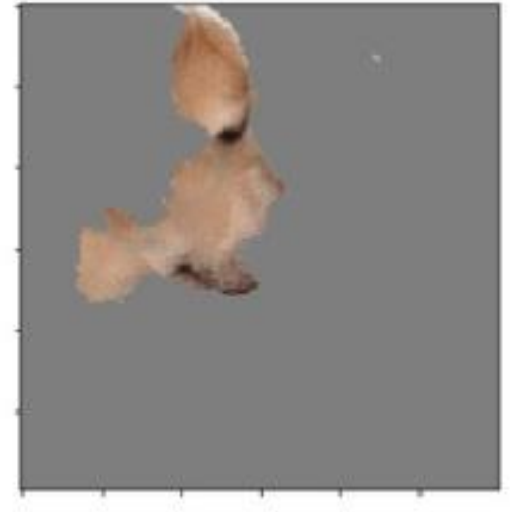
- ❑ Decision-making process is often not directly accessible or observable
- ❑ Adapt their internal representations during training, potentially resulting in decisions algorithms
- ❑ Understanding the role and interactions of each layer in the decision-making process can be difficult.
- ❑ The focus on maximizing accuracy can lead to models that are effective but hard to interpret.

Essence of AI to be explained



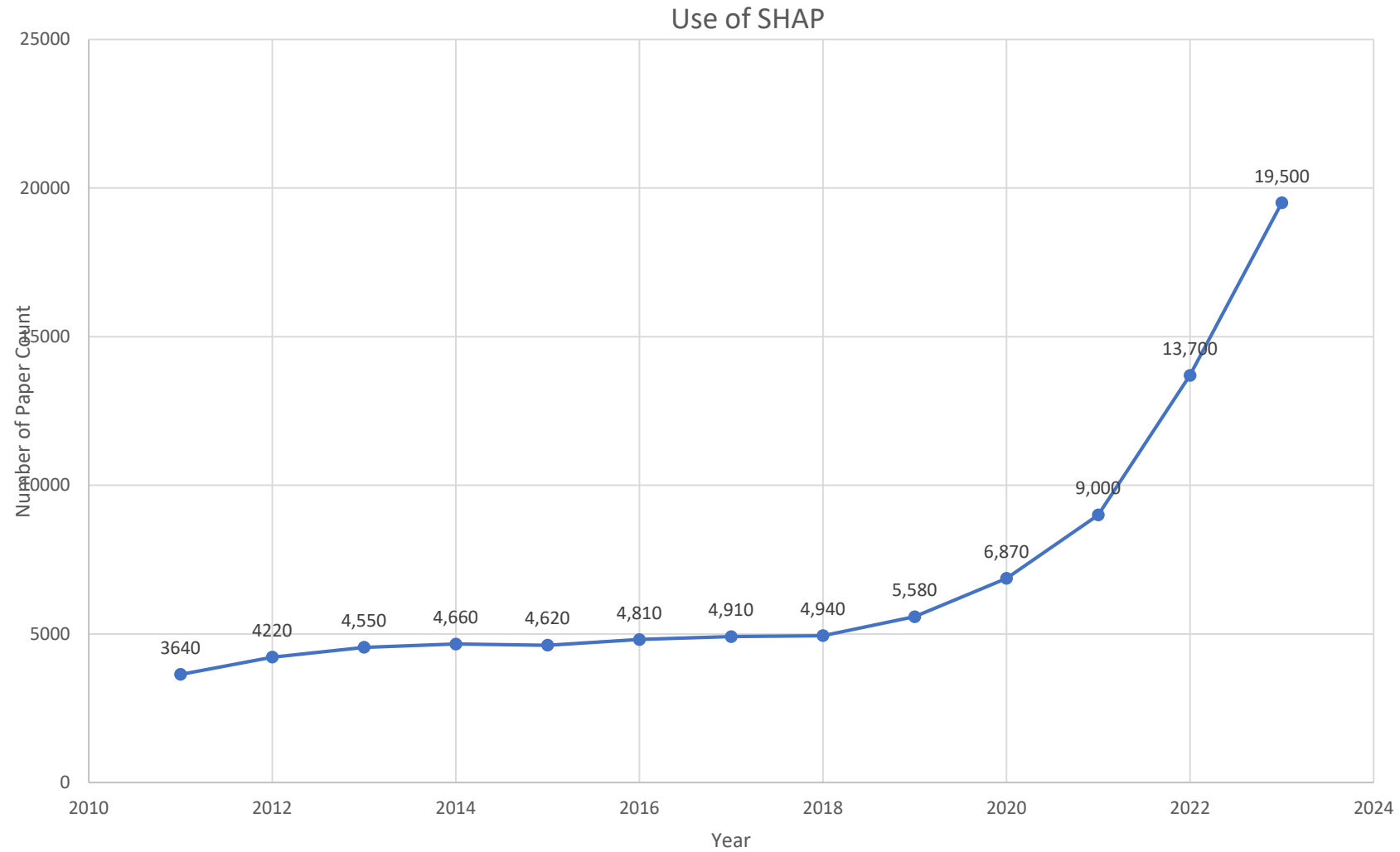
Different AI
Algorithms

DOG (90%) → Why?



XAI
(LIME)

Gaining Popularity



eXplainable AI (XAI) ??

Framework

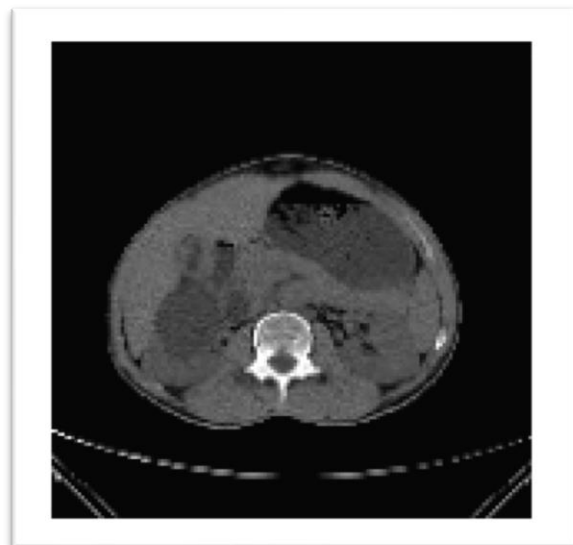
Allow humans to
understand and interpret
the outcomes and
processes of AI systems

Make AI models
transparent,
understandable, and
interpretable for users

Does not improve the
accuracy of AI algorithms

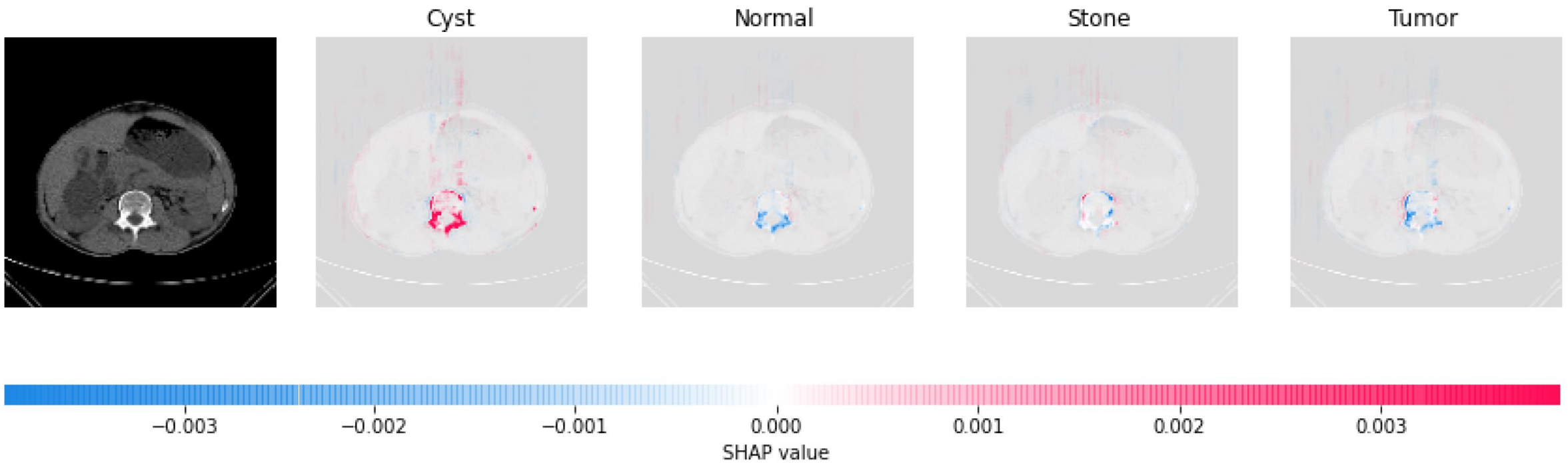
Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 148, 148, 64)	1792
max_pooling2d_5 (MaxPooling 2D)	(None, 74, 74, 64)	0
conv2d_6 (Conv2D)	(None, 72, 72, 64)	36928
max_pooling2d_6 (MaxPooling 2D)	(None, 36, 36, 64)	0
conv2d_7 (Conv2D)	(None, 34, 34, 64)	36928
max_pooling2d_7 (MaxPooling 2D)	(None, 17, 17, 64)	0
conv2d_8 (Conv2D)	(None, 15, 15, 64)	36928
max_pooling2d_8 (MaxPooling 2D)	(None, 7, 7, 64)	0
conv2d_9 (Conv2D)	(None, 5, 5, 64)	36928
max_pooling2d_9 (MaxPooling 2D)	(None, 2, 2, 64)	0
flatten_1 (Flatten)	(None, 256)	0
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
dense_3 (Dense)	(None, 4)	516
=====		
Total params: 182,916		
Trainable params: 182,916		
Non-trainable params: 0		

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	Avg ($\mu \pm \sigma$)
TrA	99.33	99.64	99.04	99.31	99.31	99.22	99.64	99.5	99.43	99.24	99.30 \pm 0.18
TrL	0.0321	0.0192	0.0445	0.0348	0.0352	0.0350	0.0223	0.2680	0.0335	0.0323	0.0557 \pm 0.07
VaA	99.76	99.68	96.47	100	99.76	99.76	99.84	99.68	99.76	99.2	99.39 \pm 0.99
VaL	0.0208	0.0192	0.1518	0.0118	0.169	0.0195	0.0142	0.0201	0.0195	0.0452	0.0491 \pm 0.06
TsA	99.84	99.76	97.19	100	100	100	100	99.68	99.84	98.88	99.52 \pm 0.84
TsL	0.0221	0.0164	0.1106	0.0018	0.0145	0.0131	0.0117	0.0208	0.0178	0.0621	0.0291 \pm 0.03



```
pred_single=model.predict(image[0])
pred_single=np.argmax(pred_single, axis=-1)
```

```
0.9939, 0.03, 0.001, 0.0051
{Cyst, Normal, Stone, Tumor}
```



Red Pixels increase the classification probability

Blue Pixels Decrease the classification probability

XAI Frameworks

Local Interpretable Model-Agnostic Explanations (LIME)

SHapley Additive
exPlanations (SHAP)

Count ++

Local Explanations

focus on interpreting individual predictions

Heatmaps (GradCAM,
GradCAM++)

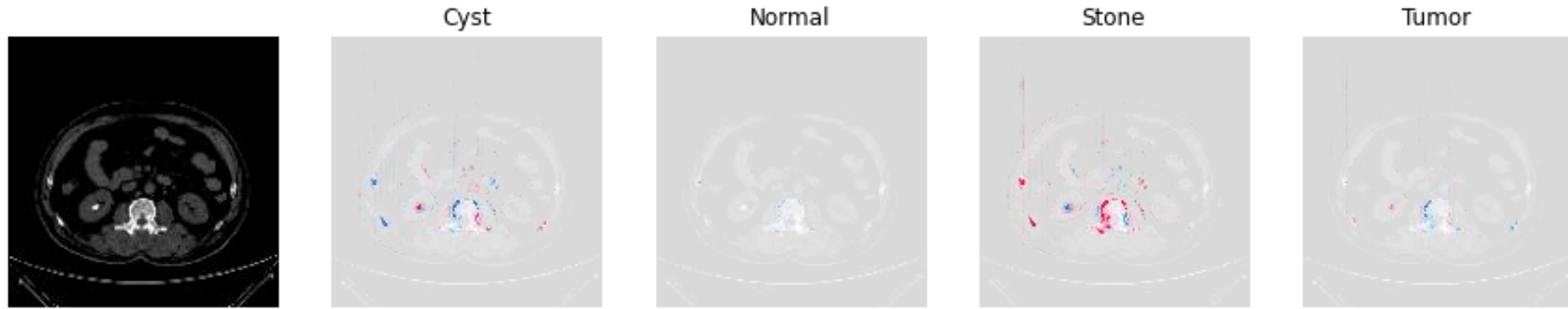
Accumulated Local Effects
(ALE)

Count ++

Global Explanations

Aim to provide insights into the overall
behavior of the model across different
inputs.

Why XAI is important in Medical Images?



Improving Diagnosis and
Treatment

Trust and Transparency

Bias Detection and
Mitigation

Patient Communication

<https://www.mdpi.com/2076-3417/13/5/3125>

<https://colab.research.google.com/drive/1uClINC9aqiAg1LR1ibUykEbcONYzFtoI?authuser=1#scrollTo=qMUyoBkpsbIX>

<https://www.frontiersin.org/journals/genetics/articles/10.3389/fgene.2022.822666/full>

<https://colab.research.google.com/drive/1YKy8WrflvSR7dn4MSkEGrg4TVq7ODbAh?authuser=1>

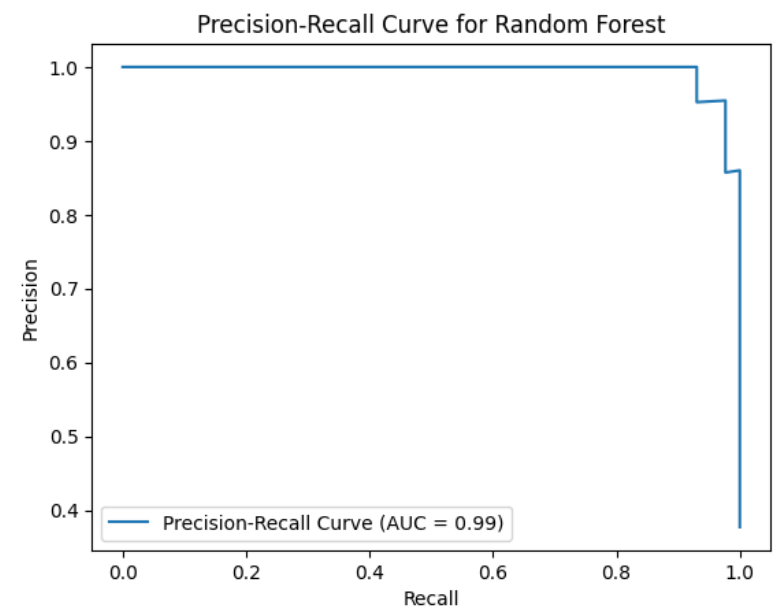
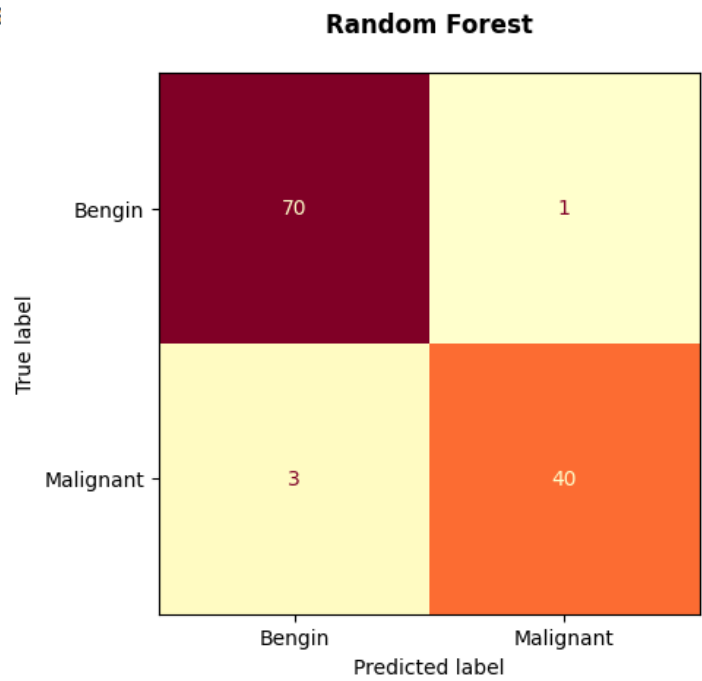
Are XAI only for Image Data?

NO

XAI on CSV Data

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...

5 rows x 32 columns



XAI on CSV Data (LIME)

```
exp = explainer.explain_instance(  
    data_row=X_test_scaled[0],  
    predict_fn=modelRF.predict_proba)
```

Prediction probabilities

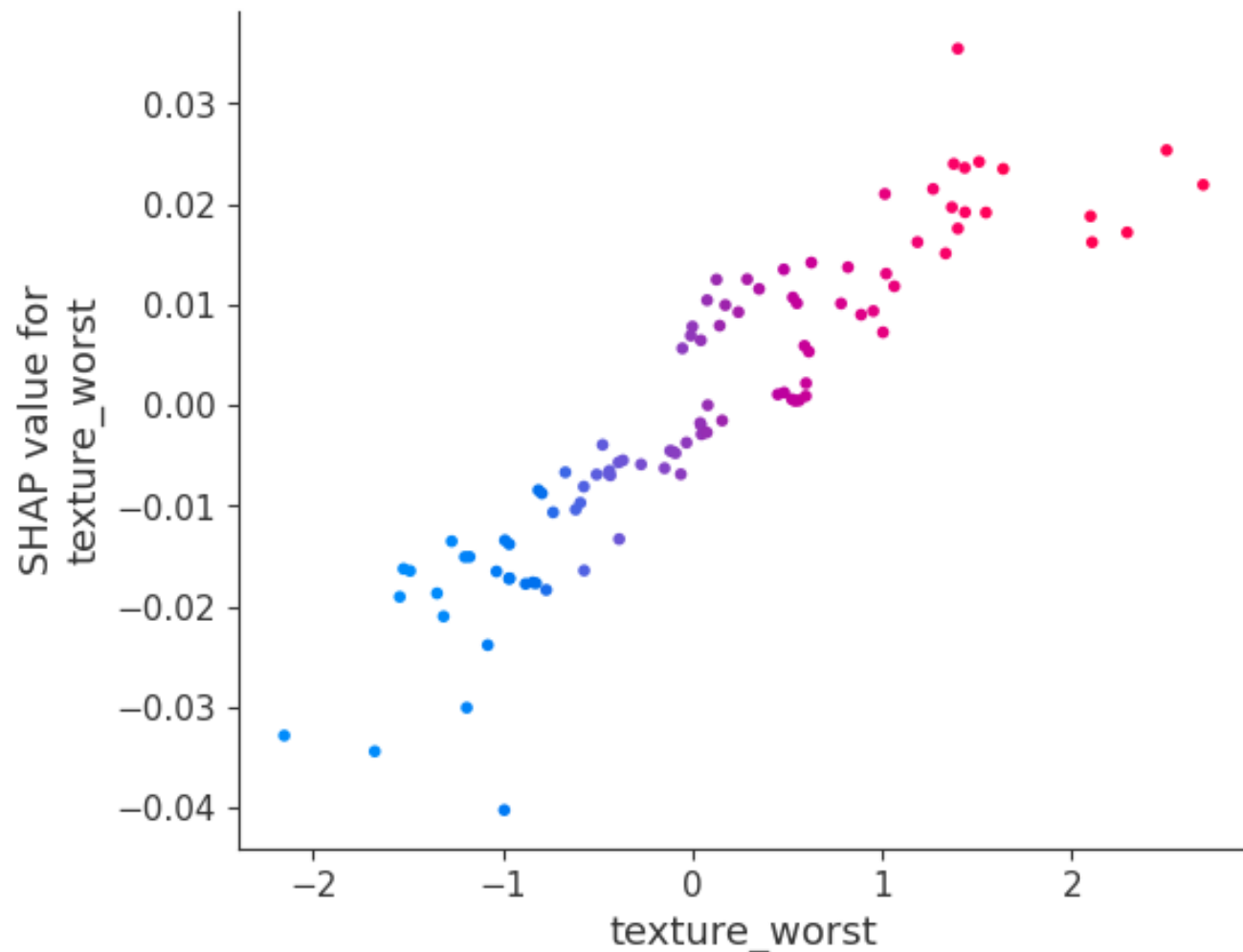
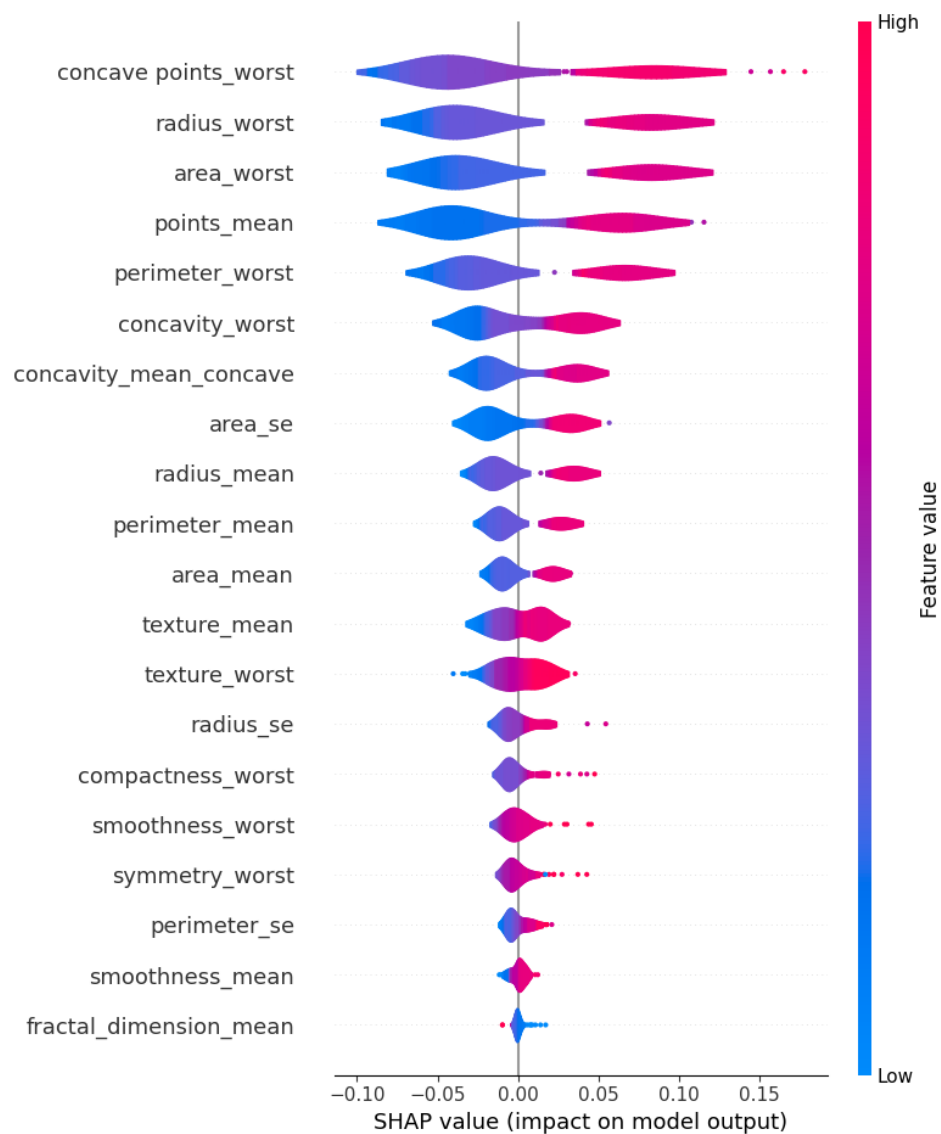
malignant	<div></div>	0.98
benign	<div></div>	0.02

malignant

-0.66 < radius_worst < ...	0.06
-0.64 < area_worst <= ...	0.05
-0.69 < perimeter_wor...	0.04
-0.74 < texture_worst <...	0.02
-0.66 < area_mean <= ...	0.01
-0.24 < concave point...	0.01
-0.39 < points_mean ...	0.01
-0.12 < symmetry_wo...	0.01
-0.71 < texture_mean <...	0.01
-0.69 < perimeter_me...	0.01

benign

XAI on CSV Data (SHAP)



Limitations of XAI algorithms

No Any Standard

Lack of Interpretability for
Complex Data Types
(For Eg: Multidimension)

Trade-offs with Model
Accuracy

Discussion