Data Analysis in Remote Sensing :
Change Detection in LULC using Time Series and Deep Learning for Unveiling Insights with Modified SHAP

Presented By:

Dr. K.R. Manjula

Data Analytics and AI

SASTRA
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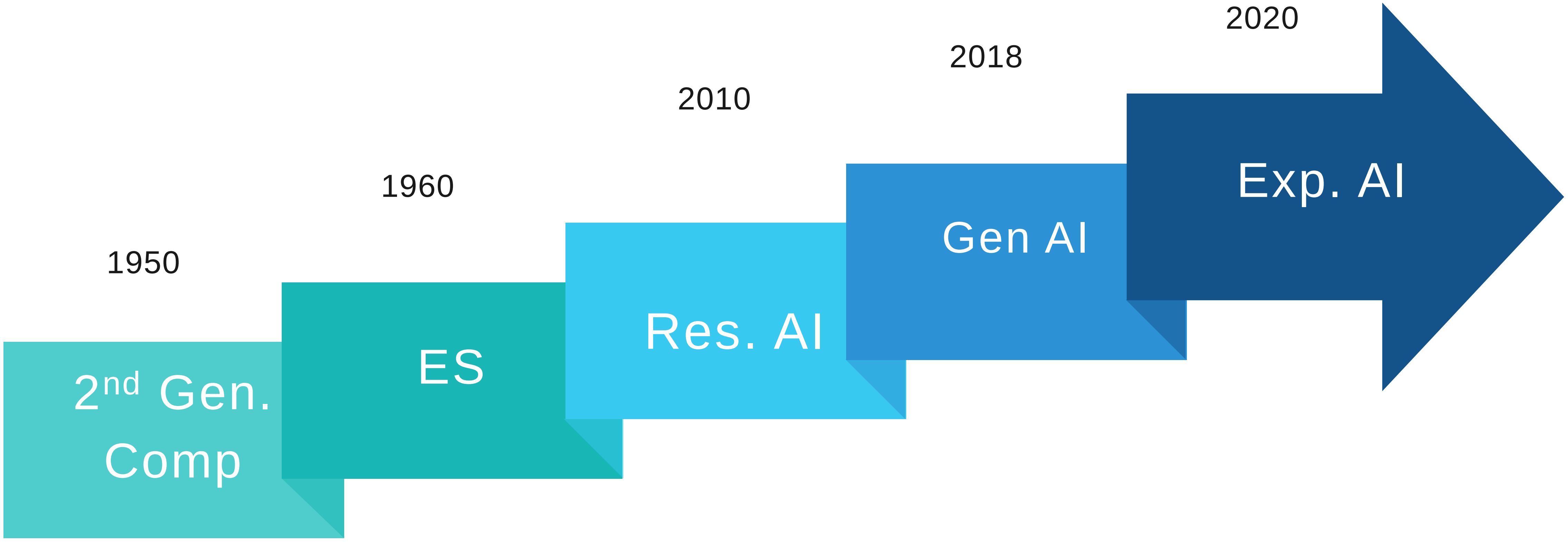
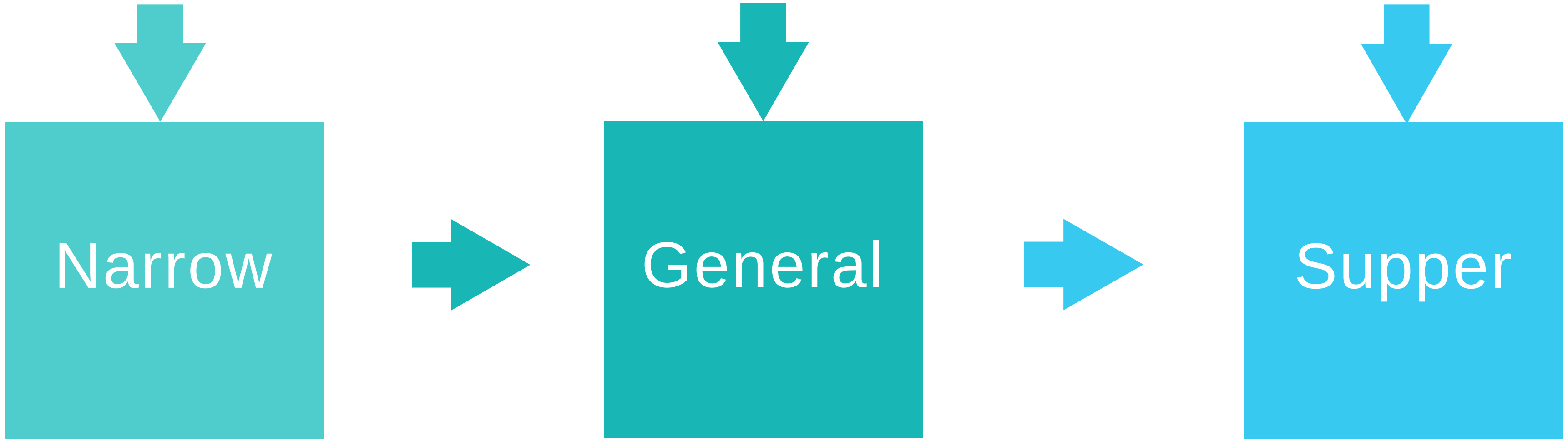
Application of Data Analytics in Remote Sensing

- Evolution & Misconception of AI
- Roots of AI
- Recent Development
- Applications in Remote Sensing
- Case Studies - Change Detection

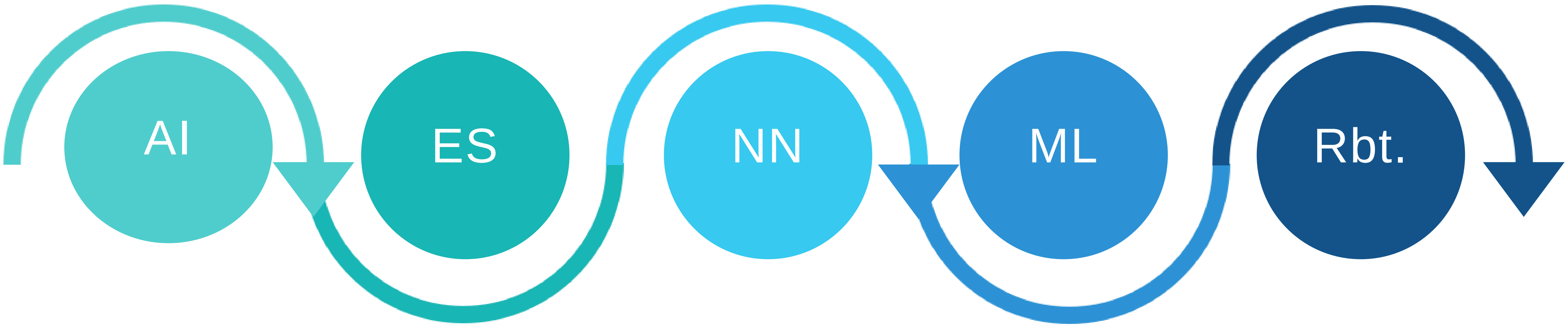
Evolution of AI



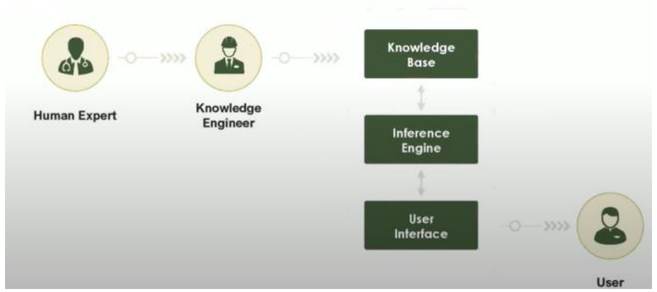
AI - Types



AI - Roots

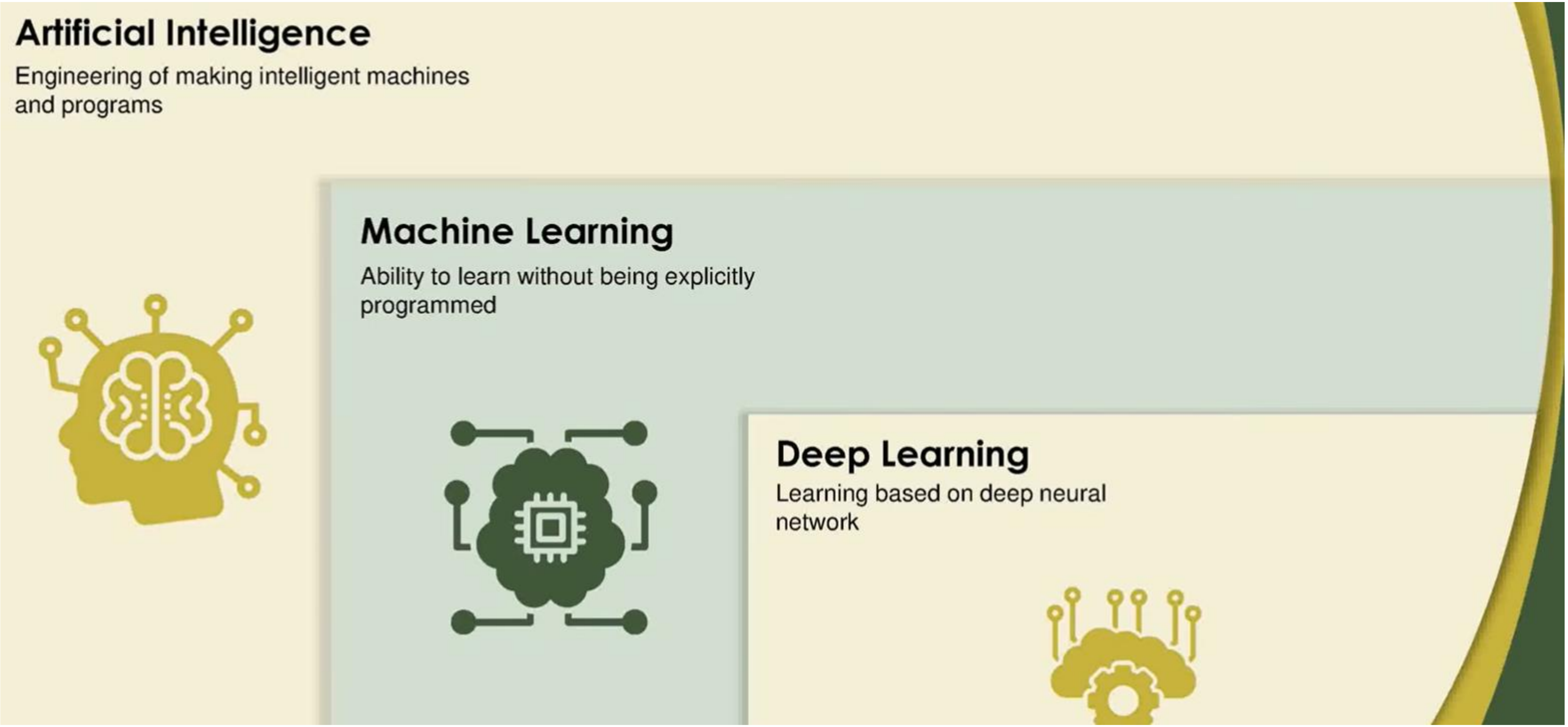


AI – Branches



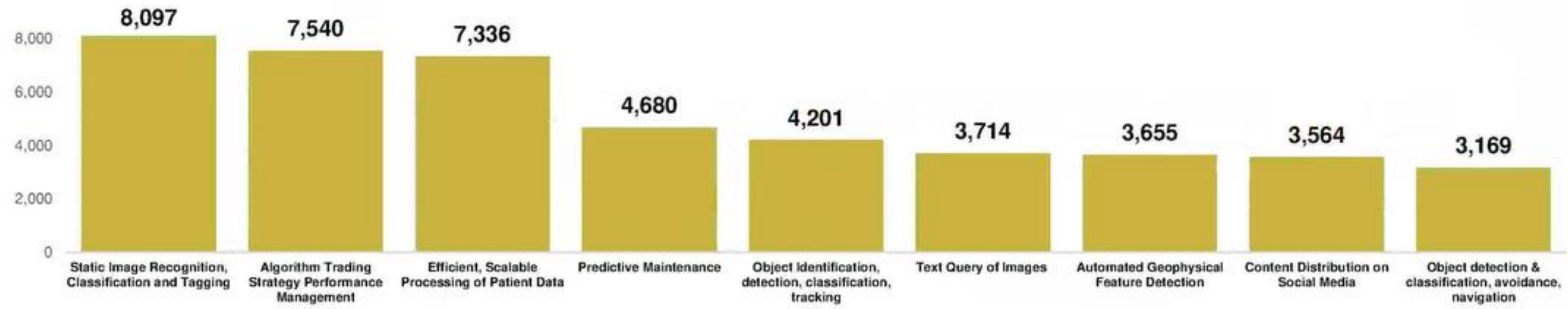
- 1960 – Expert System
- 1960 – Decision System
- 1970 – Machine Learning
- 1970 – Deep Learning
- 2020 – Reinforcement Learning

AI – ML – DL - DS

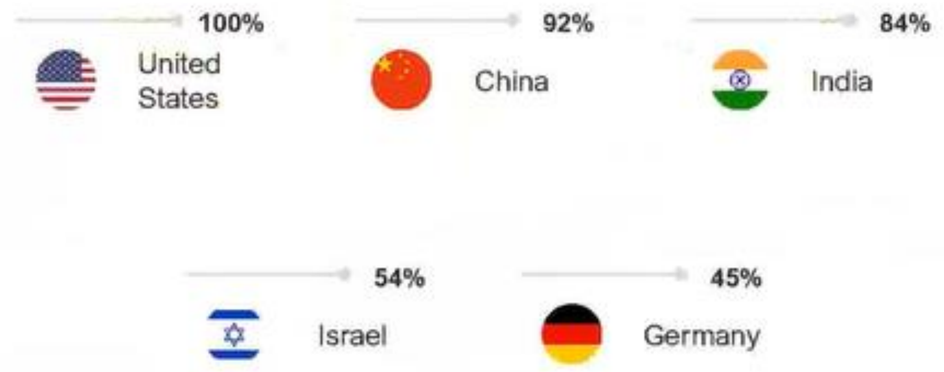


Artificial Intelligence
Engineering of making intelligent machines and programs
Machine Learning
Ability to learn without being explicitly programmed
Deep Learning
Learning based on deep neural network

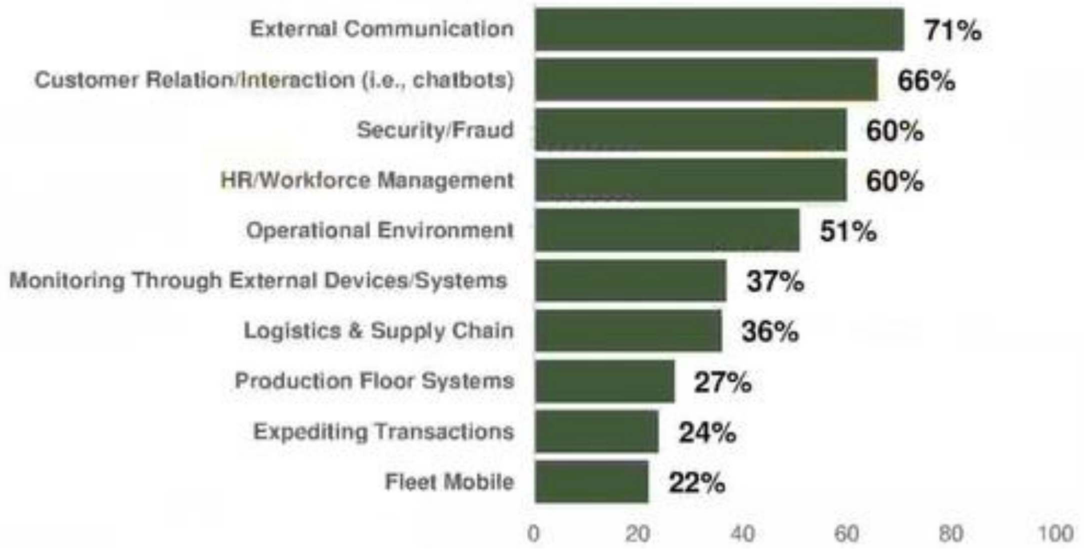
Global AI Revenue Forecast by 2025, Ranked by Use Case in millions US Dollar



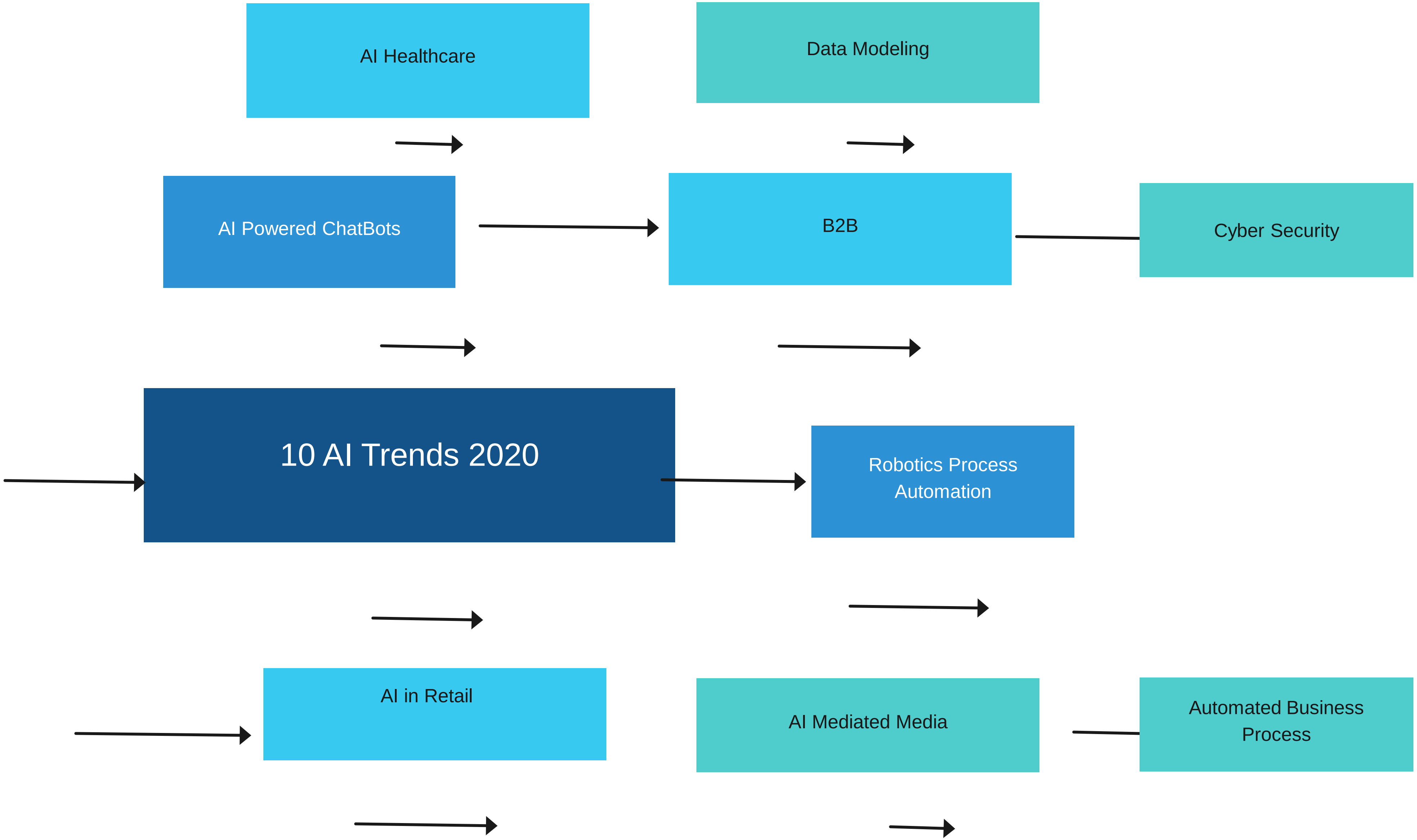
Penetration of Artificial Intelligence Skills, by Country



Organizations deploying AI, by Functional Areas



2020 Trend in AI



Case Study Objectives

- To study change/development in a particular land area which is important to analyze the growth and problems in that area with ***Time Series Analysis***

- To continuously inspect the change in land area images by implementing machine/Deep learning techniques with **ExpAI**

Conceptual Diagram - 1

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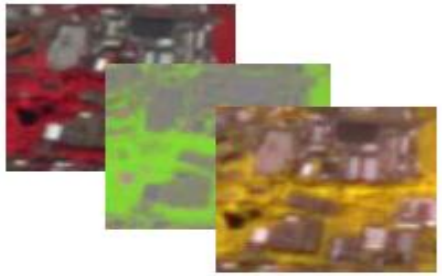
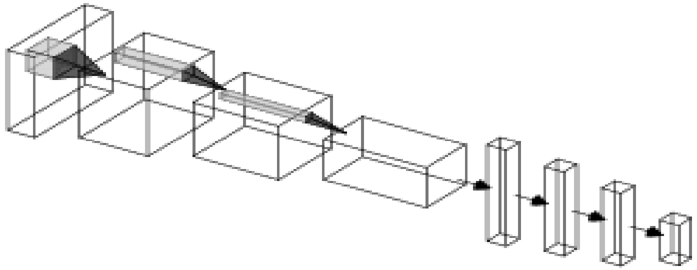
Time Series and Multi-channel images

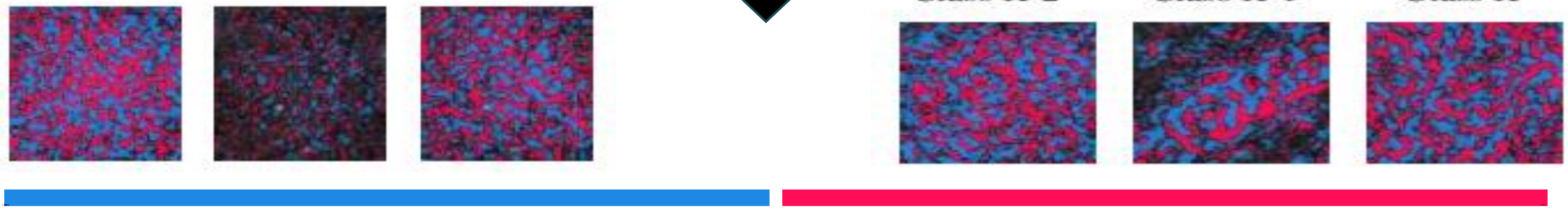


Deep Convolutional Neural Network



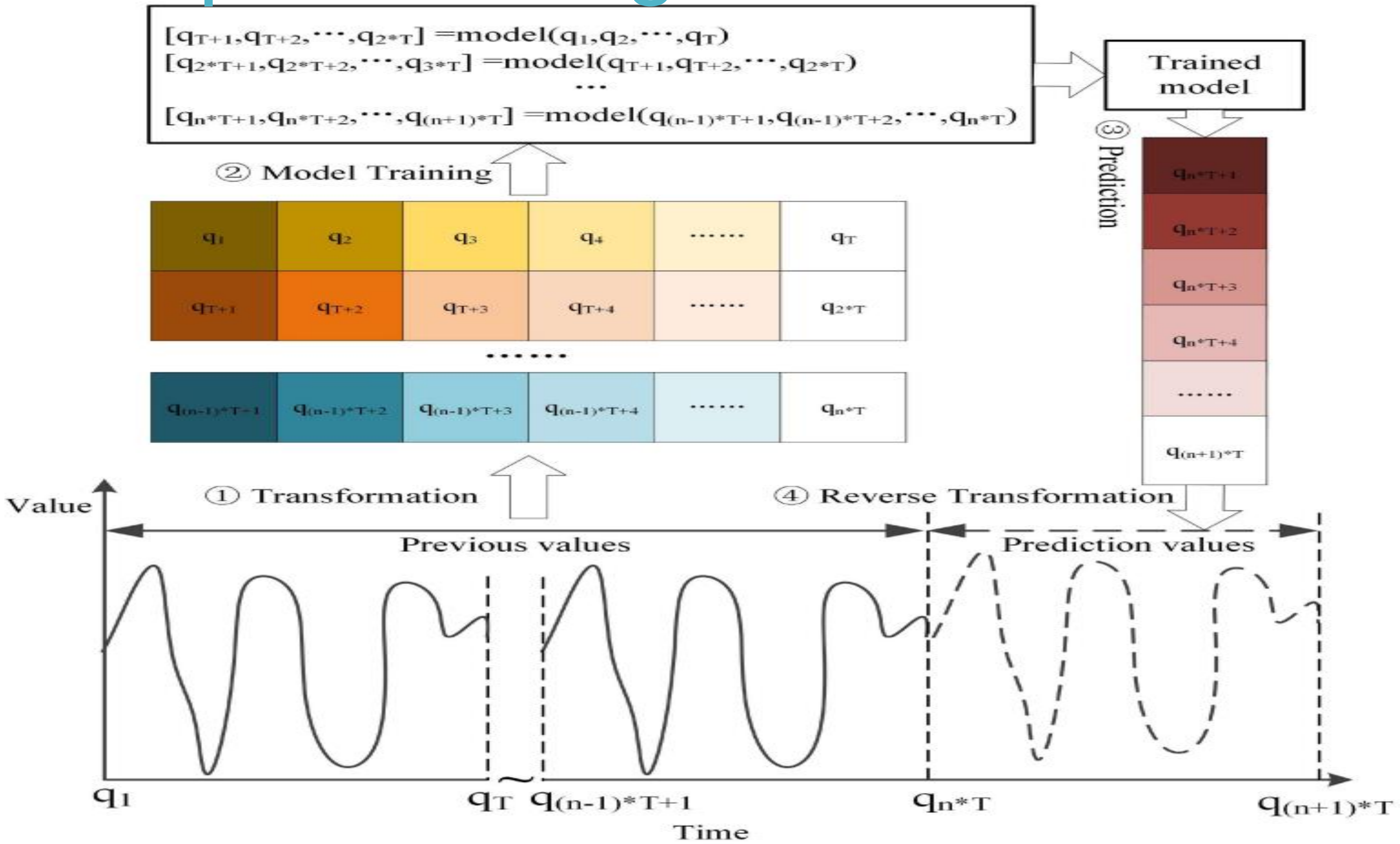
SHAP
Deep Explainer

Class 1 Class 2 Class 3 Class K-2 Class K-1 Class K



Negative SHAP Values Positive

Conceptual Diagram - 2



Methodology

- Data Collection
- Preprocessing
- Model Architecture
- Shapley Additive Explanations (SHAPs) Integration
- Training
- Evaluation
- Results Analysis
- Performance Comparison

Techniques

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- Deep Learning Architectures
  - ResNet 50 and 101
  - VGG16
  - 4.Densenet121
  - InceptionV3
  - GeoNet
  - GoogleNet
  - Shallow CNN
  - SHAP
- Modified SHAP
- SARIMA Model
- STL-AR

Dataset

- Experimental data set is retrieved from sentinel-2 hub .which of location Hyderabad, Andhra Pradesh . and time line 01-01-2017 to 01-01-2024 with 12 points of time per year .Total 84images experimental data image resolution: 150 m with image size: (512,512)
  - https://drive.google.com/drive/folders/1UKahSHn4TX23SC845W5D9RDArBkqdW4q?usp=drive_link
- The dataset covers cities are distributed over the 34 European countries and India
- Each image is 64x64 pixels with high spatial resolution (10 m to 60 m) over land and coastal waters.
- EuroSAT dataset is based on Sentinel-2 satellite images covering 13 spectral bands and consisting of 10 classes with 27000 labeled and geo-referenced samples.
  - https://www.kaggle.com/datasets/apollo2506/eurosat-dataset
  - https://zenodo.org/records/7711810#.ZAm3k-zMKEA

Class Labels

Annual Crop

Forest

Herbaceous Vegetation

Highway

Industrial

Pasture

Permanent Crop

Residential

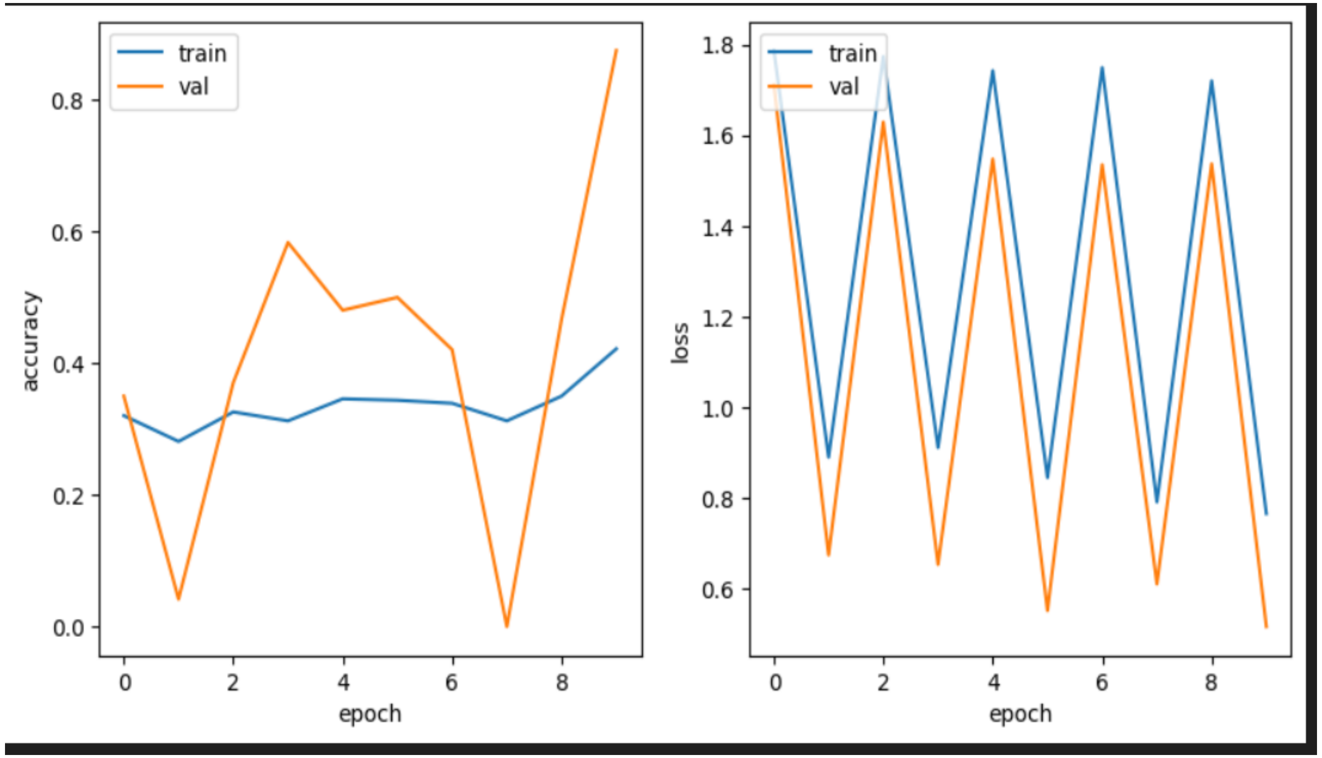
River

SeaLake

Existing Models:

1 : **RESNET50** Model

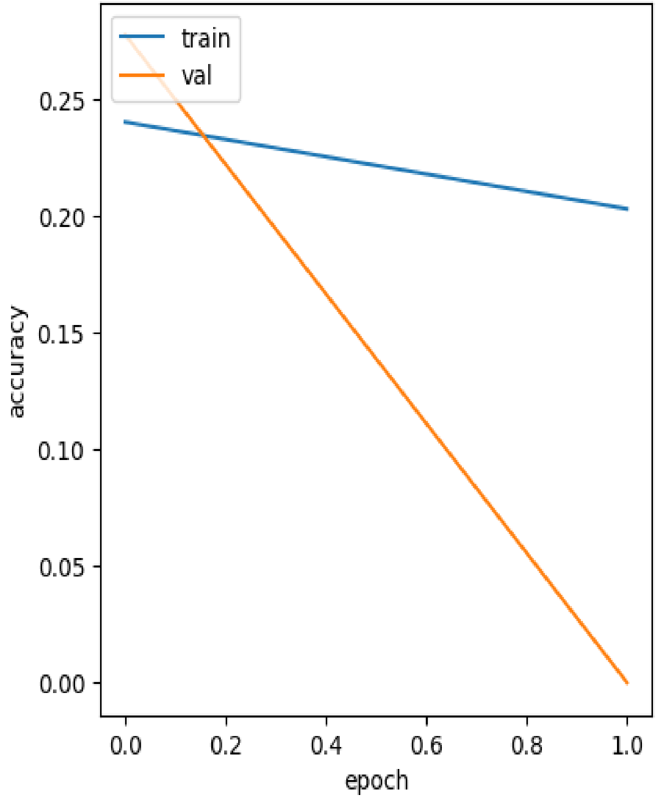
- ResNet-50 is a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one average pool layer).

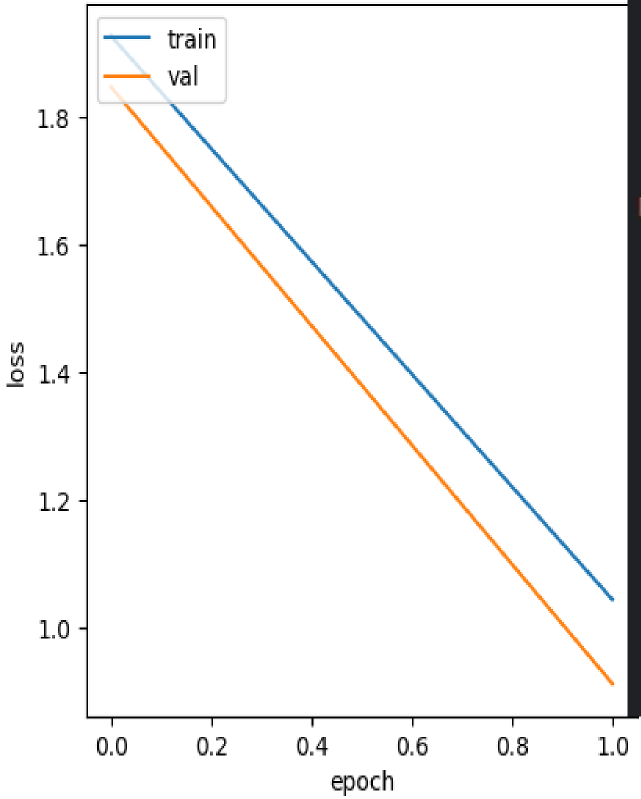


	Precision	Recall	F-Score	Support
AnnualCrop	0.121911	0.986667	0.217009	600.0
Forest	0.000000	0.000000	0.000000	600.0
HerbaceousVegetation	0.000000	0.000000	0.000000	600.0
Highway	0.000000	0.000000	0.000000	500.0
Industrial	0.763401	0.826000	0.793468	500.0
Pasture	0.000000	0.000000	0.000000	400.0
PermanentCrop	0.000000	0.000000	0.000000	500.0
Residential	0.000000	0.000000	0.000000	600.0
River	0.000000	0.000000	0.000000	500.0
SeaLake	0.333333	0.001667	0.003317	600.0

2.Resnet101 Model

- ResNet-101 is a convolutional neural network that uses residual learning and skip connections to train deeper models.





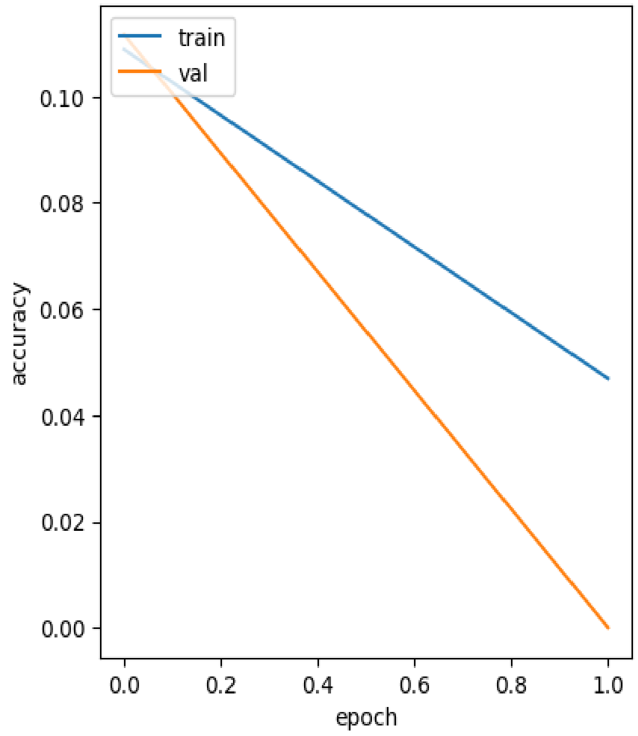

```
Found 5400 images belonging to 10 classes.
5400/5400 ━━━━━━━━━━━━━━━━━━━━ 286s 52ms/step
Accuracy: 0.15703703703703703
Global F2 Score: 0.15703703703703703
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1344: U
re ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero
  _warn_prf(average, modifier, msg_start, len(result))
```

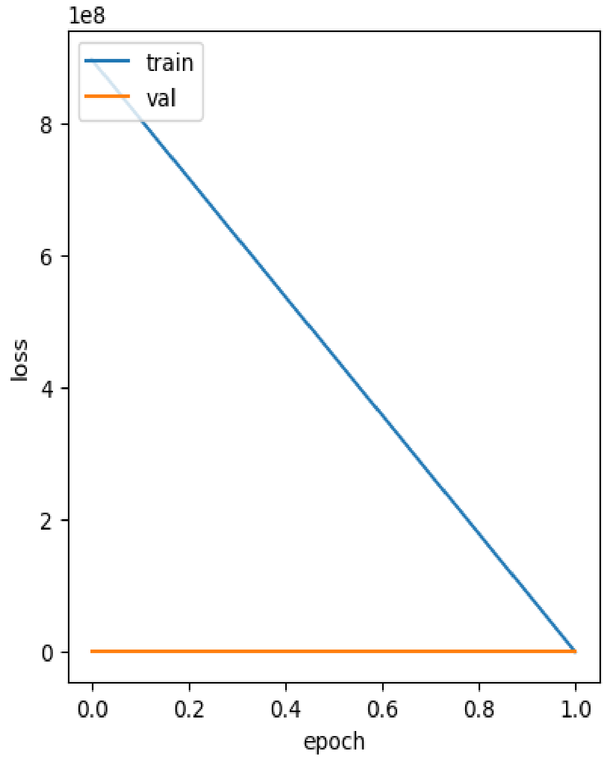
[21]:

	Precision	Recall	F-Score	Support
AnnualCrop	0.115166	0.978333	0.206073	600.0
Forest	0.000000	0.000000	0.000000	600.0
HerbaceousVegetation	0.000000	0.000000	0.000000	600.0
Highway	0.000000	0.000000	0.000000	500.0
Industrial	0.861386	0.522000	0.650062	500.0
Pasture	0.000000	0.000000	0.000000	400.0
PermanentCrop	0.000000	0.000000	0.000000	500.0
Residential	0.000000	0.000000	0.000000	600.0
River	0.000000	0.000000	0.000000	500.0
SeaLake	0.000000	0.000000	0.000000	600.0

3. VGG16 model

- VGG16 refers to the VGG model, also called VGGNet.
- It is a convolution neural network (CNN) model supporting 16 layers.





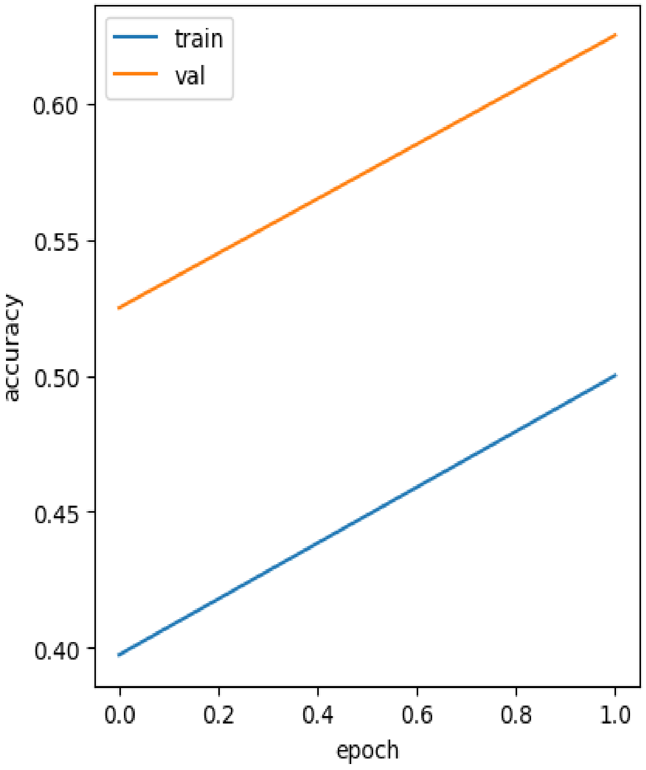

```
Found 5400 images belonging to 10 classes.
/opt/conda/lib/python3.10/site-packages/keras/src/saving/saving_lib.py:396: UserWarning: Skipping variable loading for optimizer 'adam', because it has 66 variables whereas the saved optimizer has 14 variables.
  trackable.load_own_variables(weights_store.get(inner_path))
5400/5400 243s 45ms/step
Accuracy: 0.6244444444444445
Global F2 Score: 0.6244444444444445
```

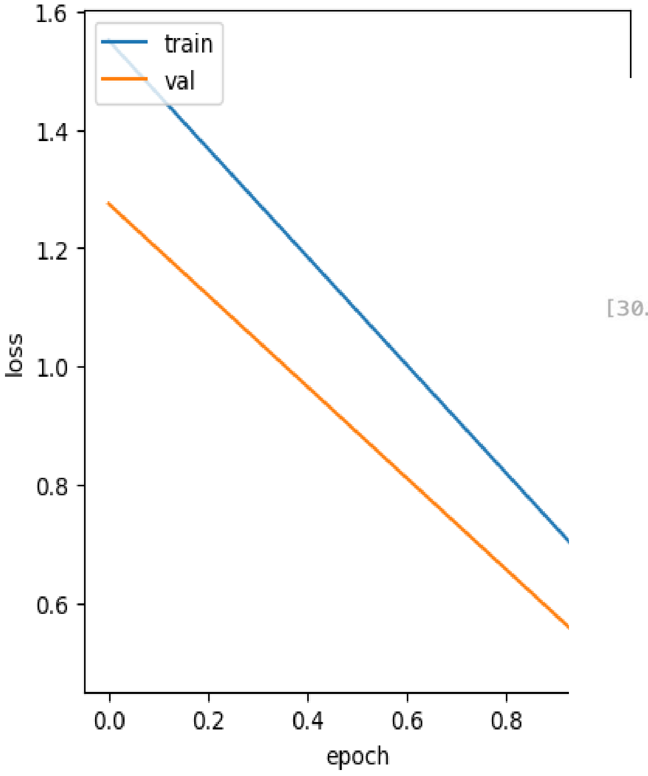
[20…

	Precision	Recall	F-Score	Support
AnnualCrop	0.285958	0.838333	0.426452	600.0
Forest	0.798611	0.766667	0.782313	600.0
HerbaceousVegetation	0.778884	0.651667	0.709619	600.0
Highway	0.618519	0.334000	0.433766	500.0
Industrial	0.756019	0.942000	0.838825	500.0
Pasture	0.846154	0.247500	0.382979	400.0
PermanentCrop	0.576446	0.558000	0.567073	500.0
Residential	0.893039	0.876667	0.884777	600.0
River	0.972222	0.070000	0.130597	500.0
SeaLake	0.993243	0.735000	0.844828	600.0

4.Densenet121

- DenseNet-121 is a model from Densely Connected Convolutional Networks (DenseNet). It's a variant of the convolutional neural network (CNN) architecture DenseNet





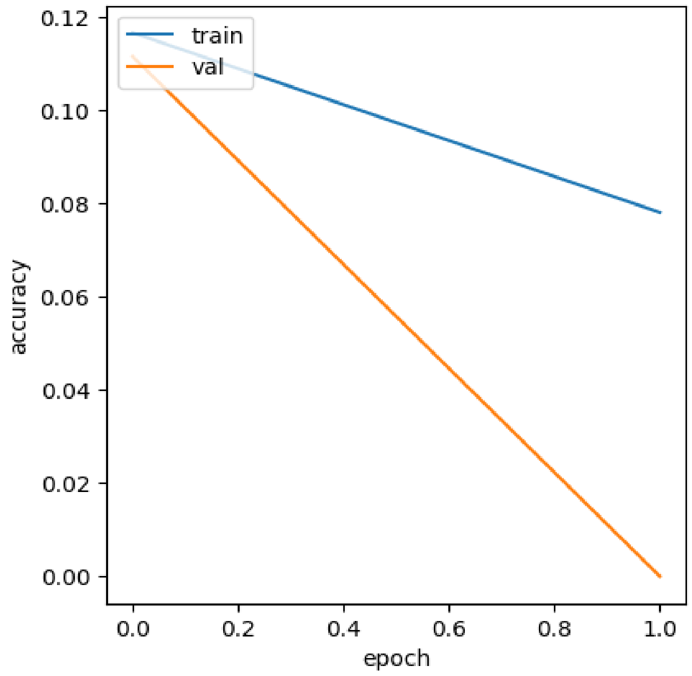

```
Found 5400 images belonging to 10 classes.
5400/5400 ━━━━━━━━━━━━━━━━━━━━ 192s 35ms/step
Accuracy: 0.36962962962962964
Global F2 Score: 0.3696296296296297
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1344
Precision and F-score are ill-defined and being set to 0.0 in labels with no pr
o_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

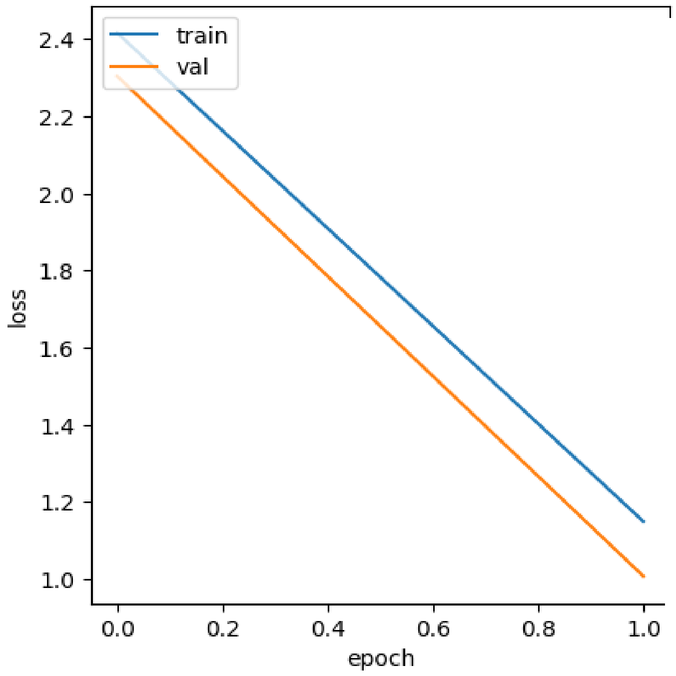
[30…

	Precision	Recall	F-Score	Support
AnnualCrop	0.166242	0.978333	0.284193	600.0
Forest	0.906188	0.756667	0.824705	600.0
HerbaceousVegetation	0.000000	0.000000	0.000000	600.0
Highway	0.000000	0.000000	0.000000	500.0
Industrial	0.604938	0.980000	0.748092	500.0
Pasture	0.000000	0.000000	0.000000	400.0
PermanentCrop	0.464789	0.132000	0.205607	500.0
Residential	0.972727	0.178333	0.301408	600.0
River	0.000000	0.000000	0.000000	500.0
SeaLake	0.954248	0.486667	0.644592	600.0

5.Inception V3

- Inception v3 is a convolutional neural network (CNN) model that helps with image analysis and object detection.
- It is a 48-layer model that uses symmetric and asymmetric building blocks, including pooling, convolutional, and auxiliary classifiers.



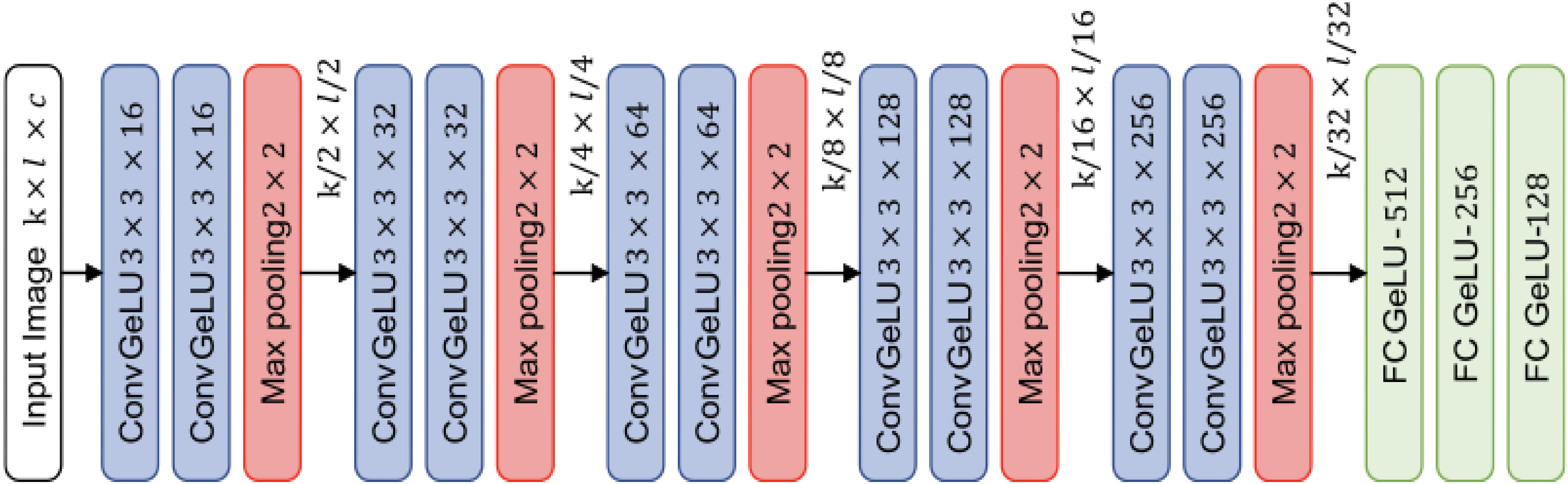



```
es.
  trackable.load_own_variables(weights_store.get(inner_path))
Found 5400 images belonging to 10 classes.
5400/5400 ━━━━━━━━━━━━━━━━━━━━ 184s 33ms/step
Accuracy: 0.4675925925925926
Global F2 Score: 0.4675925925925926
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_classification.py:134
Precision and F-score are ill-defined and being set to 0.0 in labels with no p
o_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[30…

	Precision	Recall	F-Score	Support
AnnualCrop	0.186581	0.973333	0.313137	600.0
Forest	0.853261	0.785000	0.817708	600.0
HerbaceousVegetation	0.916667	0.348333	0.504831	600.0
Highway	0.786885	0.192000	0.308682	500.0
Industrial	0.990566	0.420000	0.589888	500.0
Pasture	0.000000	0.000000	0.000000	400.0
PermanentCrop	0.960000	0.096000	0.174545	500.0
Residential	0.921569	0.235000	0.374502	600.0
River	0.628009	0.574000	0.599791	500.0
SeaLake	0.965726	0.798333	0.874088	600.0

Proposed Model Architecture



Model Execution / Usage

Tirupati Region Our new testing dataset has 64 images belonging to different classes.

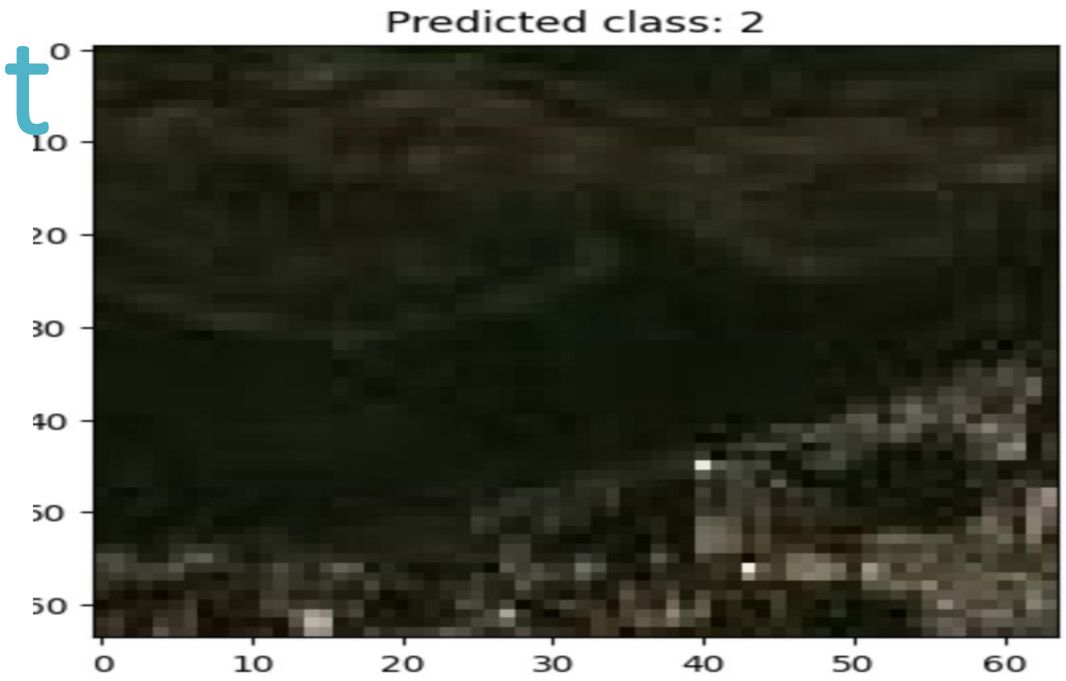
[8]:
```
print(train_generator.class_indices)
```

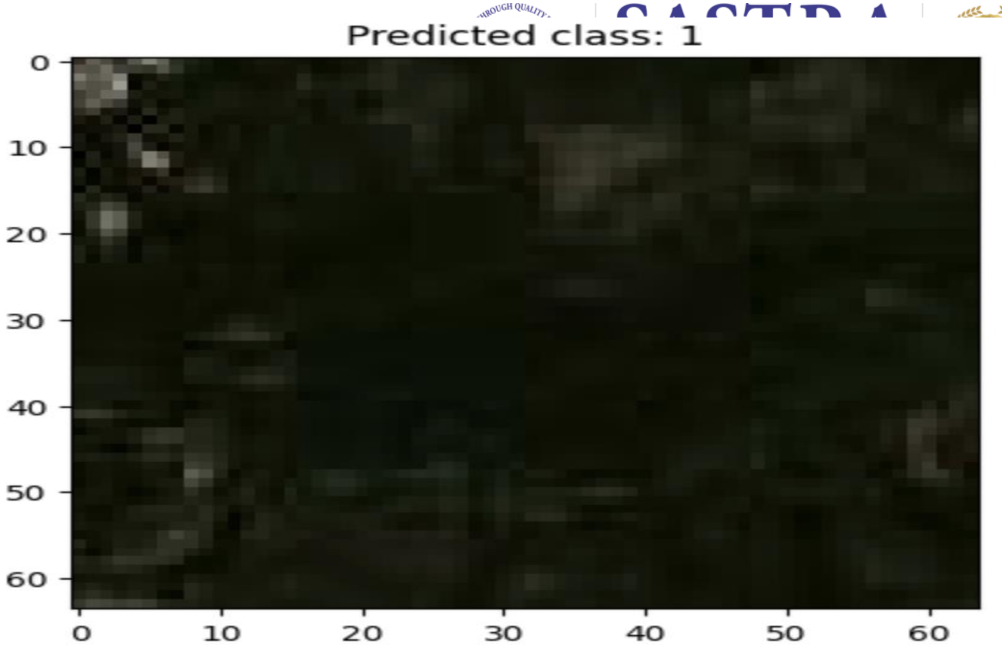
```
{'AnnualCrop': 0, 'Forest': 1, 'HerbaceousVegetation': 2, 'Highway': 3, 'Industrial': 4, 'Pasture': 5,
'PermanentCrop': 6, 'Residential': 7, 'River': 8, 'SeaLake': 9}
```

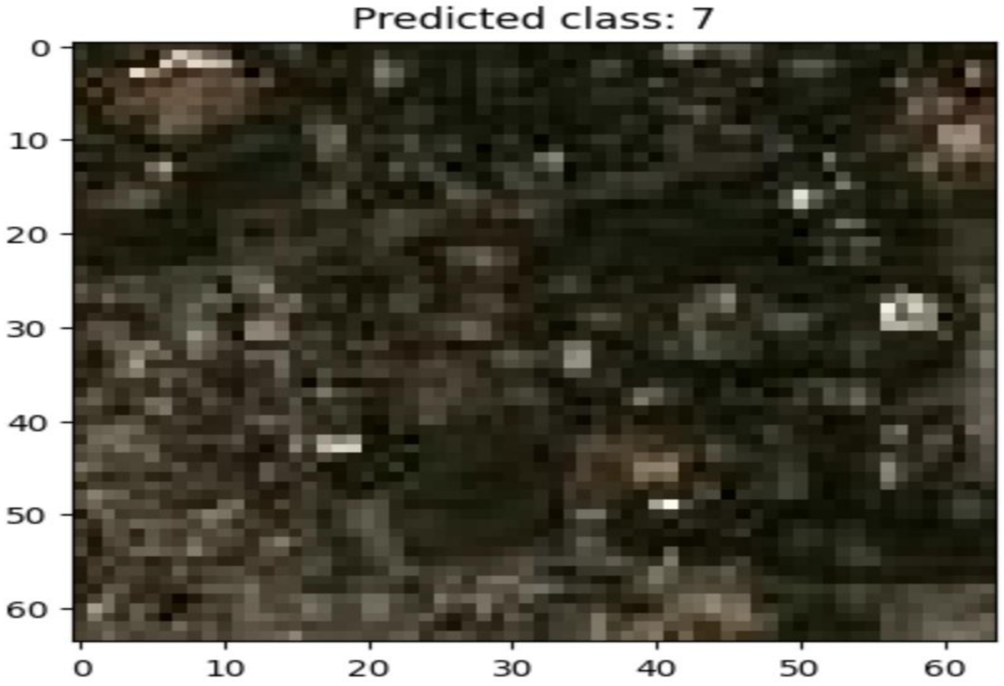
```
print(len(new_test_images))
print(predicted_classes)
```

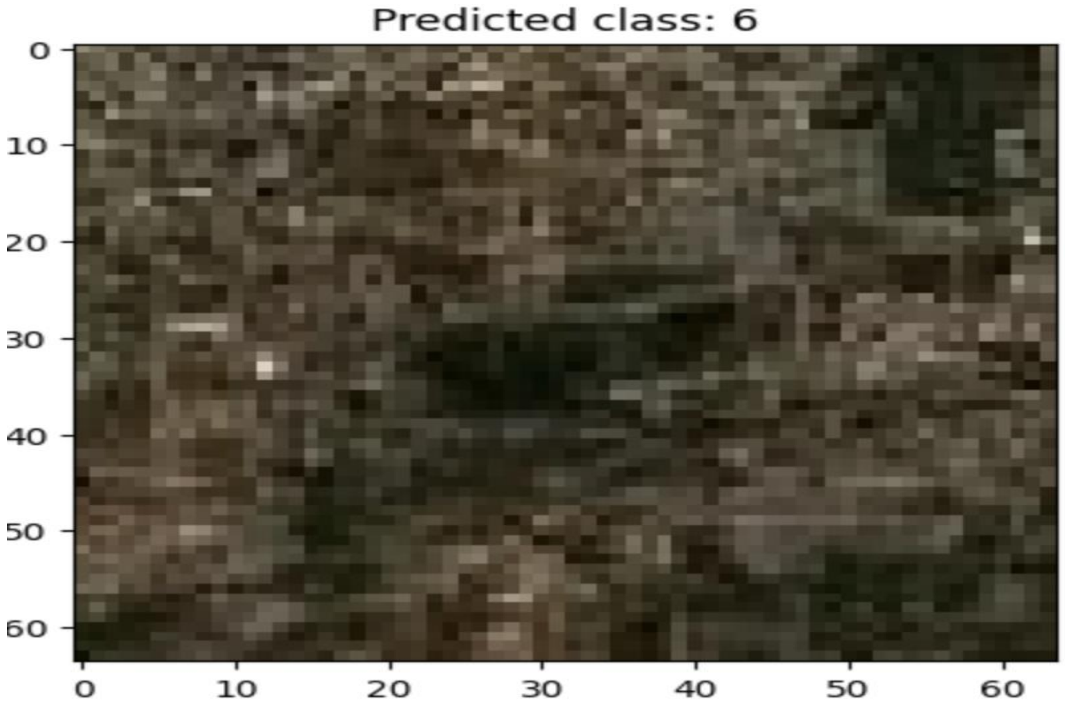
```
2/2 ━━━━━━━━━━━━━━━━━━━━ 5s 210ms/step
64
[2 1 6 1 2 2 2 7 2 7 2 2 1 1 6 1 1 2 1 1 2 7 2 1 2 1 7 2 1 2 2 7 6 1 1 6 1
 6 2 6 1 2 2 2 1 2 2 2 2 6 1 1 6 2 2 7 1 7 1 2 6 1 2 6]
```

Output

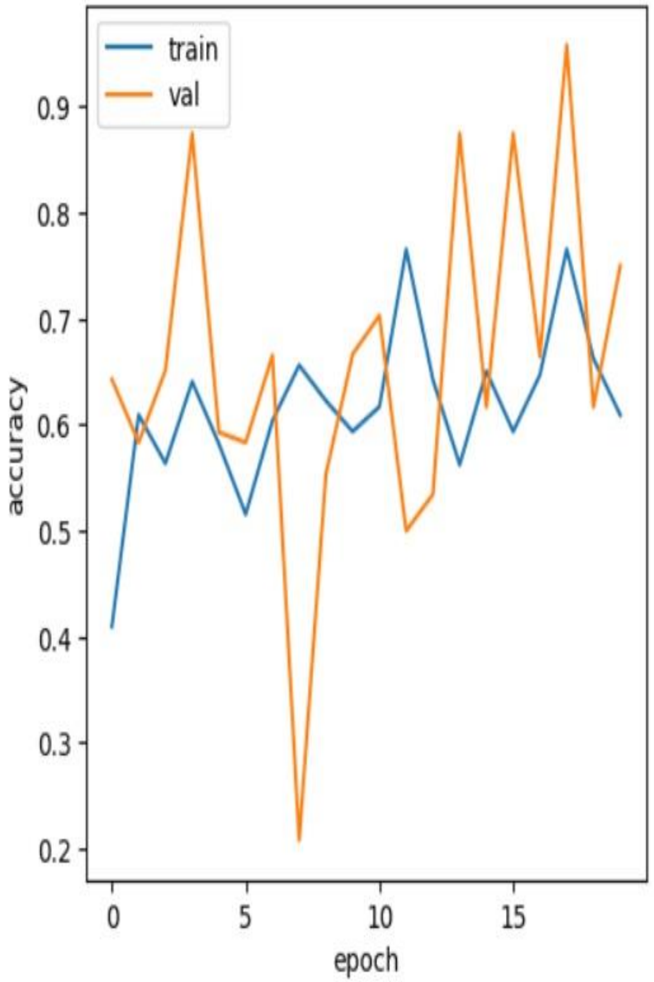

Predicted class: 2
0
10
20
30
40
50
60
0 10 20 30 40 50 60

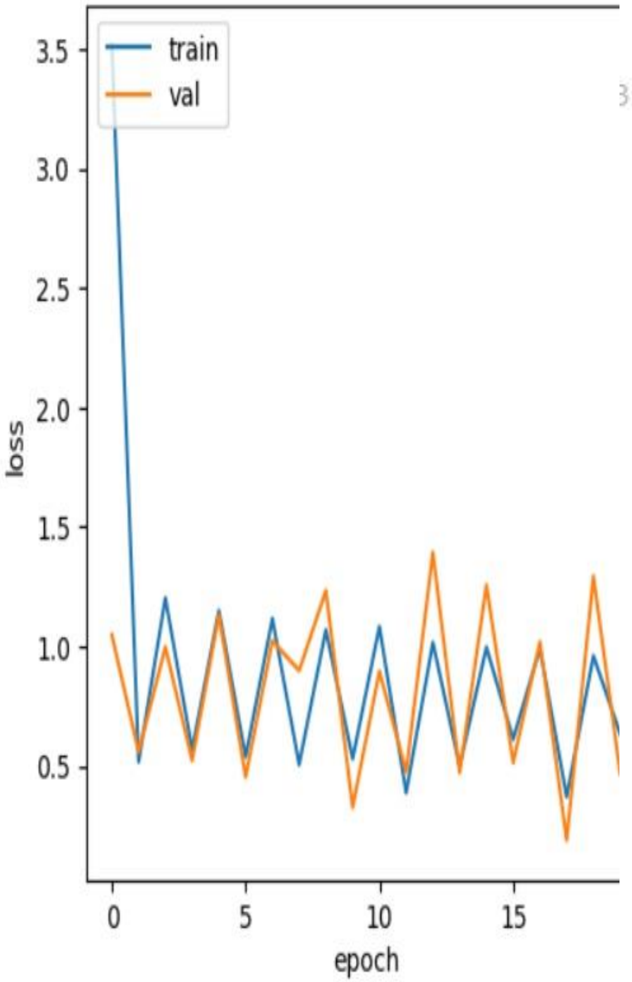

Predicted class: 1
0
10
20
30
40
50
60
0 10 20 30 40 50 60


Predicted class: 7
0
10
20
30
40
50
60
0 10 20 30 40 50 60


Predicted class: 6
0
10
20
30
40
50
60
0 10 20 30 40 50 60

Proposed Model Results





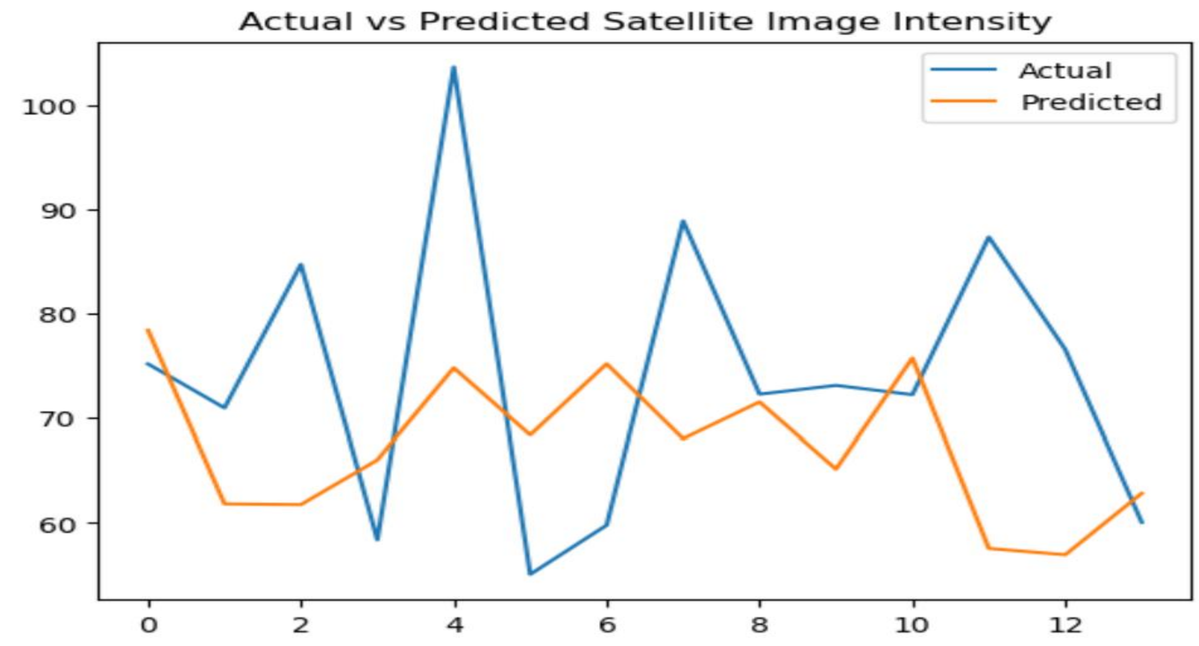

```
5400/5400 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step
Accuracy: 0.5674074074074074
Global F2 Score: 0.5674074074074074
```

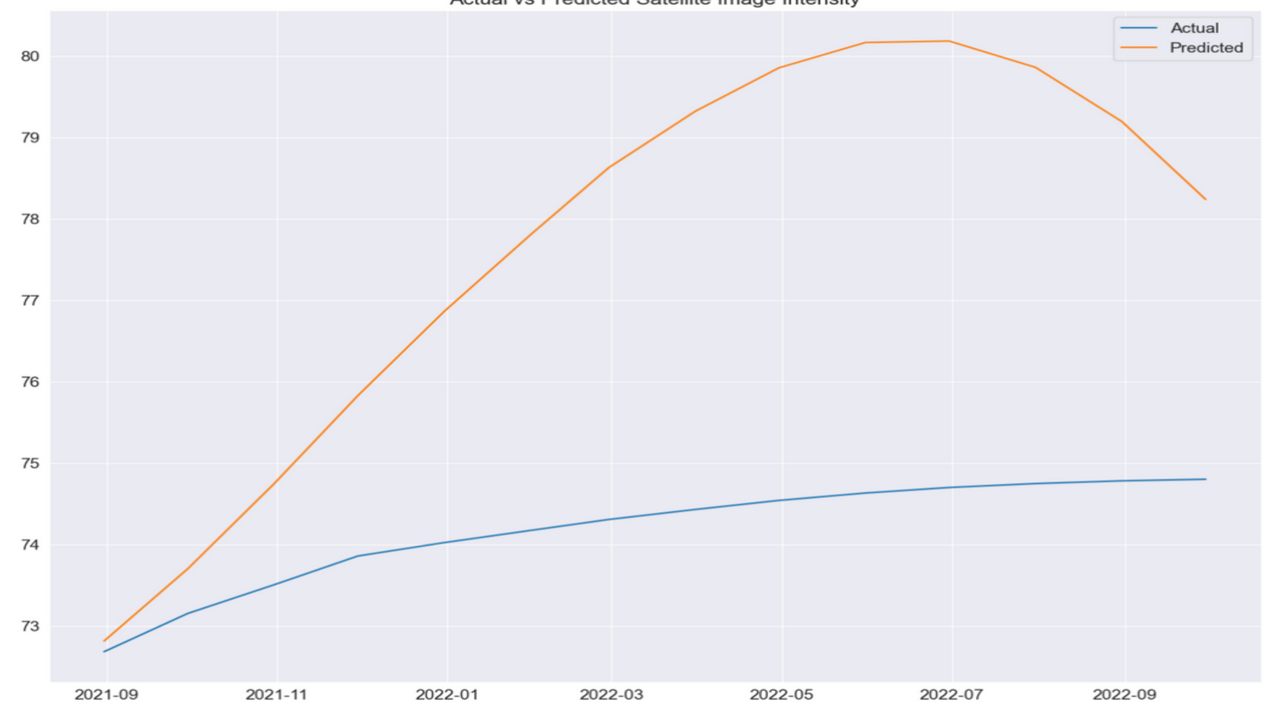
	Precision	Recall	F-Score	Support
AnnualCrop	0.265597	0.745000	0.391590	600.0
Forest	0.978049	0.668333	0.794059	600.0
HerbaceousVegetation	0.576596	0.451667	0.506542	600.0
Highway	0.800000	0.008000	0.015842	500.0
Industrial	0.763819	0.912000	0.831358	500.0
Pasture	0.660112	0.587500	0.621693	400.0
PermanentCrop	0.328358	0.088000	0.138801	500.0
Residential	0.552408	0.975000	0.705244	600.0
River	0.857143	0.132000	0.228769	500.0
SeaLake	0.911330	0.925000	0.918114	600.0

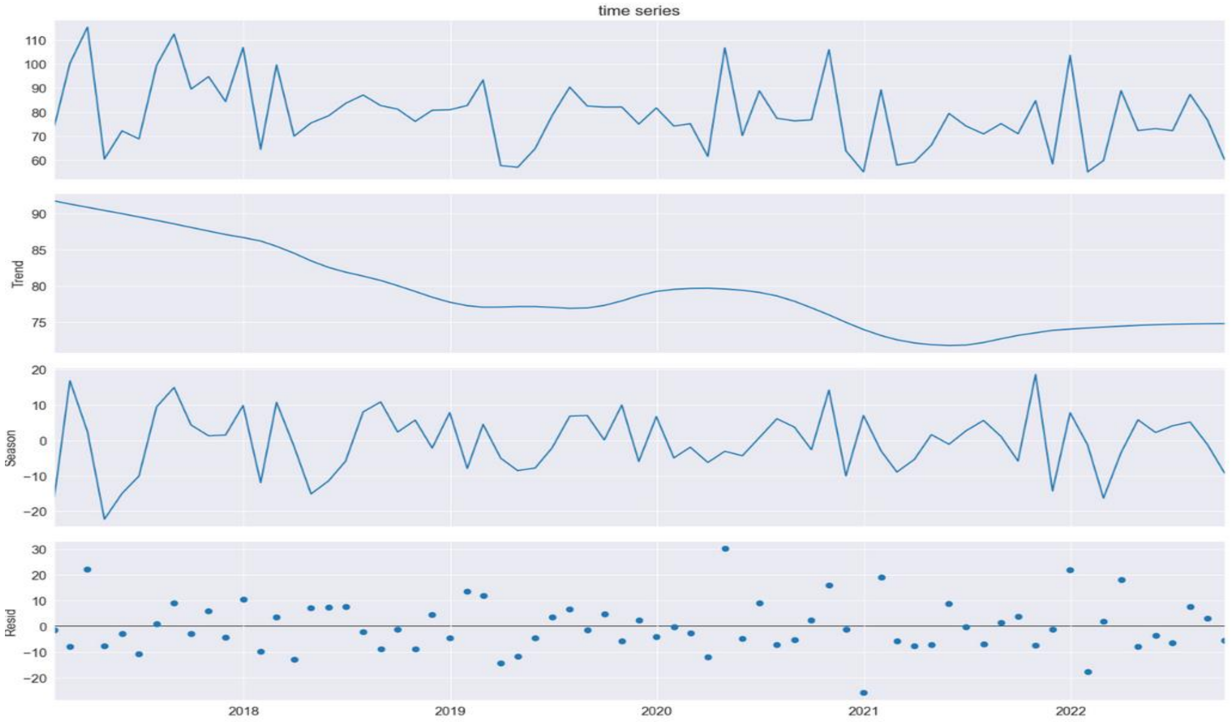
Model Comparison

MODEL	ACCURACY(IMPLEMENTED)
ResNet50	56(n_epochs =10)
ResNet101	15(n_epochs =2)
DenseNet121	36(n_epochs =2)
Inception V3	46(n_epochs =2)
VGG16	62(n_epochs =2)
Proposed Model	56(n_epochs=10)

Methods	Accuracy(implemented)	Accuracy (in base paper)
SARIMA	RMSE:16.31 PCC:0.0197 Accuracy:82.08%	RMSE:0.0554 PCC:0.9967 Accuracy:80%
STL-AR	RMSE:3.92 PCC:0.954 Accuracy:95.29%	RMSE:0.0686 PCC:0.9536 Accuracy:80%







With Minimal 2 Epochs

Mean Absolute Error: 13.286609504870144
Percentage Accuracy: 82.08802810705063 %
PCC : 0.01979689276981323
RMSE : 16.313974001724983

Percentage Error Accuracy: 95.3165889281511 %
Mean Absolute Error: 3.4876564699188464
Percentage Accuracy: 95.29775394556404 %
PCC : 0.9547030908518155
RMSE : 3.923937563515211

Expected Results

- In conclusion , the project introduces Temporal Convolutional Networks (TCN) and Liquid Neural Networks (LNN) as effective tools for analyzing multi-spectral imagery, with LNN emerging as a less complex alternative requiring less labeled data.
- The project aims to compare these models, integrating TCN elements and LNN's for land area image segmentation.
- The study seeks to determine the model best suited for predicting land use and land class changes.
- Evaluation: Time dimension evaluation using RMSE (Root Men Square Error) and PCC (Pearson Correlation Coefficient) into account and one model will be considered to be better for the task

Result Analysis

- In Conclusion, the comparative analysis of various CNN models, encompassing a compact CNN specifically designed for land use and land cover classification.
- The study underscores not only the efficiency of the proposed framework but also its interpretability, particularly through the integration of Shapley Additive Explanations (SHAPs).
- This interpretability aspect is crucial for understanding the decision-making processes of the models, enhancing transparency in land use predictions. The findings emphasize the framework's applicability in resource-constrained environments.
- Deep Convolutional Neural Networks (CNNs) have proven instrumental in the accurate classification of remote sensing images, leveraging their capacity to automatically learn and extract hierarchical features.
- Various well-established architectures have been applied to address the unique challenges posed by remote sensing data.

References

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