Anomaly Detection in Image Streams with Explainable AI

By Team Bits of Erised

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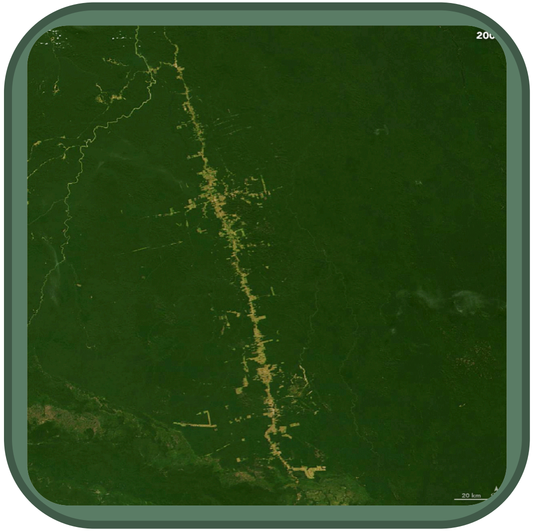
Overview

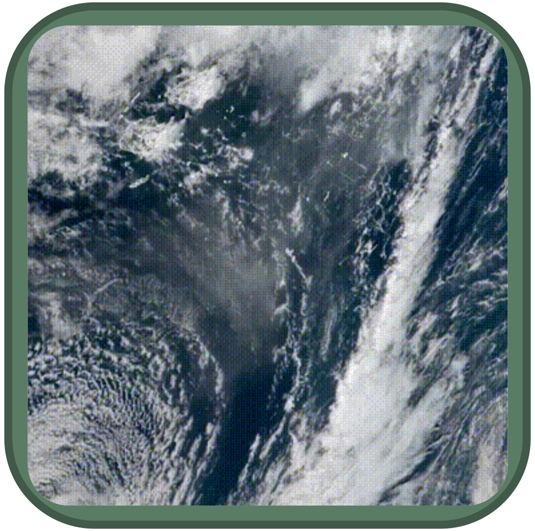
Motivation

- Benefits of extracting information and detecting anomalies from streaming data is prevalent with the availability of high-quality image streams

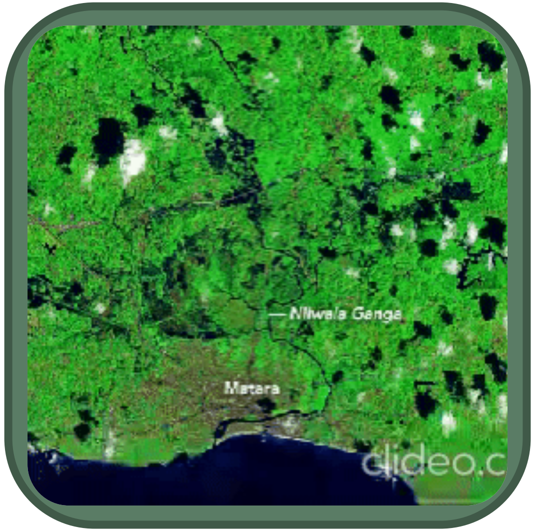


Forest Coverage of Rondônia, Brazil

1975 - 2001



Undersea Volcano Eruption near Tonga



Sri Lankan Flood Situation

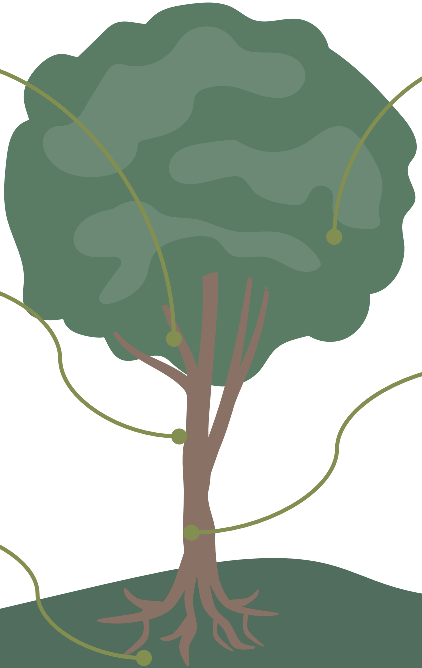
Significance of the Study

01

Deforestation in Sri Lanka –
average 1.14% annual rate

02

High density populations and inappropriate land usage due to **improper urban planning** have an impact on climate change.



03

Habitat degradation and diseases such as 'Sena caterpillar' problem.

04

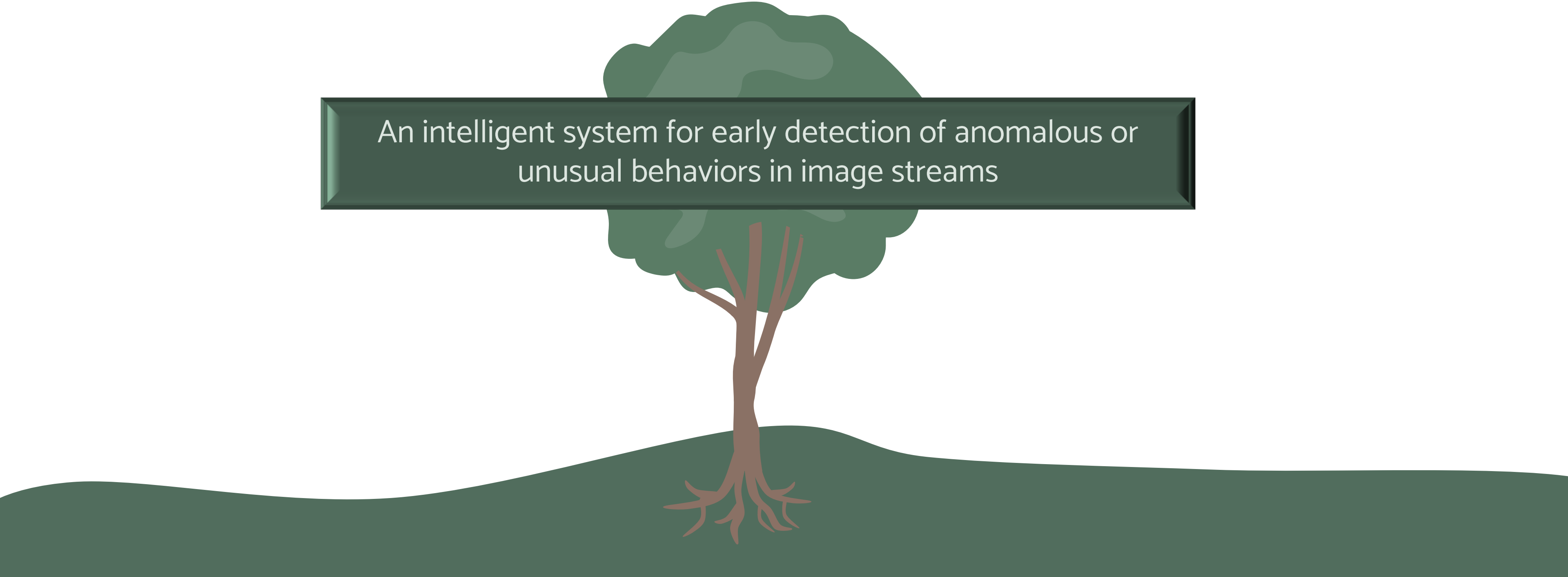
Damage of vegetation communities, loss of plant and animal habitats ascribe to **bushfires**.

05

Forest disturbances caused by both natural and man-made activities.

Significance of the Study (cont.)

An intelligent system for early detection of anomalous or unusual behaviors in image streams



Novelty of Our System

Research Gap	Novelty/Main Contribution
1. **Treat anomaly detection problem as a supervised learning problem.** **Issue:** Generalizability is low.	• Proposed a **novel anomaly detection framework**. • In the proposed framework, we treated anomaly detection problem as a **one class classification**.
2. **Most of the existing methods ignore the interdependency between the images (time dependency.**	• Integrated computer vision and **time series forecasting** to capture the interdependency between the images during the model building process.
3. **Most of the existing anomaly detection methods use manual thresholds and unrealistic assumptions.**	• Novel approach to calculate a **data driven anomalous threshold using EVT**.

Novelty of Our System (cont.)

Research Gap	Novelty/Main Contribution
4. Existing deep learning-based anomaly detection methods solely focus on the classification task. This leads to lack of explainability. **Issue:** Reduces the human trust on the system.	• Proposed a novel framework that integrated computer vision, time series forecasting and **explainable AI** to detect anomalies in image streams.
5. Existing methods suffers from class imbalance and sometimes in order to address this some researchers has used different approaches. These methods have their own limitations. - Up sampling - Down sampling - Data augmentation	• We treat the anomaly detection problem as a one class classification problem and **model for the typical behavior**.

Aim & Objectives

The aim of this research is to develop a novel framework that detects and interprets anomalies in images streams using computer vision, time series forecasting, extreme value theory, and explainable AI.

Objectives:

- Defining a pool of features that encapsulate the signal information content in image streams using computer vision.
- Propose a novel framework to detect anomalies in image streams in different application domains using time series forecasting and extreme value theory based anomalous threshold.
- Implementing a suitable explainable model for anomaly detection in image streams.

Methodology

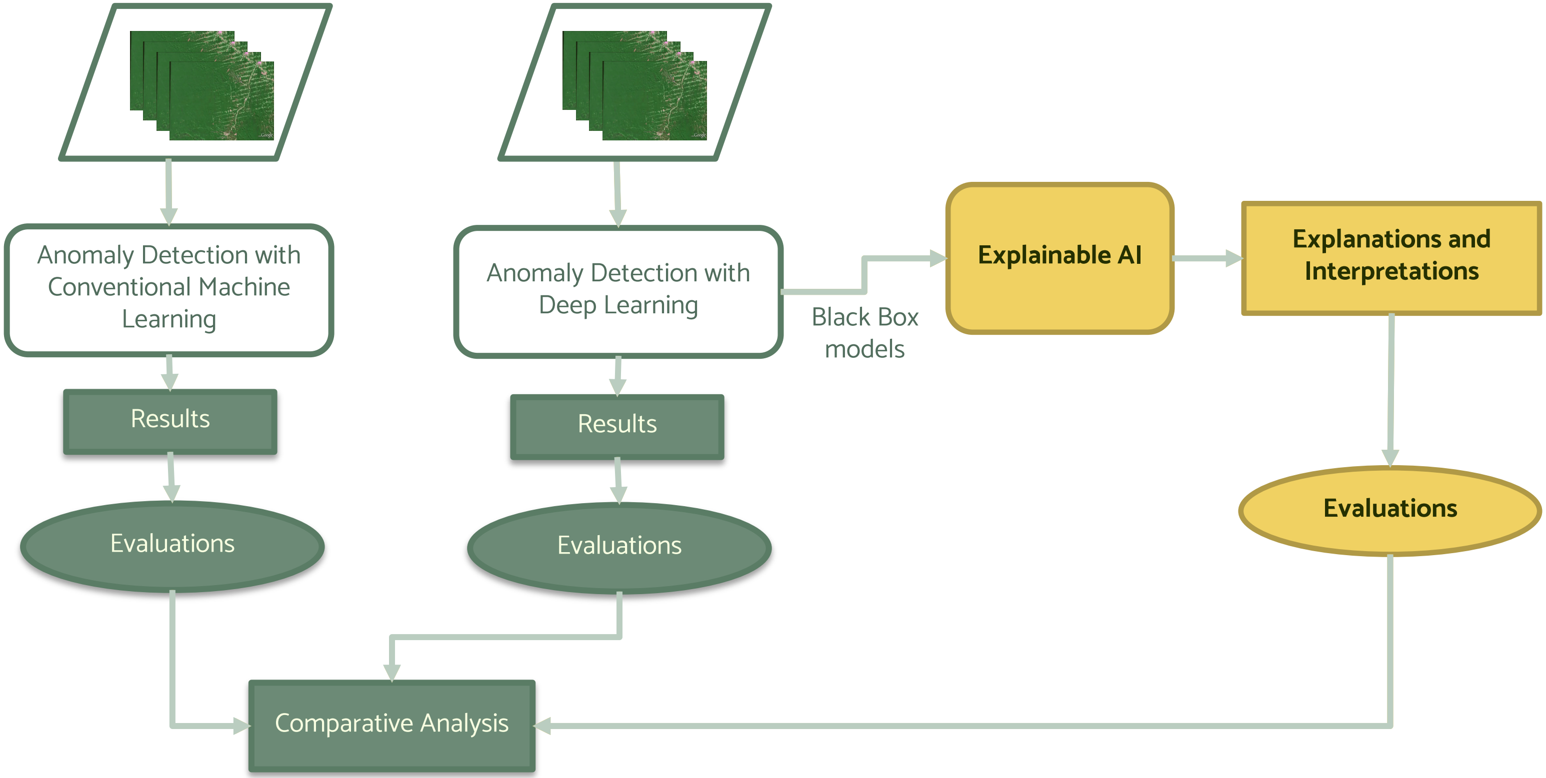
Definition of an Anomaly

In our context, we define anomaly as an observation that is very unlikely given the forecast distribution.

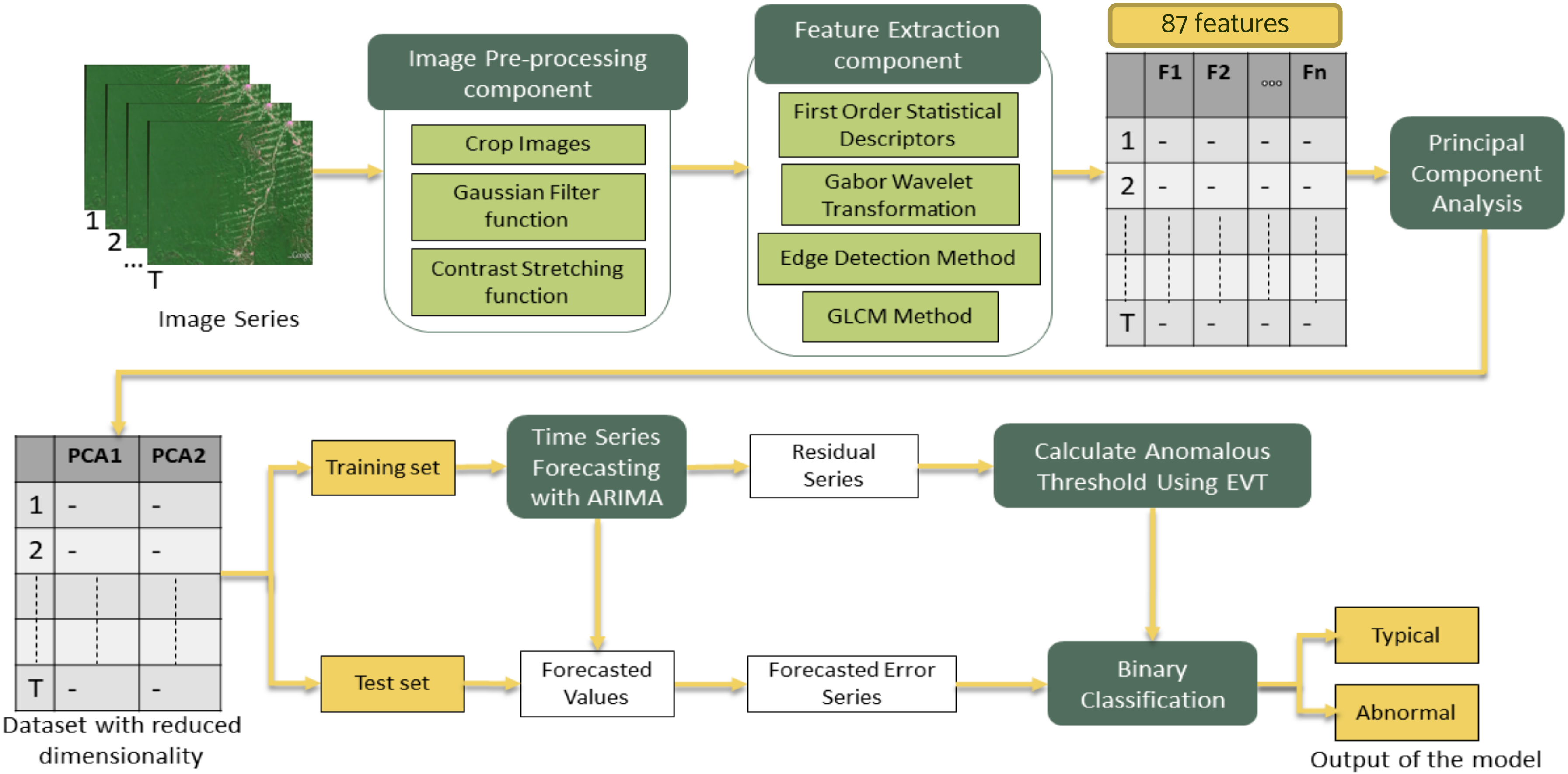
Main Assumptions

- Anomalies show a significant deviation from the typical behavior of a given system.
- A representative dataset of the system’s typical behavior is available to define a model for the typical behavior of the image streams generated by a given system.

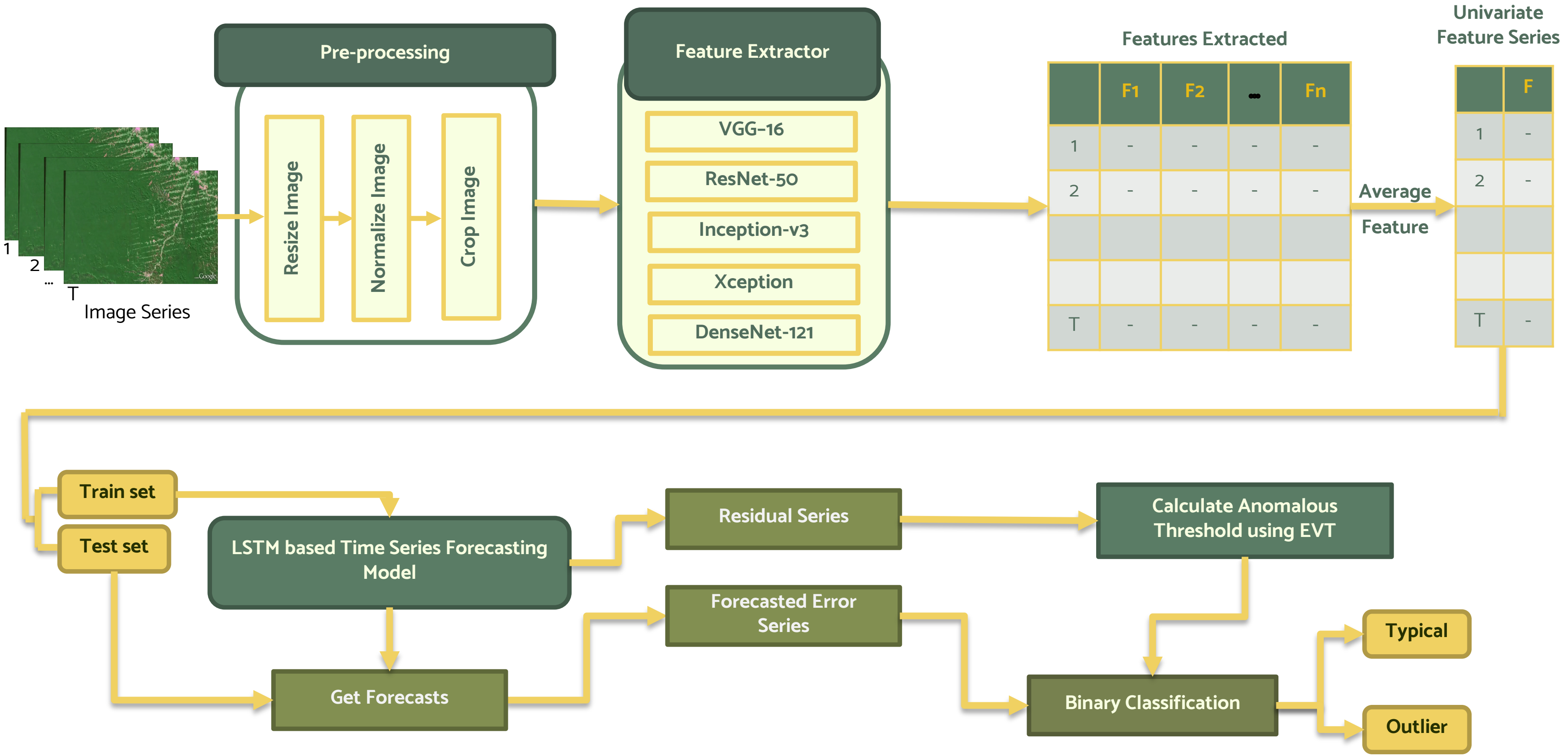
Methodology



Traditional Machine Learning Module



Deep Learning Module



EVT based Anomaly Threshold Calculation

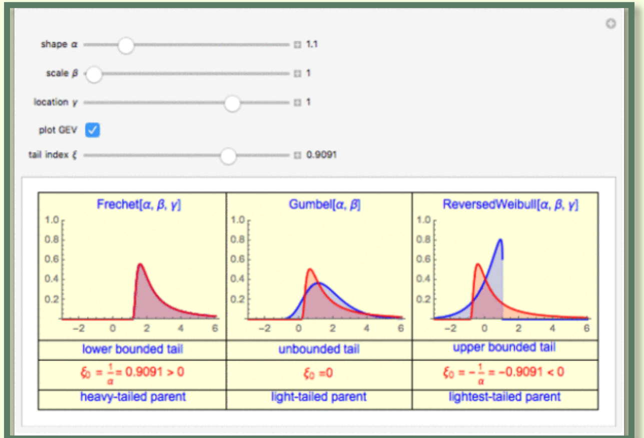
Limitations of EDA based Threshold

- Assumes the parent distribution conforms to a Guassian distribution.

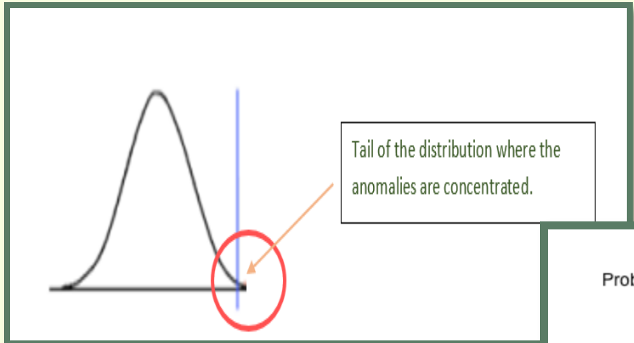
Fisher Tippet Theorem

According to the Fisher Tippett Theorem any GEV distribution of any natural distribution that satisfies a weak condition (Described in Implementation) should take one of the following shape.

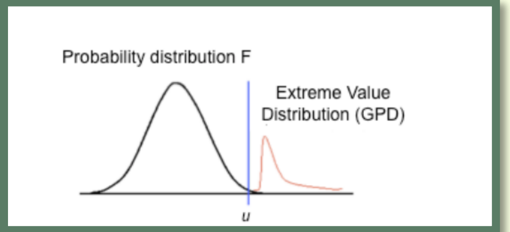
- Frechet
- Weibull
- Gumbell



Theoretical Foundation for EVT



Anomalies resides on the tails of the original distributions thus, its is difficult to correctly identify the anomaly threshold from the original curve.

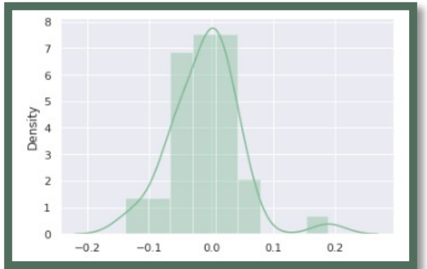


A child curve should be plotted to obtain the accurate anomaly threshold. Value

EVT based Anomaly Threshold Calculation

No	Residual Values

Identifying the Residual distribution

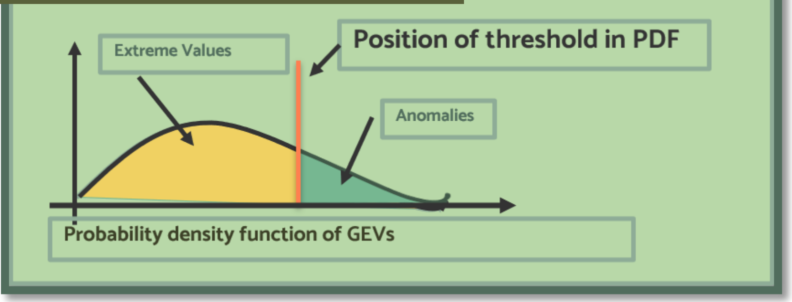


Using Fisher Tippett intuition finding the most suitable GEV distribution

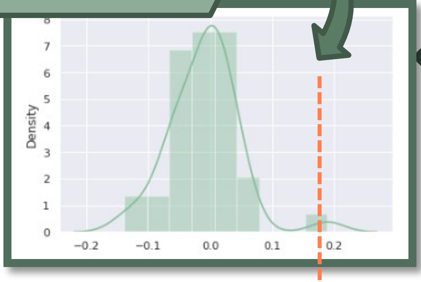
Applying the relevant transformation function to transform the residuals to their EV' probability density curve.

$$gumbel\_l.pdf(x) = exp(x - exp(x))$$

Position of the Threshold n GEV's PD.

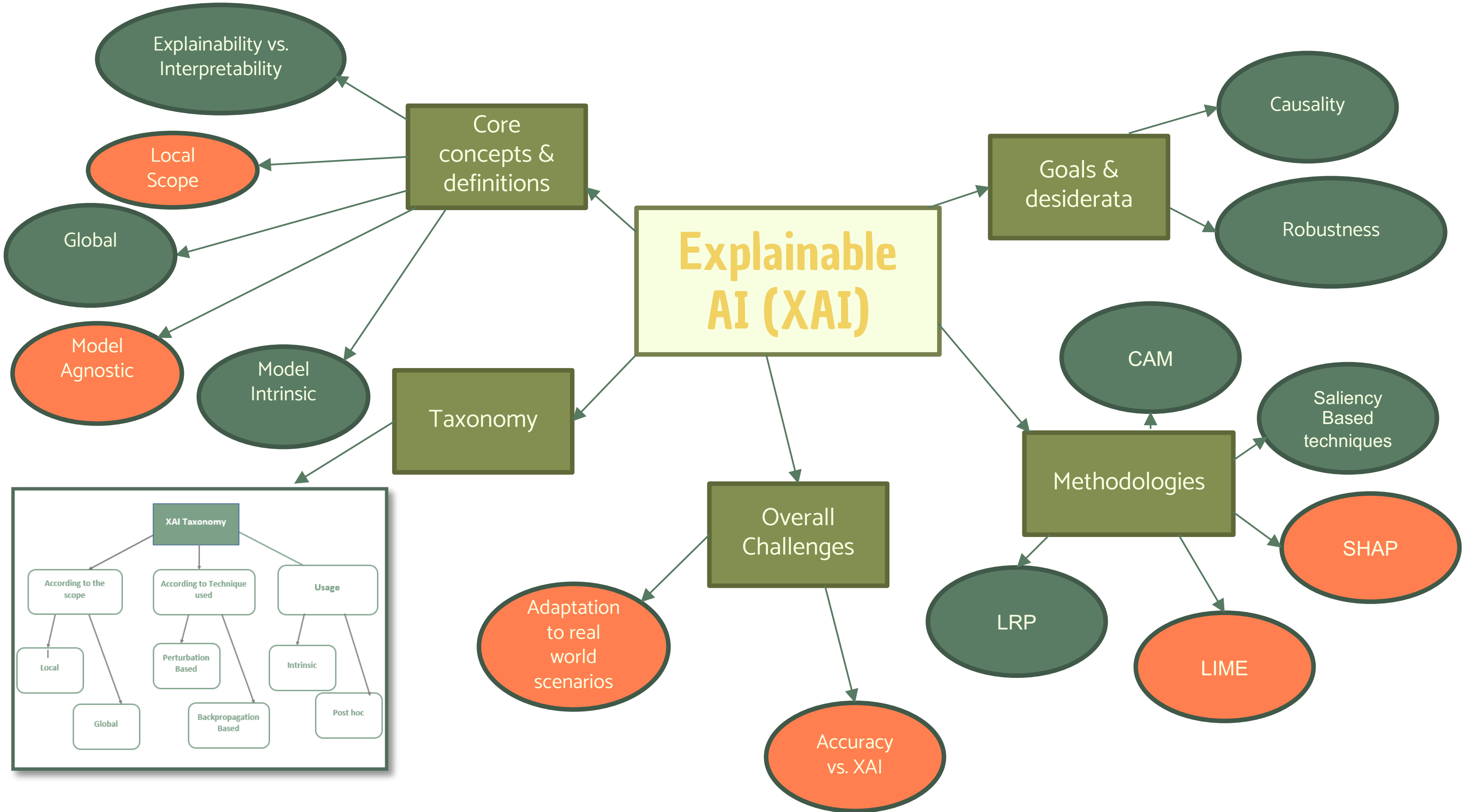


Obtaining the EVT-based anomaly threshold value by applying re-transformation



Threshold value

Explainable AI Module



Explainable AI Module - (LIME)

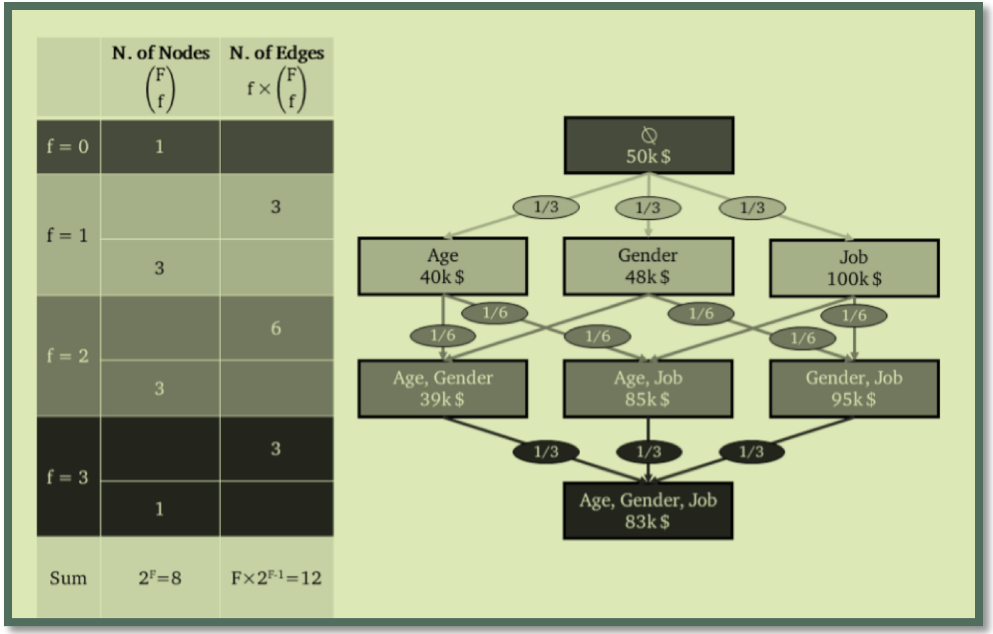
Locally Interpretable Model Agnostic Explanations (LIME)

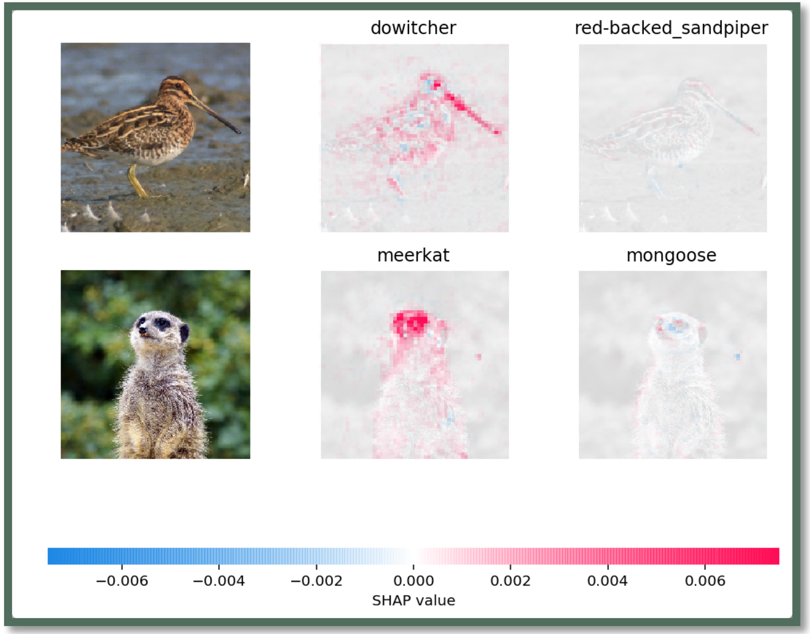
$$\varepsilon(x) = argmin\ \boxed{\text{Unfaithfulness}} + \boxed{\text{Complexity}}$$

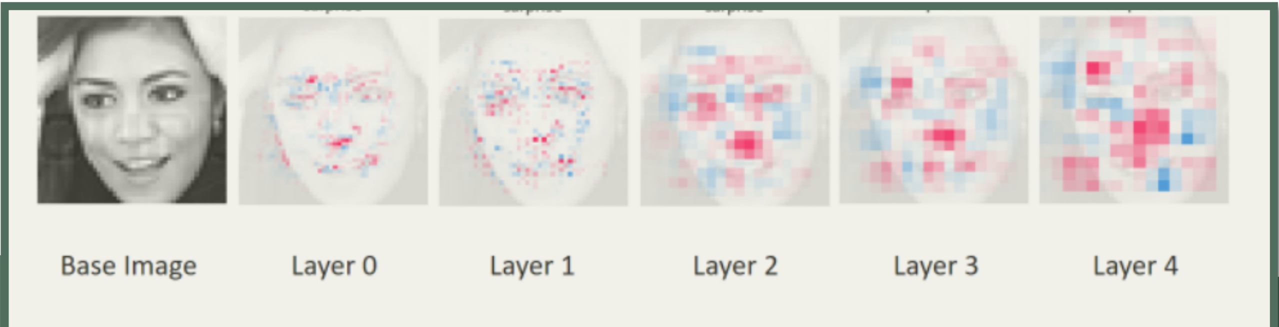
How LIME works with Images?

Decomposes the target image into homogeneous patches
Create number of images using perturbation by turning on and off the super pixels.
Get predictions of the new image set.
Build the local surrogate model with feature contributions.

Explainable AI Module(SHAP)

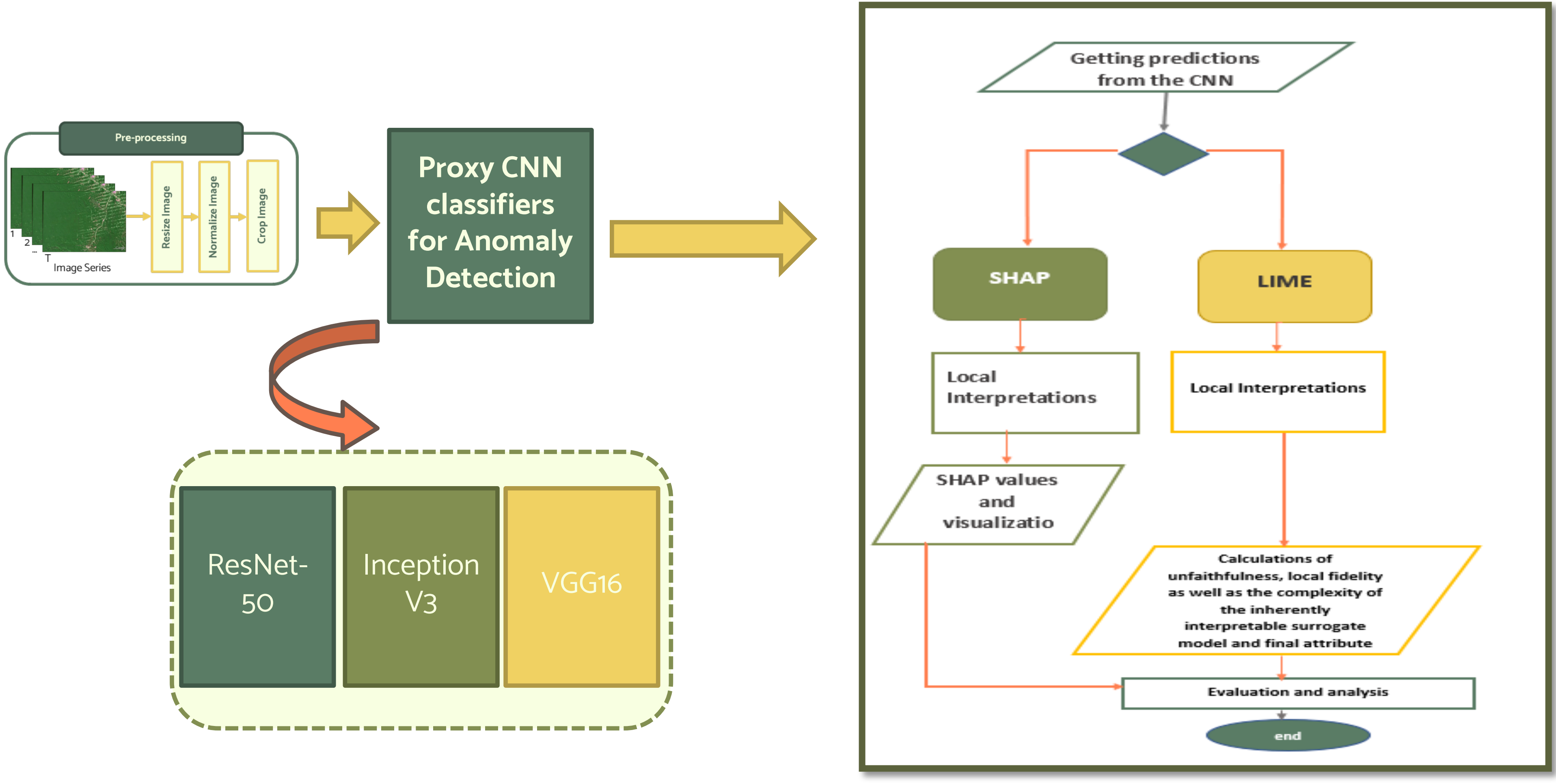






- For Images super pixels and pixels can be used as features for which the contribution towards the model’s prediction is calculated.

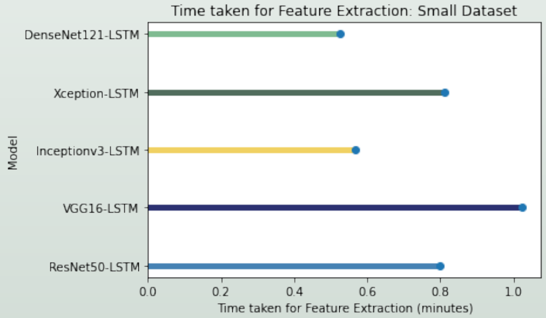
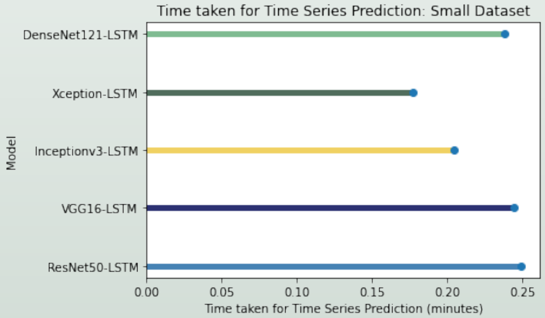
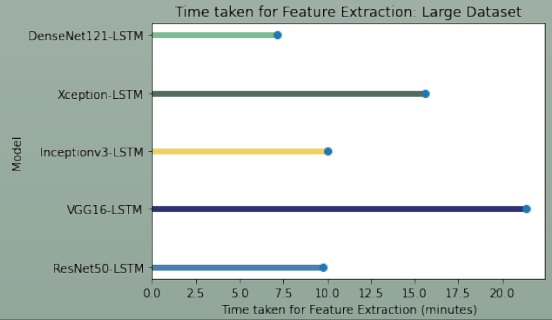
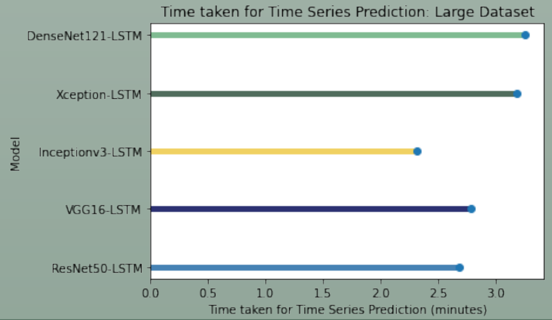
Explainable AI Module



Evaluation

	Conventional Machine Learning		Deep Learning Techniques									
	Small Dataset	Large Dataset	Small Dataset					Large Dataset				
			InceptionV3	ResNet50	VGG16	Xception	DenseNet121	InceptionV3	ResNet50	VGG16	Xception	DenseNet121
Box Plot Threshold Calculation Technique												
Accuracy	**92.98%**	80.8%	80%	93.33%	90%	90%	11..67%	**95.05%**	89.04%	75.67%	70.05%	67,65%
Sensitivity	**1.0**	1.0	0.77	0.92	0.94	1.0	0.11.	**1.0**	1.0	1.0	0.96	1.0.
Specificity	**0.05**	0.016	1.0	1.0	1.0	0.25	0.125	**0.85**	0.67	0.27	0.18	0.028
Positive Predictive Value	**0.92**	0.81	1.0	1.0	1.0	0.896	0.46	**0.93**	0.86	0.73	0.70	0.67
Negative Predictive Value	**1.0**	1.0	0.4	0.67	0.73	1.0	0.02	**1.0**	1.0	1.0	0.69	1.0
EVT Threshold Calculation Technique (with 95% confidence)												
Accuracy	**94.74%**	84%	86.7%	92.9%	90%	88.33%	86.67%	**99.6%**	92.9%	76.2%	70.05%	79.55%
Sensitivity	**1.0**	1.0	1.0	0.92	0.94	1.0	1.0	**1.0**	1.0	1.0	0.96	1.0
Specificity	**0.63**	0.18	0.0	1.0	1.0	0.125	0.0	**0.987**	0.79	0.29	0.19	0.39
Positive Predictive Value	**0.94**	0.83	0.87	1.0	1.0	0.88	0.87	**0.99**	0.90	0.74	0.70	0.77
Negative Predictive Value	**1.0**	1.0	nan	0.67	0.73	1.0	nan	**1.0**	1.0	1.0	10.69	1.0

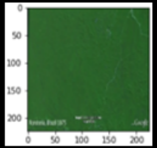
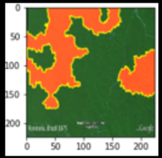
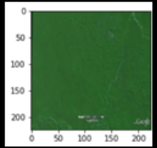
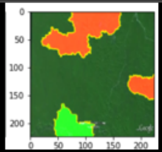
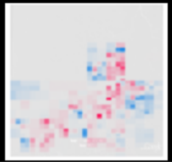
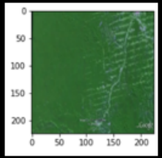
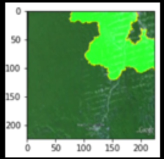
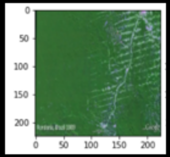
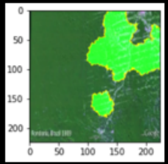
Time Comparison

<table>
<tr><th colspan="3">Time Comparison of the CNN based LSTM Model</th></tr>
<tr><th>Dataset</th><th>Feature Extraction using CNN</th><th>Time Series Prediction using LSTM</th></tr>
<tr><td>Small Dataset</td><td>
</td><td>
</td></tr>
<tr><td>Large Dataset</td><td>
</td><td>
</td></tr>
</table>

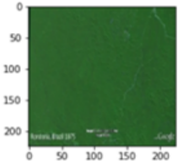
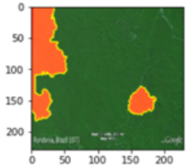
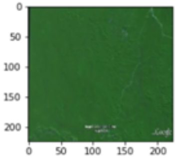
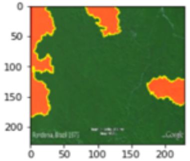
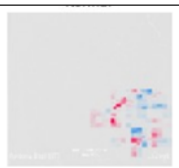
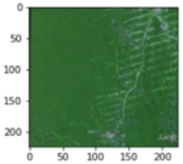
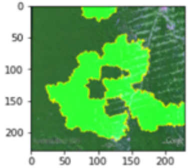
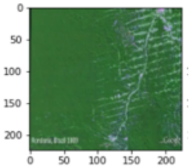
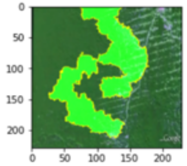
Generalizability

Performance Metrics for Different Datasets								
Model	Traditional Machine Learning Model				Deep Learning Model			
Dataset	Small Dataset		Large Dataset		Small Dataset		Large Dataset	
	Deforestation	Volcano Eruption	Deforestation	Volcano Eruption	Deforestation	Volcano Eruption	Deforestation	Volcano Eruption
Accuracy	**96.7%**	**96.7%**	86.3%	91..2%	95%	64..29%	**99.6%**	**94.79%**
Optimized Precision	**0.87**	**0.96**	0.47	0.67	0.92	0.47	**0.989**	**0.91**
Sensitivity (Sn)	**0.98**	**0.95**	1.0	1.0	0.94	1.0	**1.0**	**0.92**
Specificity (Sp)	**0.9**	**1.0**	0.59	0.74	1.0	0.47	**0.987**	**1.0**
Positive Predictive Value (PPV)	**0.98**	**1.0**	0.83	0.88	1.0	0.47	**0.99**	**1.0**
Negative Predictive Value (NPV)	**0.9**	**0.91**	1.0	1.0	0.73	1.0	**1.0**	**0.86**

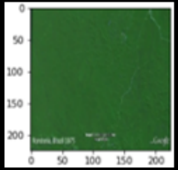
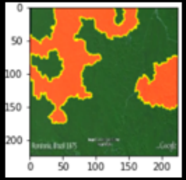
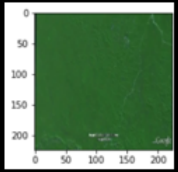
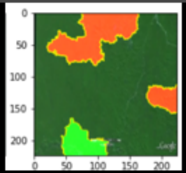
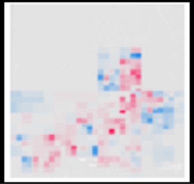
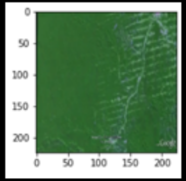
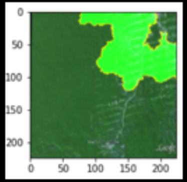
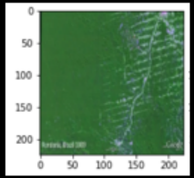
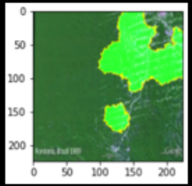
Explainable AI Module - ResNet50

Image no	Original Image	LIME results	SHAP results
100			
1900			
2250			
2450			

Explainable AI Module – InceptionV3

Image No:	Original Image	LIME Result	SHAP Result
100			
1900			
2250			
2450			

Explainable AI Module – VGG16

Image no	Original Image	LIME results	SHAP results
100			
1900			
2250			
2450			

Further Work

- **Machine Learning Module**: Can sport a more optimized feature extraction and selection procedure to increase the performance.

- **Deep Learning Module**: Can be optimized to accommodate smaller datasets, and hyperparameter tuning.

- **Explainable AI Module**:
  - Explainable AI techniques used in this study are both perturbation-based techniques and as a further study backpropagation based XAI technique such as LRP can be applied in comparison with the existing methods.
  - A proper evaluation method for XAI techniques can be applied for the XAI methods used.

THANK YOU!

Slides available at:
https://prital.netlify.app/talks/OCTAVE2022/OCTAVE2022.pdf

Q&A

Acknowledgement

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