Level 1 Submission for Open Science Data Challenge 2023

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Data Development and Preparation

Load CSV

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
crop_data = pd.read_csv("Crop_Location_Data_20221201.csv")
crop_data.head()
```

Out[2]:

	Latitude and Longitude	Class of Land
0	(10.323727047081501, 105.2516346045924)	Rice
1	(10.322364360592521, 105.27843410554115)	Rice
2	(10.321455902933202, 105.25254306225168)	Rice
3	(10.324181275911162, 105.25118037576274)	Rice
4	(10.324635504740822, 105.27389181724476)	Rice

In [3]:
```
print(f"Shape of Crop Data: {crop_data.shape}")
```

```
Shape of Crop Data: (600, 2)
```

In [4]:
```
crop_data.describe()
```

Out[4]:

	Latitude and Longitude	Class of Land
count	600	600
unique	600	2
top	(10.323727047081501, 105.2516346045924)	Rice
freq	1	300

Load Sentinel Data

In [5]:
```
# Supress Warnings
import warnings
warnings.filterwarnings('ignore')
import os

# Import common GIS tools
import numpy as np
import xarray as xr
import matplotlib.pyplot as plt
import rioxarray as rio
import rasterio.features

# Import Planetary Computer tools
import stackstac
import pystac_client
import planetary_computer as pc
import xrspatial.multispectral as ms
import odc
from odc.stac import stac_load

from tqdm import tqdm
tqdm.pandas()

# API key
pc.settings.set_subscription_key('1ef143ba7595457ebff1a921151a9918')
```

In [6]:
```
def get_sentinel_data(latlong):
    """ Returns a list of VV,VH, VV/VH values for a given latitude and longitu

    bands_of_interest = ['vh','vv']
    time_window="2021-11-01/2022-08-31"
    box_size_deg = 0.0004 # Roughly a 5x5 box

    latlong = latlong.replace('(','').replace(')','').replace(' ','').split(',
    bbox_of_interest = (float(latlong[1])-box_size_deg/2 , float(latlong[0])-b
                        float(latlong[1])+box_size_deg/2, float(latlong[0])+bo

    vv_list = []
    vh_list = []
    vv_by_vh_list = []

    catalog = pystac_client.Client.open("https://planetarycomputer.microsoft.c
    search = catalog.search(collections=["sentinel-1-rtc"], bbox=bbox_of_inter
    items = list(search.get_all_items())
    item = items[0]
    items.reverse()

    data = stac_load([items[1]],bands=bands_of_interest, patch_url=pc.sign, bb

    for item in items:
        data = stac_load([item], bands=bands_of_interest, patch_url=pc.sign, b
        if(data['vh'].values[0][0]!=-32768.0 and data['vv'].values[0][0]!=-327
            data = data.where(~data.isnull(), 0)
            vh = data["vh"].astype("float64")
            vv = data["vv"].astype("float64")
            vv_list.append(np.median(vv))
            vh_list.append(np.median(vh))
            vv_by_vh_list.append(np.median(vv)/np.median(vh))

    return vv_list, vh_list, vv_by_vh_list
```

In [7]:
```
train_band_values=crop_data.progress_apply(lambda x: get_sentinel_data(x["Lati
vh = [x[0] for x in train_band_values]
vv = [x[1] for x in train_band_values]
vv_by_vh = [x[2] for x in train_band_values]
vh_vv_data = pd.DataFrame(list(zip(vh,vv,vv_by_vh)),columns = ["vv_list","vh_l
```

```
100%|██████████| 600/600 [1:50:03<00:00, 11.01s/it]
```

In [ ]:
```
vh_vv_data
```

In [ ]:
```
for col in vh_vv_data.columns:
    vh_vv_data[col] = vh_vv_data[col].apply(lambda x: np.array(x))
```

In [21]:
```
type(vh_vv_data["vv_list"].iloc[0])
```

Out[21]:
```
numpy.ndarray
```

In [26]:
```
rvi = (vh_vv_data["vv_list"] / (vh_vv_data["vv_list"] + vh_vv_data["vh_list"]))
rvi
```

Out[26]:
```
0      [0.6770013443829713, 0.7650207626328163, 0.764...
1      [0.7603722278367199, 0.8699584958387813, 0.724...
2      [0.6809153737878286, 0.7182062469512054, 0.642...
3      [0.7392245239578717, 0.7563370627960891, 0.675...
4      [0.7793639479268326, 0.7580063304279673, 0.718...
                              ...
595    [0.8447714563137138, 0.7665128814874204, 0.762...
596    [0.8134861758083533, 0.7333147680724563, 0.830...
597    [0.7485313994319769, 0.729718541099053, 0.8171...
598    [0.8561544131010158, 0.7769415341478552, 0.815...
599    [0.8358219299271932, 0.7721834161367874, 0.834...
Length: 600, dtype: object
```

In [27]:
```
vh_vv_data["rvi"] = rvi
vh_vv_data
```

Out[27]:

	vv_list	vh_list	vv/vh_list	rvi
0	[0.07633522897958755, 0.1055772714316845, 0.12...	[0.03641968593001366, 0.03242848813533783, 0.0...	[2.0959881182467663, 3.2556951465349164, 3.246...	[0.6770013443829713, 0.7650207626328163, 0.764...
1	[0.07775161415338516, 0.21660436689853668, 0.1...	[0.024503059685230255, 0.032378047704696655, 0...	[3.1731389937498955, 6.689852608596804, 2.6265...	[0.7603722278367199, 0.8699584958387813, 0.724...
2	[0.07909337431192398, 0.0808926373720169, 0.07...	[0.037064047530293465, 0.031738849356770515, 0...	[2.133964841462034, 2.548694707319657, 1.79720...	[0.6809153737878286, 0.7182062469512054, 0.642...
3	[0.09969594702124596, 0.09643841162323952, 0.0...	[0.03516963683068752, 0.031068775802850723, 0....	[2.834716420337202, 3.1040299828740205, 2.0851...	[0.7392245239578717, 0.7563370627960891, 0.675...
4	[0.061404578387737274, 0.0796160064637661, 0.0...	[0.01738348789513111, 0.02541742566972971, 0.0...	[3.532350858364615, 3.1323395019733615, 2.5508...	[0.7793639479268326, 0.7580063304279673, 0.718...
...	...	...	...	...
595	[0.4515400826931, 0.29349878430366516, 0.18908...	[0.08297144621610641, 0.08940252289175987, 0.0...	[5.442114164396076, 3.2828915203993265, 3.2164...	[0.8447714563137138, 0.7665128814874204, 0.762...
596	[0.3343413472175598, 0.2766057103872299, 0.299...	[0.07665684446692467, 0.1005934439599514, 0.06...	[4.361532874756135, 2.749738944193551, 4.89913...	[0.8134861758083533, 0.7333147680724563, 0.830...
597	[0.23833606392145157, 0.24556903541088104, 0.2...	[0.08006883412599564, 0.09095665439963341, 0.0...	[2.976639619185762, 2.6998468339867916, 4.4684...	[0.7485313994319769, 0.729718541099053, 0.8171...
598	[0.4367031306028366, 0.3260190486907959, 0.255...	[0.07337206602096558, 0.09359946101903915, 0.0...	[5.951899057579374, 3.4831295516165426, 4.4246...	[0.8561544131010158, 0.7769415341478552, 0.815...
599	[0.35761985182762146, 0.27563905715942383, 0.2...	[0.07024622708559036, 0.08132154494524002, 0.0...	[5.090947466714268, 3.389496071982309, 5.03264...	[0.8358219299271932, 0.7721834161367874, 0.834...

600 rows × 4 columns

In [7]:
```
def generate_stastical_features(dataframe):
    '''
    Returns a  list of statistical features such as min,max,range,mean for each
    Attributes:
    dataframe - DataFrame consisting of VV,VH and VV/VH
    '''
    features_list = []
    for index, row in dataframe.iterrows():
        min_vv = min(row[0])
        max_vv = max(row[0])
        range_vv = max_vv - min_vv
        mean_vv = np.mean(row[0])

        min_vh = min(row[1])
        max_vh = max(row[1])
        range_vh = max_vh - min_vh
        mean_vh = np.mean(row[1])

        min_vv_by_vh = min(row[2])
        max_vv_by_vh = max(row[2])
        range_vv_by_vh = max_vv_by_vh - min_vv_by_vh
        mean_vv_by_vh = np.mean(row[2])

        min_rvi = min(row[3])
        max_rvi = max(row[3])
        range_rvi = max_rvi - min_rvi
        mean_rvi = np.mean(row[3])

        features_list.append([min_vv, max_vv, range_vv, mean_vv, min_vh, max_vh
                              min_vv_by_vh,  max_vv_by_vh, range_vv_by_vh, mean_vv_
    return features_list
```

In [29]:
```
features = generate_stastical_features(vh_vv_data)
features_data = pd.DataFrame(features ,columns = ['min_vv', 'max_vv', 'range_v
                             'min_vv_by_vh',  'max_vv_by_vh', 'range_vv_by_vh', 'r
```

In [30]:

```
features_data
```

Out[30]:

	min_vv	max_vv	range_vv	mean_vv	min_vh	max_vh	range_vh	mean_vh	min_vv_by
0	0.022274	0.269761	0.247487	0.116468	0.003141	0.078778	0.075636	0.025373	1.368
1	0.013224	0.491939	0.478715	0.135152	0.003354	0.090849	0.087496	0.026800	1.309
2	0.016693	0.548456	0.531762	0.109102	0.003337	0.073560	0.070223	0.024353	1.452
3	0.015995	0.478505	0.462510	0.126329	0.003879	0.052779	0.048900	0.024346	1.495
4	0.014075	0.487998	0.473923	0.129143	0.004487	0.096872	0.092384	0.025944	1.574
...	...	...	...	...	...	...	...	...	
595	0.145322	0.556387	0.411064	0.287192	0.033406	0.112107	0.078701	0.064786	2.603
596	0.159897	0.413889	0.253993	0.261459	0.039730	0.114915	0.075185	0.069592	2.404
597	0.171829	0.437881	0.266052	0.262192	0.038087	0.094669	0.056582	0.063881	2.055
598	0.209815	0.474909	0.265094	0.287283	0.047271	0.108973	0.061702	0.069803	2.841
599	0.190475	0.422875	0.232399	0.291645	0.048977	0.102211	0.053234	0.070345	2.469

600 rows × 16 columns

In [37]:
```
# Join features to original dataframe
crop_data_final = pd.concat([crop_data, features_data], axis=1)
crop_data_final
```

Out[37]:

	Latitude and Longitude	Class of Land	min_vv	max_vv	range_vv	mean_vv	min_vh	max_vh	ra
0	(10.323727047081501, 105.2516346045924)	Rice	0.022274	0.269761	0.247487	0.116468	0.003141	0.078778	C
1	(10.322364360592521, 105.27843410554115)	Rice	0.013224	0.491939	0.478715	0.135152	0.003354	0.090849	C
2	(10.321455902933202, 105.25254306225168)	Rice	0.016693	0.548456	0.531762	0.109102	0.003337	0.073560	C
3	(10.324181275911162, 105.25118037576274)	Rice	0.015995	0.478505	0.462510	0.126329	0.003879	0.052779	C
4	(10.324635504740822, 105.27389181724476)	Rice	0.014075	0.487998	0.473923	0.129143	0.004487	0.096872	C
...	...	...	...	...	...	...	...	...	
595	(10.013942985253381, 105.67361318732796)	Non Rice	0.145322	0.556387	0.411064	0.287192	0.033406	0.112107	C
596	(10.01348875642372, 105.67361318732796)	Non Rice	0.159897	0.413889	0.253993	0.261459	0.039730	0.114915	C
597	(10.013034527594062, 105.67361318732796)	Non Rice	0.171829	0.437881	0.266052	0.262192	0.038087	0.094669	C
598	(10.012580298764401, 105.67361318732796)	Non Rice	0.209815	0.474909	0.265094	0.287283	0.047271	0.108973	C
599	(10.012126069934741, 105.67361318732796)	Non Rice	0.190475	0.422875	0.232399	0.291645	0.048977	0.102211	C

600 rows × 18 columns

In [33]:
```
# scrap dataframe to csv
# import csv
# crop_data_final.to_csv('crop_data_final.csv')
```

In [8]:
```
crop_data_final = pd.read_csv("crop_data_final.csv")
crop_data_final = crop_data_final[crop_data_final.columns[1:]]
crop_data_final
```

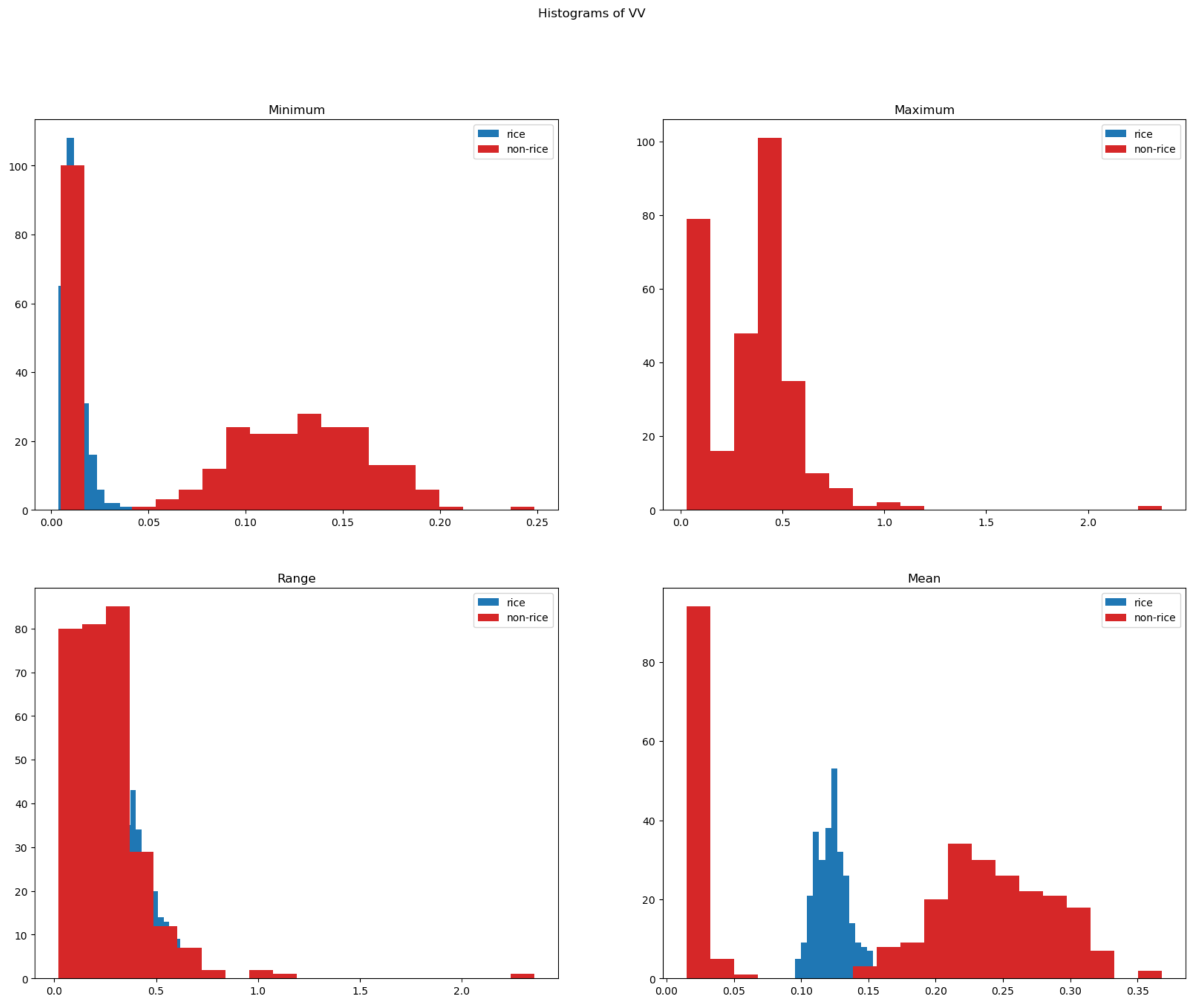
Out[8]:

	Latitude and Longitude	Class of Land	min_vv	max_vv	range_vv	mean_vv	min_vh	max_vh	ra
0	(10.323727047081501, 105.2516346045924)	Rice	0.022274	0.269761	0.247487	0.116468	0.003141	0.078778	C
1	(10.322364360592521, 105.27843410554115)	Rice	0.013224	0.491939	0.478715	0.135152	0.003354	0.090849	C
2	(10.321455902933202, 105.25254306225168)	Rice	0.016693	0.548456	0.531762	0.109102	0.003337	0.073560	C
3	(10.324181275911162, 105.25118037576274)	Rice	0.015995	0.478505	0.462510	0.126329	0.003879	0.052779	C
4	(10.324635504740822, 105.27389181724476)	Rice	0.014075	0.487998	0.473923	0.129143	0.004487	0.096872	C
...	...	...	...	...	...	...	...	...	
595	(10.013942985253381, 105.67361318732796)	Non Rice	0.145322	0.556387	0.411064	0.287192	0.033406	0.112107	C
596	(10.01348875642372, 105.67361318732796)	Non Rice	0.159897	0.413889	0.253993	0.261459	0.039730	0.114915	C
597	(10.013034527594062, 105.67361318732796)	Non Rice	0.171829	0.437881	0.266052	0.262192	0.038087	0.094669	C
598	(10.012580298764401, 105.67361318732796)	Non Rice	0.209815	0.474909	0.265094	0.287283	0.047271	0.108973	C
599	(10.012126069934741, 105.67361318732796)	Non Rice	0.190475	0.422875	0.232399	0.291645	0.048977	0.102211	C

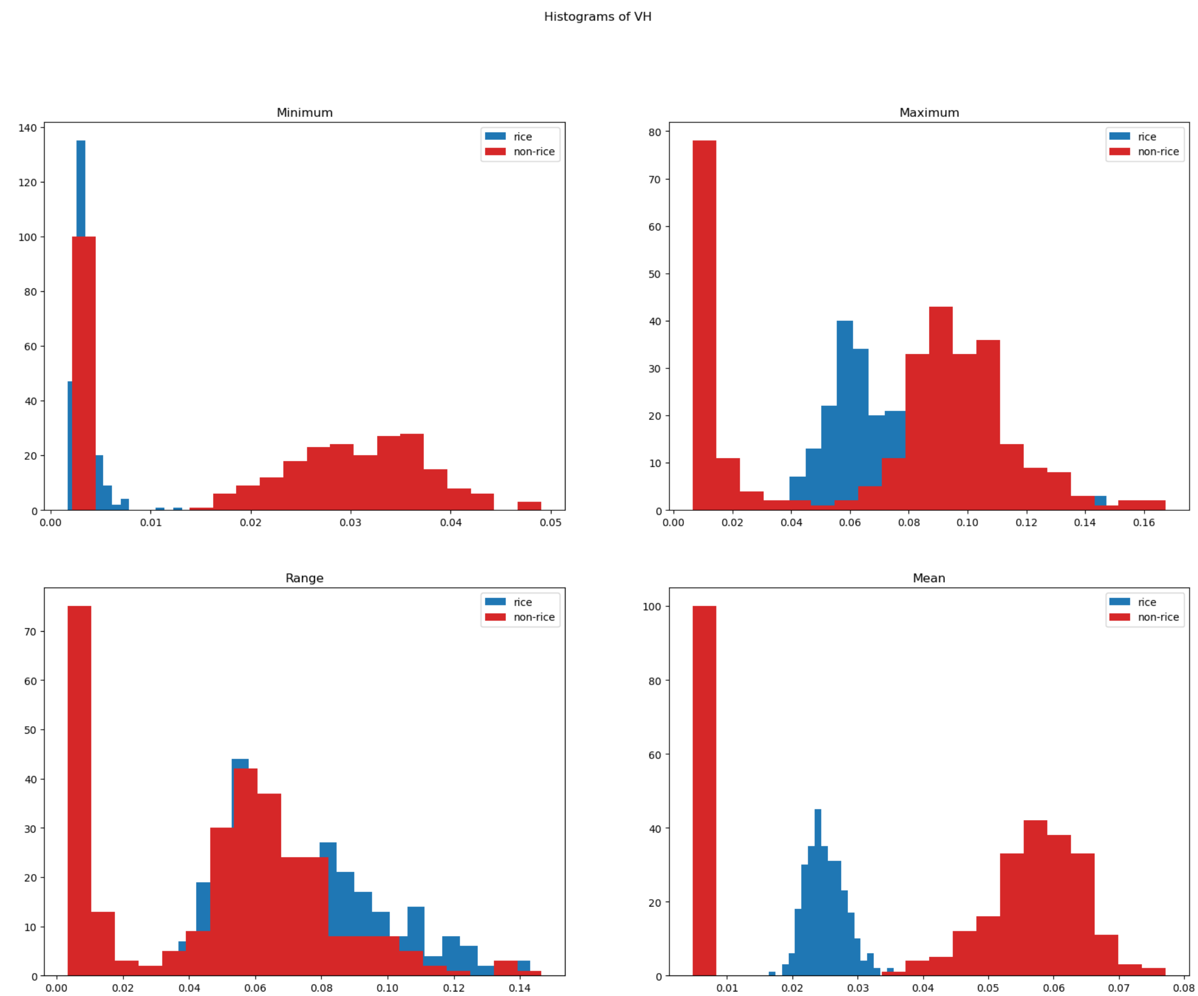
600 rows × 18 columns

Data Analysis

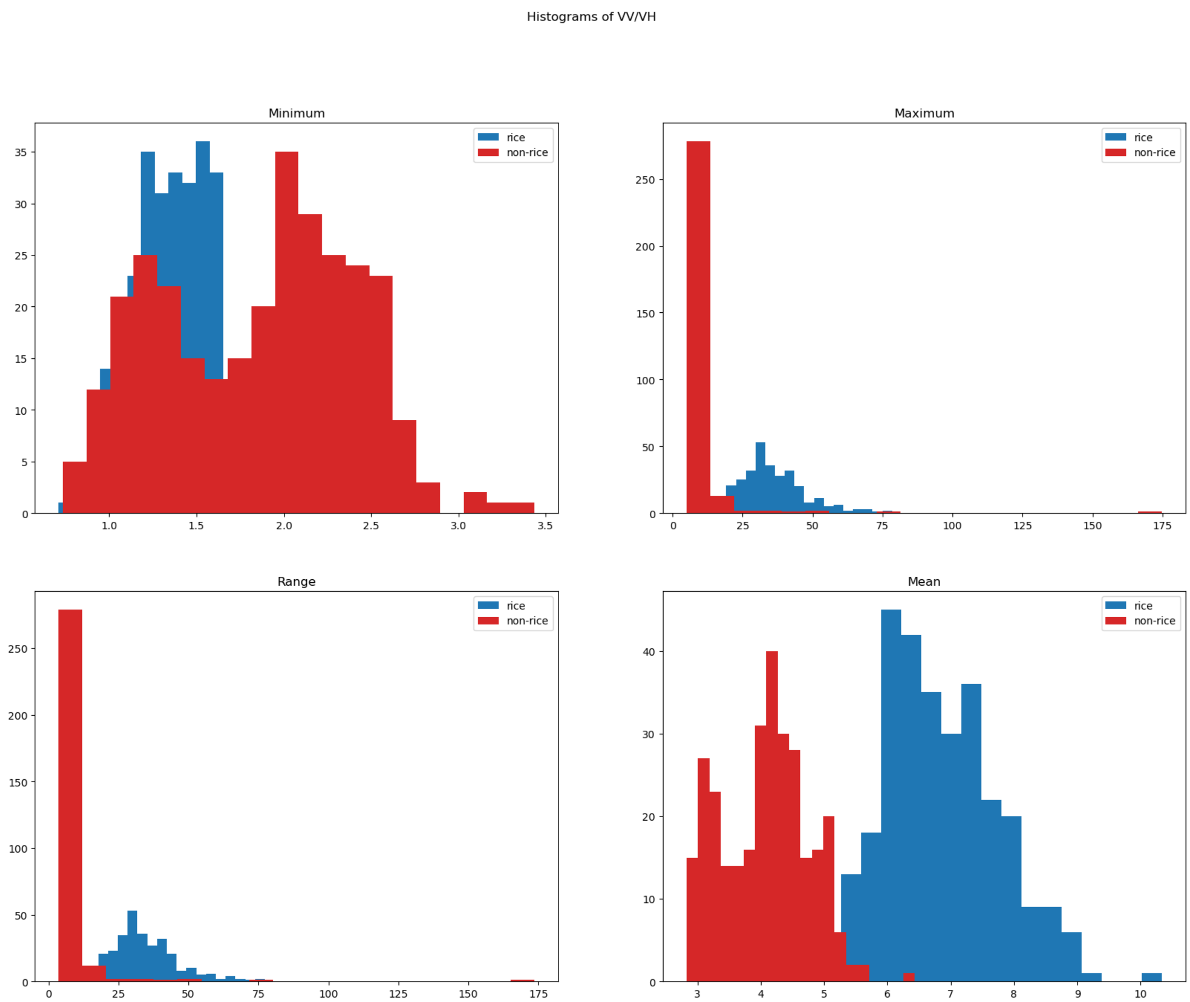
In [9]:
```
# Histogram plots for vv
n_bins = 20
fig, axs = plt.subplots(2, 2, figsize = (20,15))

axs[0, 0].hist(crop_data_final["min_vv"][:300], bins=n_bins, label = "rice", c
axs[0, 0].hist(crop_data_final["min_vv"][300:], bins=n_bins, label = "non-rice
axs[0, 0].set(title = "Minimum")
axs[0, 0].legend(loc='upper right')

axs[0, 1].hist(crop_data_final["max_vv"][:300], bins=n_bins, label = "rice", c
axs[0, 1].hist(crop_data_final["max_vv"][300:], bins=n_bins, label = "non-rice
axs[0, 1].set(title = "Maximum")
axs[0, 1].legend(loc='upper right')

axs[1, 0].hist(crop_data_final["range_vv"][:300], bins=n_bins, label = "rice",
axs[1, 0].hist(crop_data_final["range_vv"][300:], bins=n_bins, label = "non-ri
axs[1, 0].set(title = "Range")
axs[1, 0].legend(loc='upper right')

axs[1, 1].hist(crop_data_final["mean_vv"][:300], bins=n_bins, label = "rice",
axs[1, 1].hist(crop_data_final["mean_vv"][300:], bins=n_bins, label = "non-ric
axs[1, 1].set(title = "Mean")
axs[1, 1].legend(loc='upper right')

plt.suptitle("Histograms of VV")
plt.show()
```


Histograms of VV
Minimum
rice
non-rice
Maximum
rice
non-rice
Range
rice
non-rice
Mean
rice
non-rice

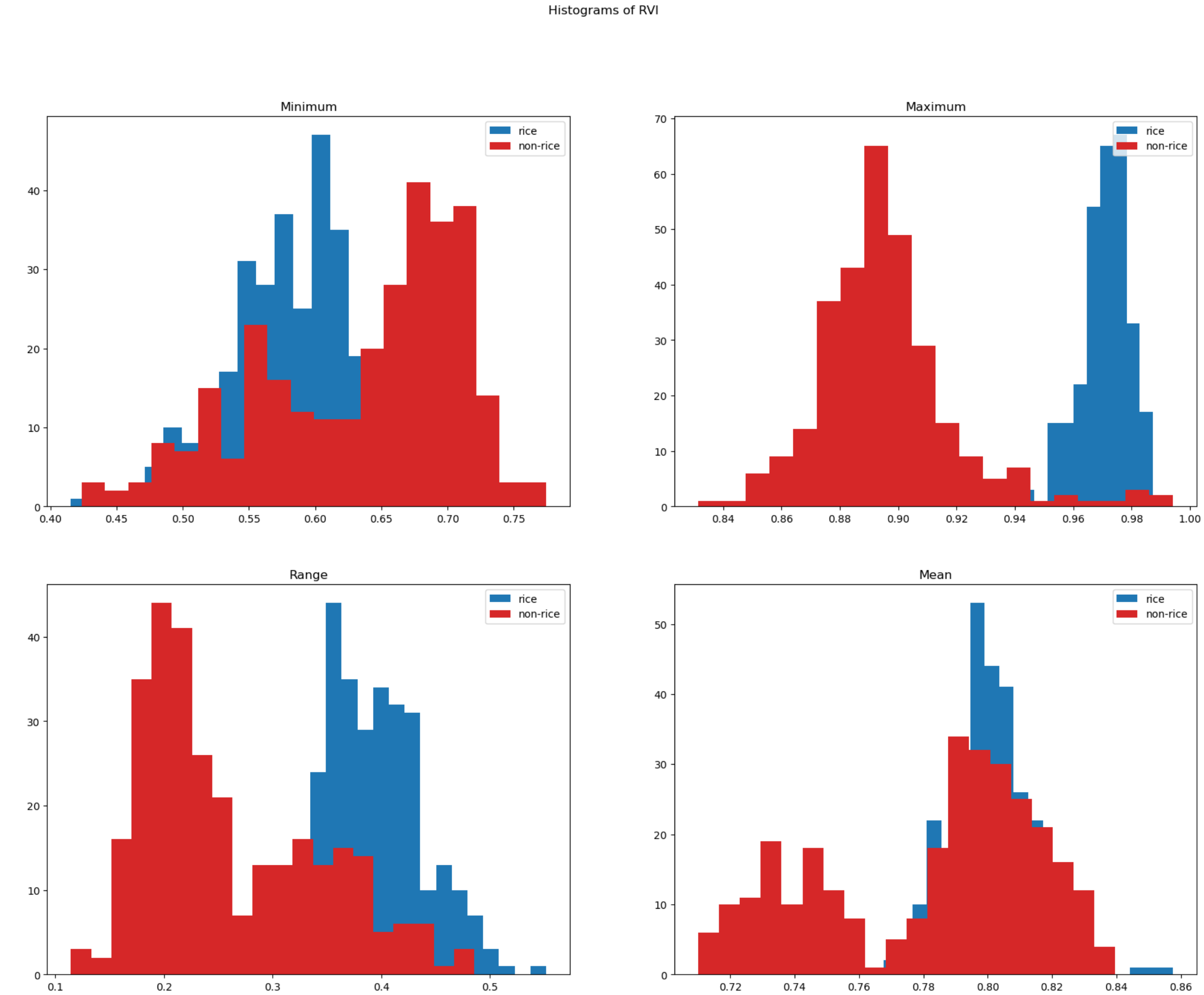
In [10]:
```
# Histogram plots for vh
n_bins = 20
fig, axs = plt.subplots(2, 2, figsize = (20,15))

axs[0, 0].hist(crop_data_final["min_vh"][:300], bins=n_bins, label = "rice", co
axs[0, 0].hist(crop_data_final["min_vh"][300:], bins=n_bins, label = "non-rice
axs[0, 0].set(title = "Minimum")
axs[0, 0].legend(loc='upper right')

axs[0, 1].hist(crop_data_final["max_vh"][:300], bins=n_bins, label = "rice", co
axs[0, 1].hist(crop_data_final["max_vh"][300:], bins=n_bins, label = "non-rice
axs[0, 1].set(title = "Maximum")
axs[0, 1].legend(loc='upper right')

axs[1, 0].hist(crop_data_final["range_vh"][:300], bins=n_bins, label = "rice",
axs[1, 0].hist(crop_data_final["range_vh"][300:], bins=n_bins, label = "non-ri
axs[1, 0].set(title = "Range")
axs[1, 0].legend(loc='upper right')

axs[1, 1].hist(crop_data_final["mean_vh"][:300], bins=n_bins, label = "rice", c
axs[1, 1].hist(crop_data_final["mean_vh"][300:], bins=n_bins, label = "non-ric
axs[1, 1].set(title = "Mean")
axs[1, 1].legend(loc='upper right')

plt.suptitle("Histograms of VH")
plt.show()
```



In [11]:
```
# Histogram plots for vv_vh
n_bins = 20
fig, axs = plt.subplots(2, 2, figsize = (20,15))

axs[0, 0].hist(crop_data_final["min_vv_by_vh"][:300], bins=n_bins, label = "ri
axs[0, 0].hist(crop_data_final["min_vv_by_vh"][300:], bins=n_bins, label = "no
axs[0, 0].set(title = "Minimum")
axs[0, 0].legend(loc='upper right')

axs[0, 1].hist(crop_data_final["max_vv_by_vh"][:300], bins=n_bins, label = "ri
axs[0, 1].hist(crop_data_final["max_vv_by_vh"][300:], bins=n_bins, label = "no
axs[0, 1].set(title = "Maximum")
axs[0, 1].legend(loc='upper right')

axs[1, 0].hist(crop_data_final["range_vv_by_vh"][:300], bins=n_bins, label = "
axs[1, 0].hist(crop_data_final["range_vv_by_vh"][300:], bins=n_bins, label = "
axs[1, 0].set(title = "Range")
axs[1, 0].legend(loc='upper right')

axs[1, 1].hist(crop_data_final["mean_vv_by_vh"][:300], bins=n_bins, label = "r
axs[1, 1].hist(crop_data_final["mean_vv_by_vh"][300:], bins=n_bins, label = "n
axs[1, 1].set(title = "Mean")
axs[1, 1].legend(loc='upper right')

plt.suptitle("Histograms of VV/VH")
plt.show()
```



In [12]:
```
# Histogram plots for rvi
n_bins = 20
fig, axs = plt.subplots(2, 2, figsize = (20,15))

axs[0, 0].hist(crop_data_final["min_rvi"][:300], bins=n_bins, label = "rice", 
axs[0, 0].hist(crop_data_final["min_rvi"][300:], bins=n_bins, label = "non-ric
axs[0, 0].set(title = "Minimum")
axs[0, 0].legend(loc='upper right')

axs[0, 1].hist(crop_data_final["max_rvi"][:300], bins=n_bins, label = "rice", 
axs[0, 1].hist(crop_data_final["max_rvi"][300:], bins=n_bins, label = "non-ric
axs[0, 1].set(title = "Maximum")
axs[0, 1].legend(loc='upper right')

axs[1, 0].hist(crop_data_final["range_rvi"][:300], bins=n_bins, label = "rice"
axs[1, 0].hist(crop_data_final["range_rvi"][300:], bins=n_bins, label = "non-r
axs[1, 0].set(title = "Range")
axs[1, 0].legend(loc='upper right')

axs[1, 1].hist(crop_data_final["mean_rvi"][:300], bins=n_bins, label = "rice", 
axs[1, 1].hist(crop_data_final["mean_rvi"][300:], bins=n_bins, label = "non-ri
axs[1, 1].set(title = "Mean")
axs[1, 1].legend(loc='upper right')

plt.suptitle("Histograms of RVI")
plt.show()
```



In [13]:
```
crop_data_final.describe()
```

Out[13]:

	min_vv	max_vv	range_vv	mean_vv	min_vh	max_vh	range_vh	m
count	600.000000	600.000000	600.000000	600.000000	600.000000	600.000000	600.000000	600.
mean	0.051225	0.387562	0.336337	0.147177	0.012618	0.074903	0.062285	0.
std	0.059832	0.188393	0.184405	0.083570	0.013522	0.034965	0.030834	0.
min	0.003896	0.029297	0.021753	0.014748	0.001731	0.006505	0.003419	0.
25%	0.007964	0.330177	0.248252	0.110536	0.003069	0.057207	0.049463	0.
50%	0.013214	0.404597	0.344461	0.127159	0.003684	0.081842	0.062593	0.
75%	0.104092	0.475000	0.428733	0.215759	0.025718	0.099704	0.080763	0.
max	0.248402	2.363277	2.355309	0.368260	0.049050	0.167438	0.146424	0.

Data Preparation

In [14]:
```
# Select X and Y
X = crop_data_final.iloc[..., 2:]
Y = crop_data_final.iloc[..., 1]
```

In [15]:
```
X.describe()
```

Out[15]:

	min_vv	max_vv	range_vv	mean_vv	min_vh	max_vh	range_vh	m
count	600.000000	600.000000	600.000000	600.000000	600.000000	600.000000	600.000000	600.
mean	0.051225	0.387562	0.336337	0.147177	0.012618	0.074903	0.062285	0.
std	0.059832	0.188393	0.184405	0.083570	0.013522	0.034965	0.030834	0.
min	0.003896	0.029297	0.021753	0.014748	0.001731	0.006505	0.003419	0.
25%	0.007964	0.330177	0.248252	0.110536	0.003069	0.057207	0.049463	0.
50%	0.013214	0.404597	0.344461	0.127159	0.003684	0.081842	0.062593	0.
75%	0.104092	0.475000	0.428733	0.215759	0.025718	0.099704	0.080763	0.
max	0.248402	2.363277	2.355309	0.368260	0.049050	0.167438	0.146424	0.

In [16]:
```
X.dtypes
```

Out[16]:
```
min_vv            float64
max_vv            float64
range_vv          float64
mean_vv           float64
min_vh            float64
max_vh            float64
range_vh          float64
mean_vh           float64
min_vv_by_vh      float64
max_vv_by_vh      float64
range_vv_by_vh    float64
mean_vv_by_vh     float64
min_rvi           float64
max_rvi           float64
range_rvi         float64
mean_rvi          float64
dtype: object
```

In [17]:
```
Y
```

Out[17]:
```
0          Rice
1          Rice
2          Rice
3          Rice
4          Rice
         ...
595    Non Rice
596    Non Rice
597    Non Rice
598    Non Rice
599    Non Rice
Name: Class of Land, Length: 600, dtype: object
```

In [18]:
```
Y = np.where(Y == "Rice", 1, 0)
```

In [19]:
```
class_names = ["Non Rice", "Rice"]
Y
```

Out[19]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0])
```

In [20]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2, ran

# Check dimensions
print(f"Shape of x train: {x_train.shape}")
print(f"Shape of x test: {x_test .shape}")
print(f"Shape of y train: {y_train.shape}")
print(f"Shape of y test: {y_test.shape}")
```

```
Shape of x train: (480, 16)
Shape of x test: (120, 16)
Shape of y train: (480,)
Shape of y test: (120,)
```

Model Creation

In [42]:
```
# !pip install tensorflow
```

In [43]:
```
import tensorflow as tf
from tensorflow import keras
```

In [44]:
```
# Clear any previous models
keras.backend.clear_session()
# keras.layers.Dropout(rate=.2), kernel_initializer = "he_normal"
# Initialize MLP model
mlp = keras.models.Sequential([keras.layers.Flatten(input_shape = [16, 1]),
                               keras.layers.Dense(256, activation = "relu", ke
                               keras.layers.Dropout(rate=.2),
                               keras.layers.Dense(128, activation = "relu", ke
                               keras.layers.Dropout(rate = .1),
                               keras.layers.Dense(1, activation = "sigmoid")])
# Compile the model
mlp.compile(loss = keras.losses.binary_crossentropy, optimizer = keras.optimiz

mlp.summary ()
```

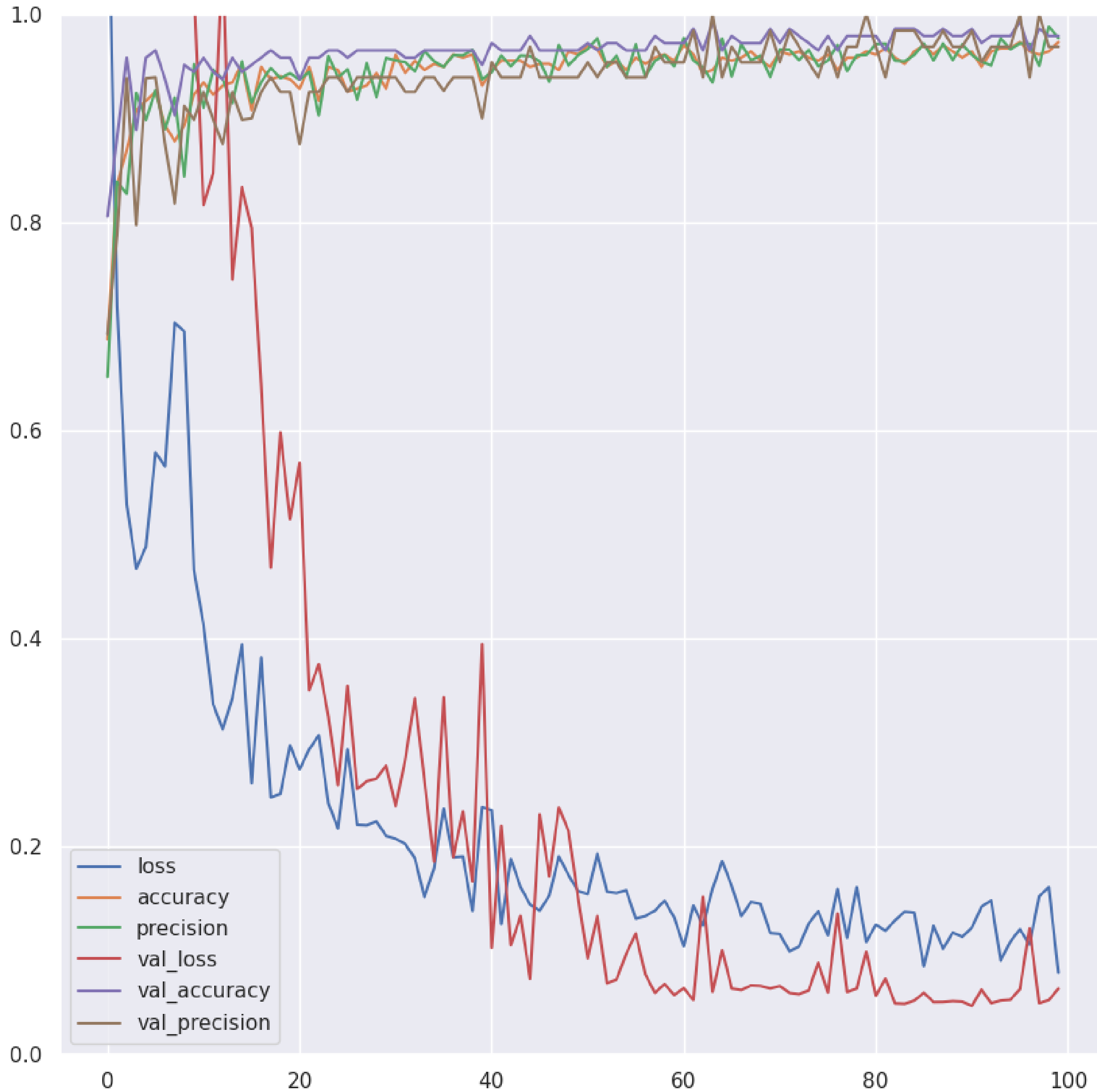
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 16)                0

 dense (Dense)               (None, 256)               4352

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 dropout_1 (Dropout)         (None, 128)               0

 dense_2 (Dense)             (None, 1)                 129

=================================================================
Total params: 37,377
Trainable params: 37,377
Non-trainable params: 0
_________________________________________________________________
```

Training Set Evaluation

In [45]:
```
# Fit model with training data and get history to plot
# Set seed for replicability
tf.random.set_seed(123)
# Fit mlp with a 70-30 split
mlp_hist = mlp.fit(x_train, y_train, validation_split = 0.3, epochs = 100, verl
```

```
Epoch 71/100
11/11 - 0s - loss: 0.1155 - accuracy: 0.9643 - precision: 0.9661 - val_los
s: 0.0655 - val_accuracy: 0.9722 - val_precision: 0.9538 - 84ms/epoch - 8m
s/step
Epoch 72/100
11/11 - 0s - loss: 0.0988 - accuracy: 0.9613 - precision: 0.9659 - val_los
s: 0.0588 - val_accuracy: 0.9861 - val_precision: 0.9841 - 76ms/epoch - 7m
s/step
Epoch 73/100
11/11 - 0s - loss: 0.1034 - accuracy: 0.9643 - precision: 0.9558 - val_los
s: 0.0576 - val_accuracy: 0.9792 - val_precision: 0.9688 - 101ms/epoch - 9m
s/step
Epoch 74/100
11/11 - 0s - loss: 0.1255 - accuracy: 0.9583 - precision: 0.9657 - val_los
s: 0.0612 - val_accuracy: 0.9722 - val_precision: 0.9538 - 72ms/epoch - 7m
s/step
Epoch 75/100
11/11 - 0s - loss: 0.1374 - accuracy: 0.9554 - precision: 0.9500 - val_los
s: 0.0879 - val_accuracy: 0.9653 - val_precision: 0.9394 - 67ms/epoch - 6m
s/step
Epoch 76/100
```

In [47]:
```
# Plot history
pd.DataFrame(mlp_hist.history).plot()
plt.grid(True)
plt.gca().set_ylim(0.0, 1.0)
plt.show()
```



Validation Set Evaluation

In [48]:
```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
```

In [49]:
```
mlp.evaluate(x_test, y_test)
```

```
4/4 [==============================] - 0s 3ms/step - loss: 0.1033 - accuracy:
0.9583 - precision: 0.9231
```

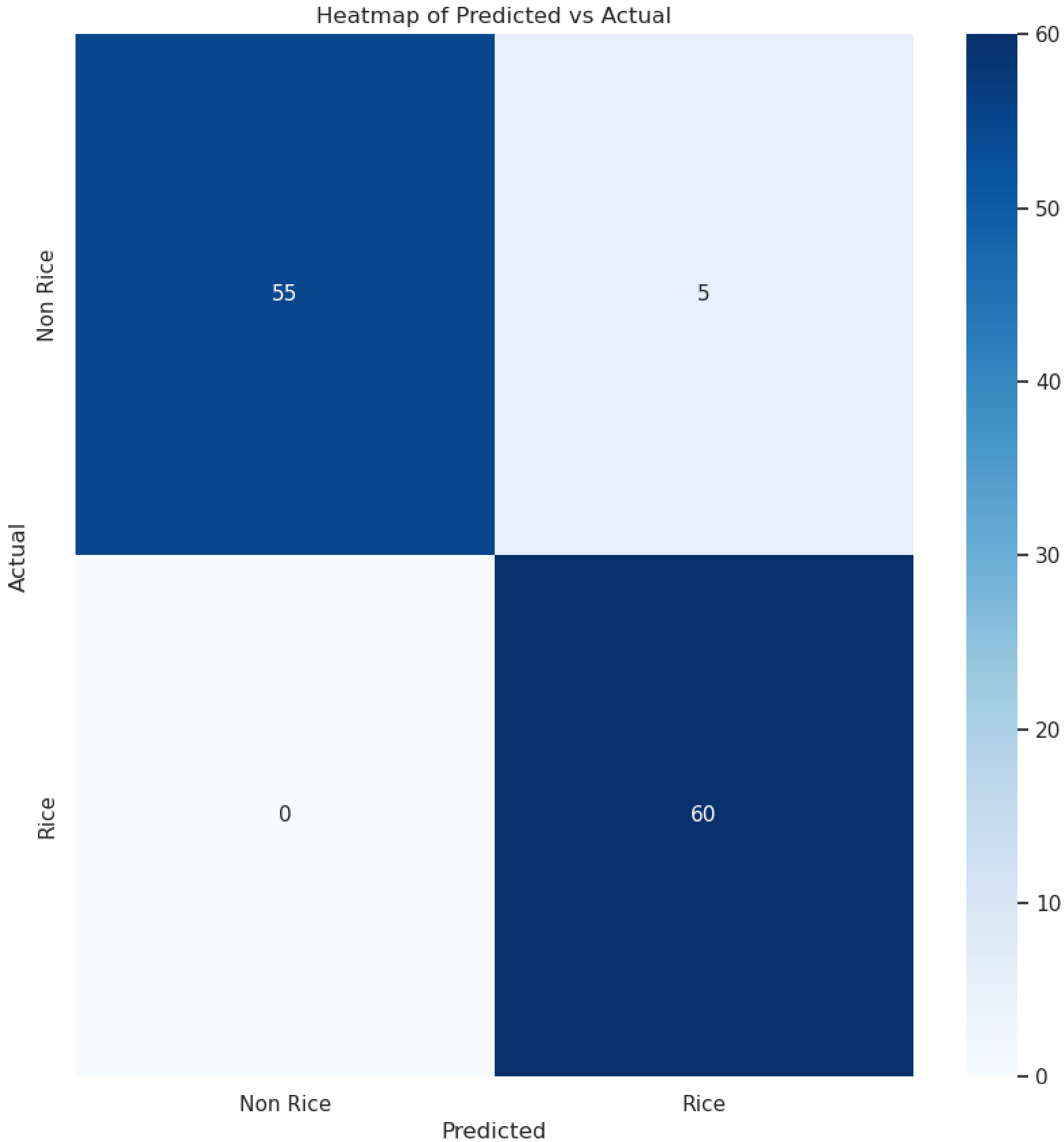
Out[49]:
```
[0.10334441065788269, 0.9583333134651184, 0.9230769276618958]
```

In [50]:
```
# Plot results
pred_vals = np.concatenate(mlp.predict(x_test).round(), axis = 0).astype(int)
pred_vals
```

```
4/4 [==============================] - 0s 2ms/step
```

Out[50]:
```
array([0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0,
       1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1,
       0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 1, 0, 1, 1, 0, 0, 0])
```

In [51]:
```
cm = confusion_matrix(y_test, pred_vals)
df_cm = pd.DataFrame(cm, columns = class_names, index = class_names)
df_cm.index.name = "Actual"
df_cm.columns.name = "Predicted"

sns.set(font_scale = 0.9)
sns.set(rc={"figure.figsize": (10, 10)})
sns.heatmap(df_cm, cmap = "Blues", annot = True, annot_kws = {"size": 11}, fmt
plt.show()
```



In [52]:
```
# Classification report
print("Classification Report on Test Set")
print(classification_report(y_test, pred_vals, target_names = class_names))
```

```
Classification Report on Test Set
              precision    recall  f1-score   support

    Non Rice       1.00      0.92      0.96        60
        Rice       0.92      1.00      0.96        60

    accuracy                           0.96       120
   macro avg       0.96      0.96      0.96       120
weighted avg       0.96      0.96      0.96       120
```

Challenge Set

In [53]:
```
challenge = pd.read_csv("challenge_1_submission_template_correct_columns_fixed
challenge
```

Out[53]:

	id	target
0	(10.18019073690894, 105.32022315786804)	NaN
1	(10.561107033461816, 105.12772097986661)	NaN
2	(10.623790611954897, 105.13771401411867)	NaN
3	(10.583364246115156, 105.23946127195805)	NaN
4	(10.20744446668854, 105.26844107128906)	NaN
...	...	...
245	(10.308283266873062, 105.50872812216863)	NaN
246	(10.582910017285496, 105.23991550078767)	NaN
247	(10.581547330796518, 105.23991550078767)	NaN
248	(10.629241357910818, 105.15315779432643)	NaN
249	(10.574733898351617, 105.10410108072531)	NaN

250 rows × 2 columns

In [54]:
```
train_band_values=challenge.progress_apply(lambda x: get_sentinel_data(x["id"]
vh = [x[0] for x in train_band_values]
vv = [x[1] for x in train_band_values]
vv_by_vh = [x[2] for x in train_band_values]
vh_vv_data = pd.DataFrame(list(zip(vh,vv,vv_by_vh)),columns = ["vv_list","vh_l
```

```
100%|██████████| 250/250 [48:32<00:00, 11.65s/it]
```

In [55]:
```
for col in vh_vv_data.columns:
    vh_vv_data[col] = vh_vv_data[col].apply(lambda x: np.array(x))
```

In [56]:
```
rvi = (vh_vv_data["vv_list"] / (vh_vv_data["vv_list"] + vh_vv_data["vh_list"])
rvi
```

Out[56]:
```
0      [0.6934660316485579, 0.5475368882842185, 0.700...
1      [0.8627907653862491, 0.7926160181292811, 0.834...
2      [0.9643852217834891, 0.948557126296569, 0.8718...
3      [0.6553383569142758, 0.7794217710843198, 0.800...
4      [0.7061504258271251, 0.7220776450247584, 0.871...
                              ...
245    [0.6372886073808575, 0.6730416311342043, 0.766...
246    [0.7325926589532095, 0.8466471567453002, 0.845...
247    [0.6716225045804242, 0.8010827535161774, 0.765...
248    [0.9879620103625607, 0.9786252689524993, 0.934...
249    [0.8436008759317494, 0.6524801716814794, 0.681...
Length: 250, dtype: object
```

In [57]:
```
vh_vv_data["rvi"] = rvi
vh_vv_data
```

Out[57]:

	vv_list	vh_list	vv/vh_list	rv
0	[0.010586533695459366, 0.008605285547673702, 0...	[0.004679583478718996, 0.007111072074621916, 0...	[2.2622811931025444, 1.2101249231299953, 2.339...	[0.6934660316485579 0.5475368882842185 0.700..
1	[0.009555697441101074, 0.010459705255925655, 0...	[0.0015196383465081453, 0.002736729104071 8555,...	[6.288139189866024, 3.8219731870294114, 5.0551...	[0.8627907653862491 0.7926160181292811 0.834..
2	[0.11977537721395493, 0.07649119198322296, 0.0...	[0.004423308651894331, 0.004148328676819801, 0...	[27.078231848609477, 18.439038451953802, 6.802...	[0.9643852217834891 0.9485571262965 69 0.8718..
3	[0.007301058620214462, 0.013919728808104992, 0...	[0.0038398406468331814, 0.0039393166080117226,...	[1.9013962535752205, 3.533538984857236, 4.0222...	[0.6553383569142758 0.7794217710843198 0.800..
4	[0.009329406078904867, 0.008071513380855322, 0...	[0.003882235148921609, 0.003106665913946926 6, ...	[2.403101749644493, 2.5981272542436673, 6.7950...	[0.7061504258271251 0.7220776450247584 0.871..
...	...	...	...	..
245	[0.00872089434415102, 0.012391516007483006, 0....	[0.004963477607816458, 0.006019701715558767, 0...	[1.757012931904317, 2.058493359472511, 3.28009...	[0.6372886073808575 0.6730416311342043 0.766..
246	[0.008095650933682919, 0.01522239949554205, 0....	[0.002955034375190735, 0.0027572268154472113, ...	[2.739613116399155, 5.520909418934777, 5.45269...	[0.7325926589532095 0.8466471567453002 0.845..
247	[0.009455842897295952, 0.012584727257490158, 0...	[0.00462326081469655, 0.003124919719994068, 0....	[2.0452756779884567, 4.027216179977272, 3.2614...	[0.6716225045804242 0.8010827535161774 0.765..
248	[0.2817420959472656, 0.2392944097518921, 0.164...	[0.0034329340560361743, 0.005226570181548595, ...	[82.07034896341067, 45.7842143967903, 14.33527...	[0.9879620103625607 0.9786252689524993 0.934..
249	[0.08136387541890144, 0.04158054664731026, 0.1...	[0.015084430575370789, 0.022146365605294704, 0...	[5.39389770216112, 1.8775336499172248, 2.14380...	[0.8436008759317494 0.6524801716814794 0.681..

250 rows × 4 columns

In [59]:
```
features = generate_stastical_features(vh_vv_data)
challenge_data_final = pd.DataFrame(features ,columns = ['min_vv', 'max_vv', '
                            'min_vv_by_vh',  'max_vv_by_vh', 'range_vv_by_vh', '

challenge_data_final
```

Out[59]:

	min_vv	max_vv	range_vv	mean_vv	min_vh	max_vh	range_vh	mean_vh	min_vv_by
0	0.007284	0.422283	0.414999	0.091416	0.002965	0.073937	0.070972	0.018676	1.175
1	0.006580	0.281788	0.275208	0.085067	0.001520	0.073306	0.071786	0.020657	1.71
2	0.020353	0.300508	0.280156	0.120844	0.002518	0.094339	0.091820	0.021423	1.479
3	0.006193	0.112329	0.106137	0.016201	0.002629	0.022532	0.019903	0.004483	1.326
4	0.005279	0.301543	0.296264	0.100702	0.002547	0.052177	0.049631	0.017986	1.243
...	...	...	...	...	...	...	...	...	
245	0.008685	0.127352	0.118667	0.017930	0.003380	0.013583	0.010203	0.005466	1.290
246	0.006412	0.197399	0.190986	0.018214	0.002365	0.042182	0.039816	0.004737	1.357
247	0.008257	0.129412	0.121154	0.018787	0.002384	0.017801	0.015417	0.004862	1.497
248	0.008001	0.371705	0.363704	0.125352	0.003101	0.067941	0.064840	0.020231	1.885
249	0.009776	0.297083	0.287307	0.103813	0.003195	0.088627	0.085431	0.027013	1.652

250 rows × 16 columns

In [60]:
```
# Get Challenge Values
challenge_vals = np.concatenate(mlp.predict(challenge_data_final).round(), axi
challenge_vals
```

```
8/8 [==============================] - 0s 2ms/step
```

Out[60]:
```
array([1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0,
       1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1,
       1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0,
       0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1,
       1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1,
       1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1,
       1, 0, 0, 0, 0, 0, 1, 1])
```

In [61]:
```
target = np.where(challenge_vals == 1, "Rice", "Non Rice")
target
```

Out[61]:
```
array(['Rice', 'Rice', 'Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Non Rice', 'Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice', 'Rice',
       'Rice', 'Non Rice', 'Rice', 'Non Rice', 'Rice', 'Rice', 'Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Rice', 'Rice', 'Rice',
       'Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Rice',
       'Rice', 'Non Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Rice',
       'Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice', 'Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice', 'Rice',
       'Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Rice', 'Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice', 'Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Rice', 'Non Rice', 'Non Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Rice', 'Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Rice', 'Rice', 'Non Rice', 'Rice',
       'Rice', 'Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Rice', 'Rice', 'Rice',
       'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Rice', 'Rice',
       'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Rice', 'Non Rice', 'Rice', 'Rice', 'Non Rice', 'Non Rice',
       'Non Rice', 'Non Rice', 'Non Rice', 'Rice', 'Rice'], dtype='<U8')
```

In [62]:
```
challenge["target"] = target
challenge
```

Out[62]:

	id	target
0	(10.18019073690894, 105.32022315786804)	Rice
1	(10.561107033461816, 105.12772097986661)	Rice
2	(10.623790611954897, 105.13771401411867)	Rice
3	(10.583364246115156, 105.23946127195805)	Non Rice
4	(10.20744446668854, 105.26844107128906)	Rice
...	...	...
245	(10.308283266873062, 105.50872812216863)	Non Rice
246	(10.582910017285496, 105.23991550078767)	Non Rice
247	(10.581547330796518, 105.23991550078767)	Non Rice
248	(10.629241357910818, 105.15315779432643)	Rice
249	(10.574733898351617, 105.10410108072531)	Rice

250 rows × 2 columns

In [63]:
```
challenge.to_csv("level_1_final_submission.csv",index = False)
```

In [ ]: