MLMAPPER_Task_1

March 25, 2021

1 Predictive model for the Lunar albedo based on the chemical composition data from the Lunar Prospector.

Data source - https://github.com/ML4SCI/ML4SCI_GSoC/tree/main/Messenger/Moon

Note - For final results jump to last section of this notebook

1.0.1 Importing important python libraries for plotting and data preprocessing

[84]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib as mpl

mpl.style.use('classic')
%matplotlib inline

from sklearn import metrics
sns.set()
```

2 Part 1- Data Preprocessing and Exploratory Data Analysis

The data is stored in a CSV files with 360 rows and 720 columns.

The goal of data preprocessing is to convert the data in a format suitable for training and testing .

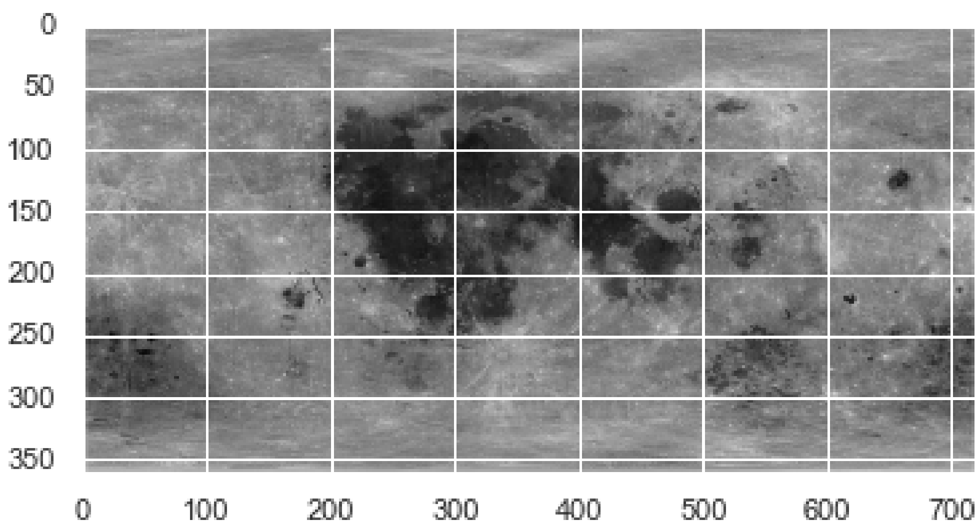
Step 1 - > Converting all the data frames into Numpy Matrix to divide the Left Side as Training and Right as Testing

[85]:
```
albedo = pd.read_csv("Albedo_Map.csv",header=None);
Ti =  pd.read_csv("LPTi_Map.csv",header=None);
Fe =  pd.read_csv("LPFe_Map.csv",header=None);
K  =  pd.read_csv("LPK_Map.csv",header=None);
Th =  pd.read_csv("LPK_Map.csv",header=None);



alb = albedo.to_numpy()
```

```
ti = Ti.to_numpy()
fe = Fe.to_numpy()
k = K.to_numpy()
th = Th.to_numpy()

alb_train = alb[:,:360]
alb_test = alb[:,360:]
ti_train = ti[:,:360]
ti_test = ti[:,360:]
fe_train = fe[:,:360]
fe_test = fe[:,360:]
k_train = k[:,:360]
k_test = k[:,360:]
th_train = th[:,:360]
th_test = th[:,360:]
```

Plotting to the original to check if the above conversion of successful

[86]:
```
alb_final = np.concatenate((alb_train,alb_test), axis=1)

plt.imshow(alb_final, cmap="gray")
plt.show()
```



Step 2-> Flattening all the Matrices and stacking the left side and right side data to their respectively dataframes.

[87]:
```
flat_alb_train = alb_train.flatten()
flat_alb_test = alb_test.flatten()
```

```
flat_ti_train = ti_train.flatten()
flat_ti_test = ti_test.flatten()

flat_fe_train = fe_train.flatten()
flat_fe_test= fe_test.flatten()

flat_k_train = k_train.flatten()
flat_k_test = k_test.flatten()

flat_th_train = th_train.flatten()
flat_th_test = th_test.flatten()

data_train = {'Ti':flat_ti_train,
        'Fe':flat_fe_train,
        'K':flat_k_train,
        'Th':flat_th_train,
        'Albedo':flat_alb_train}
data_test = {'Ti':flat_ti_test,
        'Fe':flat_fe_test,
        'K':flat_k_test,
        'Th':flat_th_test,
        'Albedo':flat_alb_test}

LEFT = pd.DataFrame(data= data_train)
RIGHT = pd.DataFrame(data= data_test)
```

Step 3-> Lets do some EDA Top five rows of the Left side Dataframe

[88]:
```
LEFT.head()
```

[88]:

	Ti	Fe	K	Th	Albedo
0	0.190154	4.04409	788.81	788.81	0.331936
1	0.190154	4.04409	788.81	788.81	0.332611
2	0.190154	4.04409	788.81	788.81	0.332240
3	0.190154	4.04409	788.81	788.81	0.331028
4	0.190154	4.04409	788.81	788.81	0.331094

Lets get some insights about the data using info() and describe() methods.

[89]:
```
LEFT.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 129600 entries, 0 to 129599
Data columns (total 5 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Ti      129600 non-null  float64
 1   Fe      129600 non-null  float64
```

```
 2   K        129600 non-null   float64
 3   Th       129600 non-null   float64
 4   Albedo   129600 non-null   float64
dtypes: float64(5)
memory usage: 4.9 MB
```

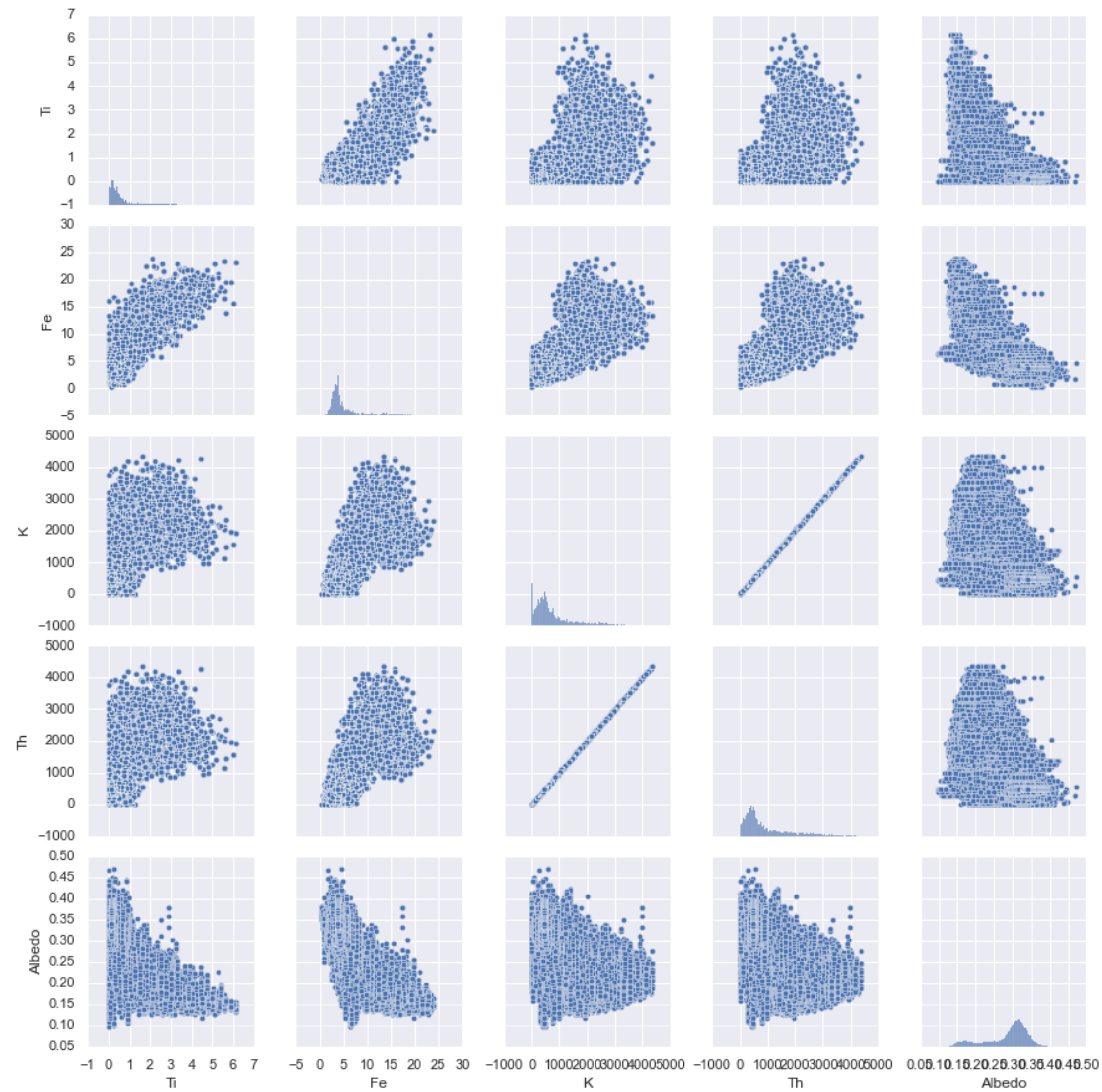
[90]:
```
LEFT.describe()
```

[90]:
```
                  Ti             Fe              K             Th  \
count  129600.000000  129600.000000  129600.000000  129600.000000
mean        0.604026       5.734629     853.252498     853.252498
std         0.904006       4.134721     824.795878     824.795878
min         0.000000       0.271907       0.000000       0.000000
25%         0.069470       3.306880     310.490000     310.490000
50%         0.277718       4.019060     539.460000     539.460000
75%         0.626194       6.295210    1116.425000    1116.425000
max         6.135470      23.901800    4356.400000    4356.400000

              Albedo
count  129600.000000
mean        0.285794
std         0.057578
min         0.096897
25%         0.258126
50%         0.303909
75%         0.324932
max         0.470428
```

Let's explore some relationships among the variables if any across the entire data set

[91]:
```
sns.pairplot(LEFT)
```

[91]:
```
<seaborn.axisgrid.PairGrid at 0x1ee10275bc8>
```

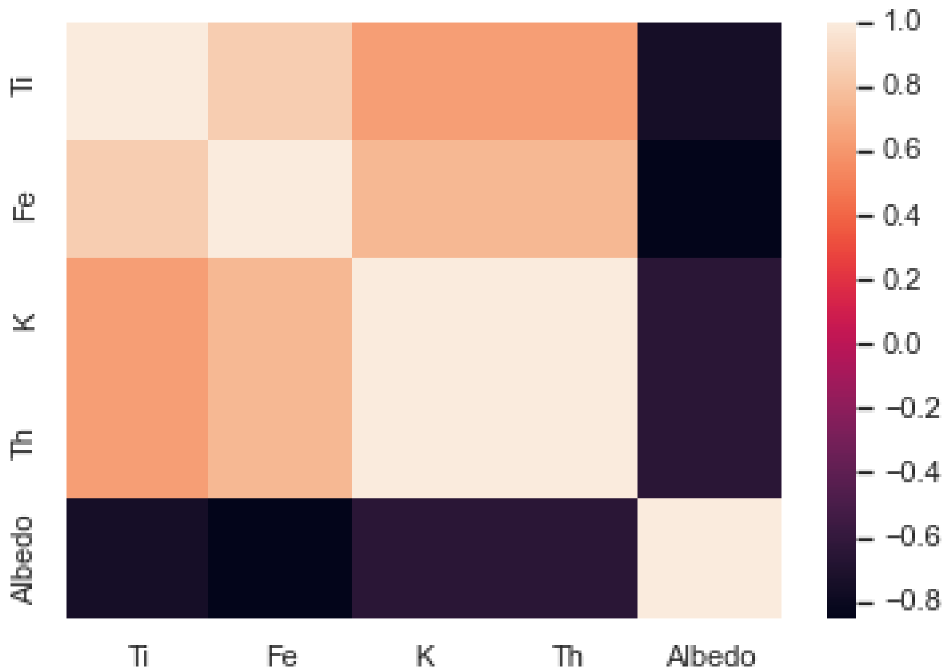


2.1 Ingsights from the plots above

1) Almost all of the variables are heavly skewed.
2) Some correlation can also be obeserved , so lets plot the correlation matrix to understand it better

[92]:
```
sns.heatmap(LEFT.corr())
```

[92]: <AxesSubplot:>



3 Part 2- Machine Learning

The goal is to build a regression model using different machine learning algorithms to predict the brightness of each pixel using the left side of the albedo as training data and right side as the test data.

****For all the models these steps will be followed :-****

1) Fitting the regressor object on the hyperparameters obtained using GridSearch

2) Print the details about the model (Correlation(R) bewtween actual and predicted values, evaluation metrics etc.)

3) Plotting the predictions and 2-D image and residuals as 1-D histogram

Note the final peformace would be compared using **Mean Square Error(MSE)** as its a good evaluation metric for regression models

First and foremost lets divide the data in train and test and do feature scaling

[93]:
```
X_train = LEFT.iloc[:, :-1].values
y_train = LEFT.iloc[:, 4].values
X_test = RIGHT.iloc[:, :-1].values
y_test = RIGHT.iloc[:, 4].values
```

[94]:
```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
```

```
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

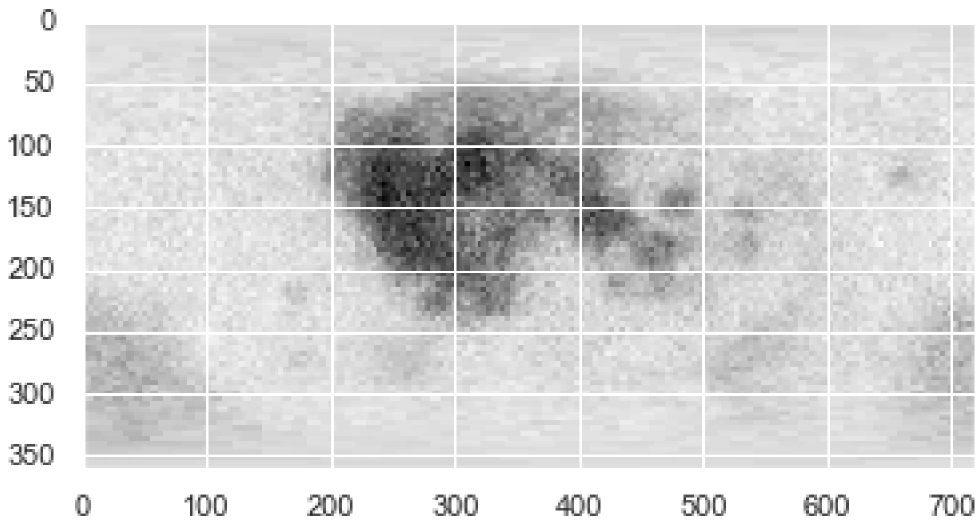
3.1 1)Linear Regression

[95]:
```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predicting the Test set results
y_pred_train = regressor.predict(X_train)
y_pred_test = regressor.predict(X_test)
residuals  = y_test-y_pred_test
```

[96]:
```
print("About Model")
print("R:",regressor.score(X_train, y_train))
print("Adj R^2:",(1 - (1-regressor.score(X_train, y_train))*(len(y_train)-1)/
 ↪(len(y_train)-X_train.shape[1]-1)),"\n")

print("Model Evaluation")

print('MAE:', metrics.mean_absolute_error(y_test, y_pred_test))
print('MSE:', metrics.mean_squared_error(y_test, y_pred_test))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_test)))
```

```
About Model
R: 0.7269141920289073
Adj R^2: 0.7269057631293983

Model Evaluation
MAE: 0.024634054761986993
MSE: 0.001025152221398643
RMSE: 0.03201799839775502
```

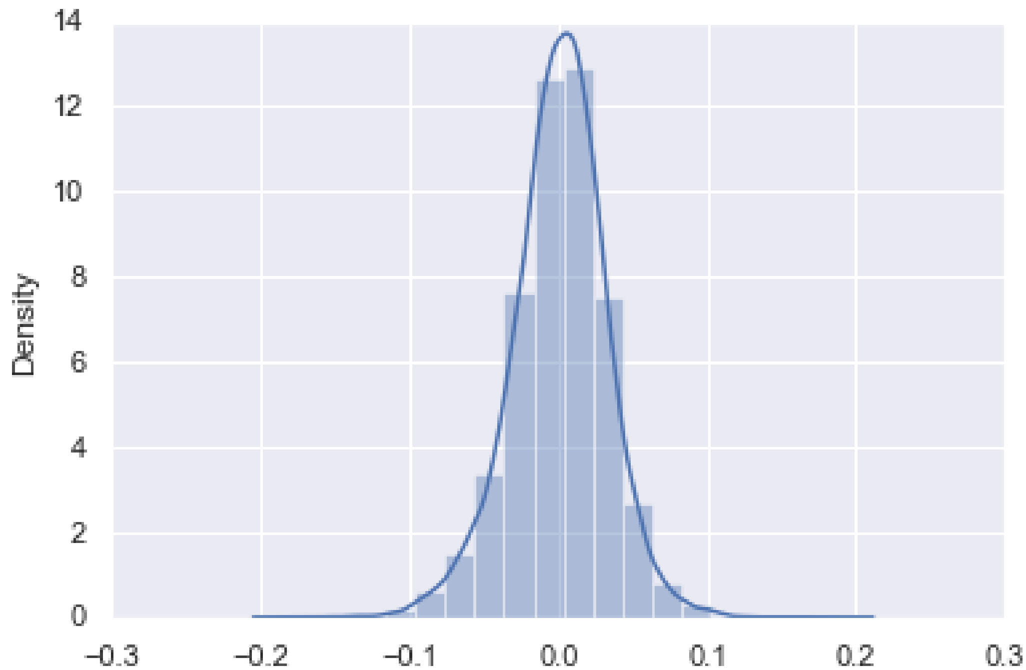
[97]:
```
y_pred_train= y_pred_train.reshape(360,360)
y_pred_test= y_pred_test.reshape(360,360)
y_img = np.concatenate([y_pred_train,y_pred_test],axis=1)
plt.imshow(y_img, cmap="gray")
plt.show()
```



[98]:
```
sns.distplot(residuals,bins=20)
```

```
C:\Users\shiva\Anaconda3\envs\tf\lib\site-
packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[98]:
```
<AxesSubplot:ylabel='Density'>
```



3.2 The MSE is 0.001025152221398643

3.3 Insights

- As expected the Linear Regression doesnt perform well as the data doesnt seem to be linearly seperable and there is correlation among the features .

3.4 2)Support Vector Machine Regressor

[99]:
```
from sklearn.svm import SVR
```

Note - Many instances of Grid Seach using different values of hyperparameter have been done but all have not been shown

[ ]:
```
from sklearn.model_selection import GridSearchCV
param_grid = {'C': [0.1,1,10,500],
              'gamma': [ 0.003, 0.03,0.3,1],
              'kernel': ['linear']}

grid = GridSearchCV(SVR(), param_grid, refit = True, verbose =␣
 ↪4,cv=3,scoring='neg_mean_squared_error'
)

# fitting the model for grid search
grid.fit(X_train, y_train)
```

```
Fitting 2 folds for each of 8 candidates, totalling 16 fits
[CV] C=0.1, degree=2, gamma=0.003, kernel=poly ...

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[CV]  C=0.1, degree=2, gamma=0.003, kernel=poly, score=-0.003, total=   3.2s
[CV] C=0.1, degree=2, gamma=0.003, kernel=poly ...

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    3.1s remaining:    0.0s

[CV]  C=0.1, degree=2, gamma=0.003, kernel=poly, score=-0.003, total=   3.1s
[CV] C=0.1, degree=2, gamma=0.03, kernel=poly ...

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    6.2s remaining:    0.0s

[CV]  C=0.1, degree=2, gamma=0.03, kernel=poly, score=-0.003, total=   2.3s
[CV] C=0.1, degree=2, gamma=0.03, kernel=poly ...

[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    8.5s remaining:    0.0s

[CV]  C=0.1, degree=2, gamma=0.03, kernel=poly, score=-0.002, total=   1.9s
[CV] C=0.1, degree=2, gamma=0.3, kernel=poly ...
[CV]  C=0.1, degree=2, gamma=0.3, kernel=poly, score=-0.003, total=   2.8s
[CV] C=0.1, degree=2, gamma=0.3, kernel=poly ...
[CV]  C=0.1, degree=2, gamma=0.3, kernel=poly, score=-0.002, total=   3.6s
[CV] C=0.1, degree=2, gamma=1, kernel=poly ...
[CV]  C=0.1, degree=2, gamma=1, kernel=poly, score=-0.003, total=   4.2s
[CV] C=0.1, degree=2, gamma=1, kernel=poly ...
[CV]  C=0.1, degree=2, gamma=1, kernel=poly, score=-0.002, total=   5.6s
[CV] C=500, degree=2, gamma=0.003, kernel=poly ...
[CV]  C=500, degree=2, gamma=0.003, kernel=poly, score=-0.003, total=   2.8s
[CV] C=500, degree=2, gamma=0.003, kernel=poly ...
[CV]  C=500, degree=2, gamma=0.003, kernel=poly, score=-0.002, total=   2.6s
[CV] C=500, degree=2, gamma=0.03, kernel=poly ...
[CV]  C=500, degree=2, gamma=0.03, kernel=poly, score=-0.003, total=   7.5s
[CV] C=500, degree=2, gamma=0.03, kernel=poly ...
[CV]  C=500, degree=2, gamma=0.03, kernel=poly, score=-0.002, total=  10.8s
[CV] C=500, degree=2, gamma=0.3, kernel=poly ...
[CV]  C=500, degree=2, gamma=0.3, kernel=poly, score=-0.003, total= 2.9min
[CV] C=500, degree=2, gamma=0.3, kernel=poly ...
```

[20]:
```
print(grid.best_params_)
print(grid.best_estimator_)
```

```
{'C': 10, 'gamma': 0.003, 'kernel': 'linear'}
SVR(C=10, gamma=0.003, kernel='linear')
```

The linear model was performing poorly and using gussian kernel gave better results

[211]:
```
print(grid.best_params_)
print(grid.best_estimator_)
```

```
{'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
SVR(C=1000, gamma=0.001)
```

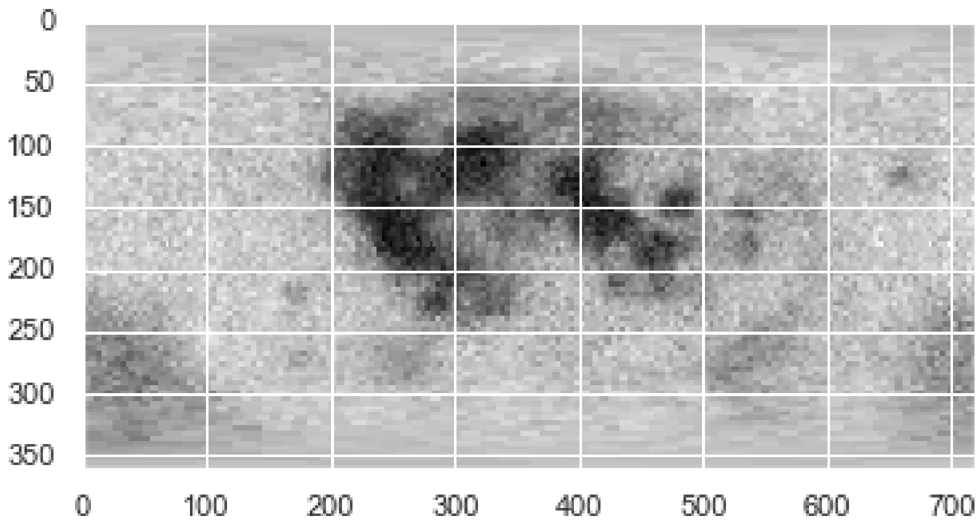
After doing grid search and experimenting with the hyperparameters C=2700 and gamma = 0.00008 gave the best results

[100]:
```
regressor =SVR(C=2700, gamma=0.00008)
regressor.fit(X_train,y_train)

# Predicting the Test set results

y_pred_train = regressor.predict(X_train)
y_pred_test = regressor.predict(X_test)
residuals  = y_test-y_pred_test
```

[101]:
```
print("About Model")
print("R:",regressor.score(X_train, y_train))
print("Adj R^2:",(1 - (1-regressor.score(X_train, y_train))*(len(y_train)-1)/
 ↪(len(y_train)-X_train.shape[1]-1)),"\n")

print("Model Evaluation")

print('MAE:', metrics.mean_absolute_error(y_test, y_pred_test))
print('MSE:', metrics.mean_squared_error(y_test, y_pred_test))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_test)))
```

```
About Model
R: 0.7315202355908725
Adj R^2: 0.7315119488586865

Model Evaluation
MAE: 0.025486332051266228
MSE: 0.0010564847231500207
RMSE: 0.03250361092478835
```

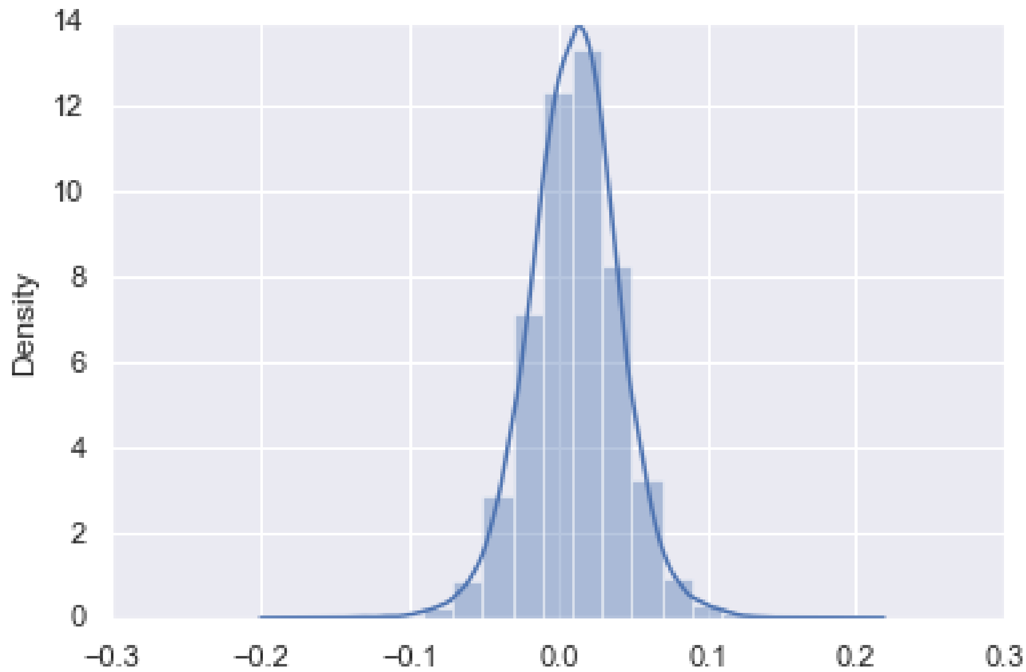
[102]:
```
y_pred_train= y_pred_train.reshape(360,360)
y_pred_test= y_pred_test.reshape(360,360)
y_img = np.concatenate([y_pred_train,y_pred_test],axis=1)
plt.imshow(y_img, cmap="gray")
plt.show()
```



[103]:
```
sns.distplot(residuals,bins=20)
```

```
C:\Users\shiva\Anaconda3\envs\tf\lib\site-
packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[103]: <AxesSubplot:ylabel='Density'>



3.5 The MSE is 0.0010564847231500207

3.6 Insights

- The image looks better than the one obtained through Linear Regression even though the MSE is slightly higher , their is scope for improvement

4 3)Random Forest

[104]:
```
from sklearn.ensemble import RandomForestRegressor
```

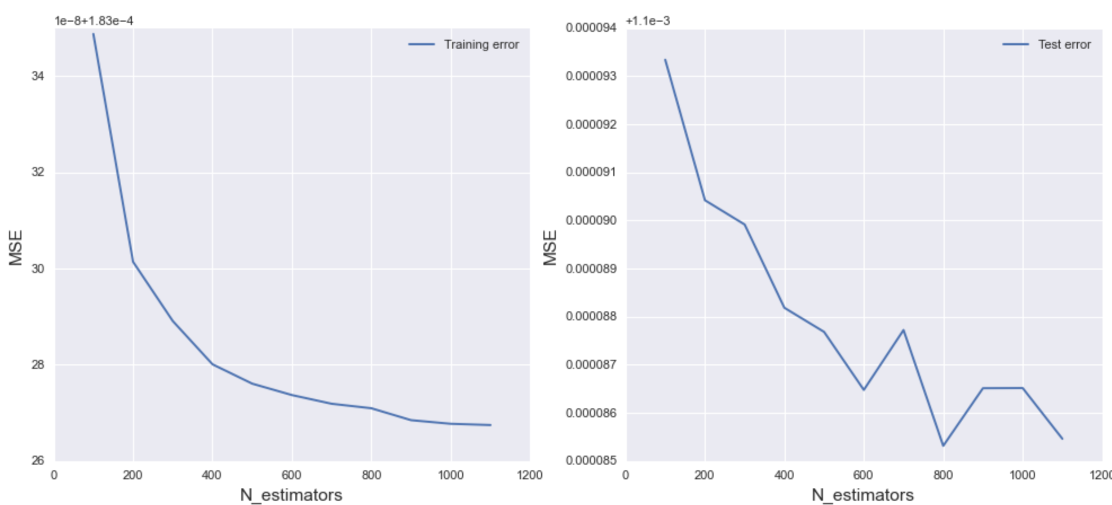
4.0.1 Tuning the hyperparameter n_estimators and plotting the results

[ ]:
```
rf = RandomForestRegressor(n_estimators=100)
error_rate_test = []
error_rate_train=[]

for iter in range(10):
    rf.fit(X_train, y_train)
    y_train_predicted = rf.predict(X_train)
    y_test_predicted = rf.predict(X_test)
    mse_train = metrics.mean_squared_error(y_train, y_train_predicted)
    mse_test = metrics.mean_squared_error(y_test, y_test_predicted)
```

```
    error_rate_train.append( metrics.mean_squared_error(y_train,␣
↪y_train_predicted))
    error_rate_test.append(metrics.mean_squared_error(y_test, y_test_predicted))
    print("Iteration: {} Train mse: {} Test mse: {}".format(iter, mse_train,␣
↪mse_test))
    rf.n_estimators += 100
```

[264]:
```
plt.figure(figsize=(15,6))

plt.subplot(1, 2, 1)

plt.style.use('seaborn')
plt.plot(range(100,1200,100),error_rate_train, label = 'Training error')
# plt.plot(range(100,1200,100),error_rate_test, label = 'Validation error')
plt.ylabel('MSE', fontsize = 14)
plt.xlabel('N_estimators', fontsize = 14)
plt.legend()
plt.subplot(1, 2, 2)

plt.style.use('seaborn')
plt.plot(range(100,1200,100),error_rate_test, label = 'Test error')
# plt.plot(range(100,1200,100),error_rate_test, label = 'Validation error')
plt.ylabel('MSE', fontsize = 14)
plt.xlabel('N_estimators', fontsize = 14)
plt.legend()
```

[264]: <matplotlib.legend.Legend at 0x19be26a9248>



Note - Many instances of Grid Seach using different values of hyperparameter have been done but all have not been shown

[79]:
```
from sklearn.model_selection import GridSearchCV

param_grid = [
{'n_estimators': [50,250,500,1000],
 'max_depth': [5,10],
 'max_features' :["sqrt"],
'min_samples_leaf':[5,10]



}
]

grid_search_forest = GridSearchCV(regressor, param_grid, cv=10,␣
 ↪scoring='neg_mean_squared_error',verbose=5)
grid_search_forest.fit(X_train, y_train)

grid_search_forest.best_params_
```

[79]:
```
{'max_depth': 10,
 'max_features': 'sqrt',
 'min_samples_leaf': 3,
 'n_estimators': 800}
```

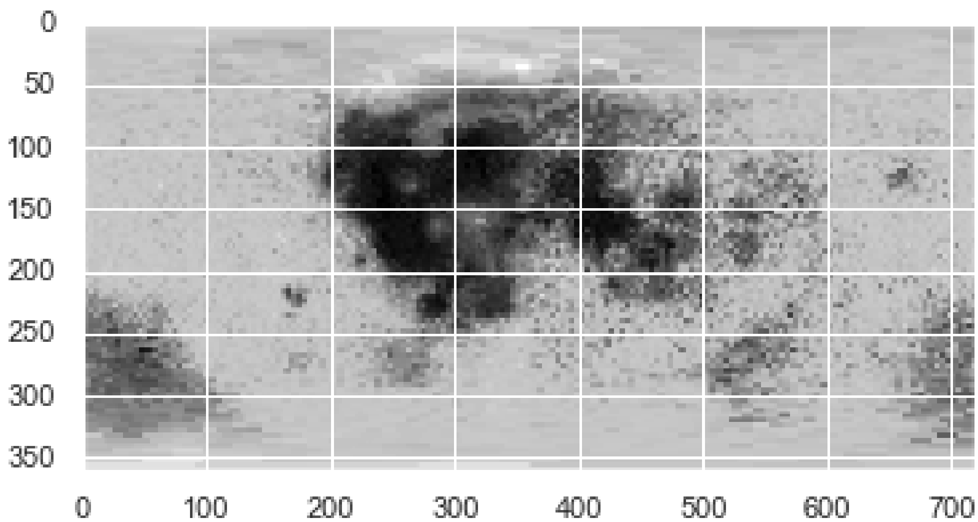
After analying the above graph and doing grid search and experimenting with the hyperparameters max_features='sqrt',max_depth=10,min_samples_leaf=5,n_estimators=600 gave the best results

[105]:
```
# create regressor object
regressor =␣
 ↪RandomForestRegressor(max_features='sqrt',max_depth=10,min_samples_leaf=5,n_estimators=600)

# fit the regressor with x and y data
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)
y_pred_train = regressor.predict(X_train)
y_pred_test = regressor.predict(X_test)
```

[106]:
```
print("About Model")
print("R:",regressor.score(X_train, y_train))
print("Adj R^2:",(1 - (1-regressor.score(X_train, y_train))*(len(y_train)-1)/
 ↪(len(y_train)-X_train.shape[1]-1)),"\n")

print("Model Evaluation")

print('MAE:', metrics.mean_absolute_error(y_test, y_pred_test))
print('MSE:', metrics.mean_squared_error(y_test, y_pred_test))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_test)))
```

```
About Model
R: 0.8650076764859093
Adj R^2: 0.8650035098954231

Model Evaluation
MAE: 0.02397092104795579
MSE: 0.0009863683743361737
RMSE: 0.03140650210284765
```

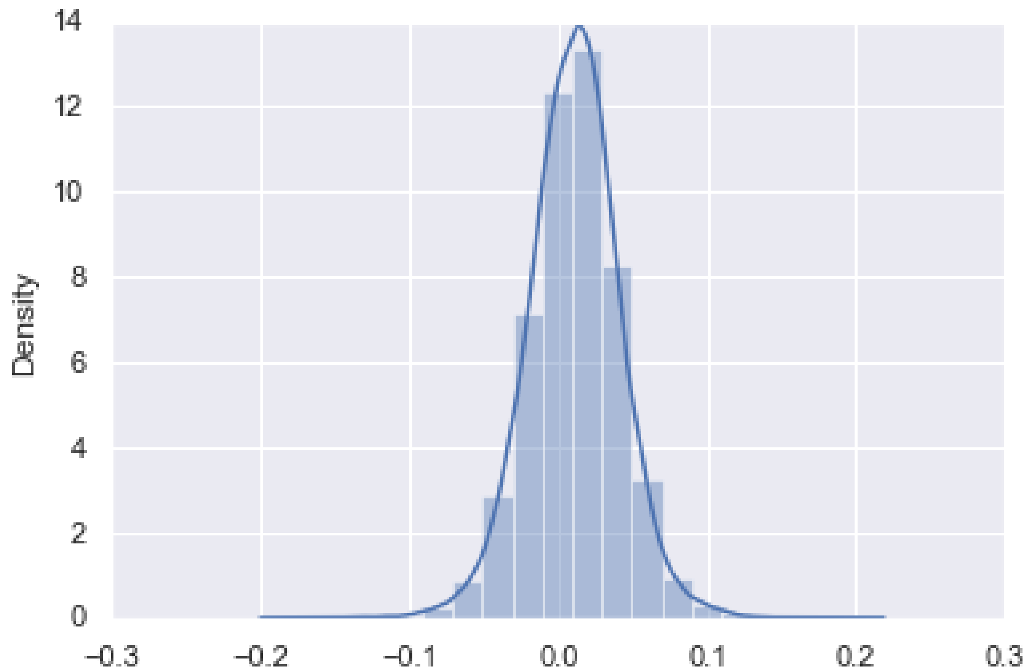
[107]:
```
y_pred_train= y_pred_train.reshape(360,360)
y_pred_test= y_pred_test.reshape(360,360)
y_img = np.concatenate([y_pred_train,y_pred_test],axis=1)
plt.imshow(y_img, cmap="gray")
plt.show()
```



[108]:
```
sns.distplot(residuals,bins=20)
```

```
C:\Users\shiva\Anaconda3\envs\tf\lib\site-
packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[108]:
```
<AxesSubplot:ylabel='Density'>
```



4.1 The MSE is 0.000986584356014296

4.2 Insights

- The Model perform better than all the above ones wrt MSE but even after doing hours of grid search and hyperparameter tuning it has overfitted to the left portion as its clearly visible from the image .

5 4)XGBOOST

[109]:
```
import pickle
import xgboost
regressor=xgboost.XGBRegressor()
```

Hyperparameter tuning using RandomizedSearchCV

[135]:
```
# Hyper Parameter Optimization

booster=['gbtree','gblinear']
base_score=[0.25,0.5,0.75,1]

n_estimators = [100, 500, 900, 1100, 1500]
max_depth = [2, 3, 5, 10, 15]
booster=['gbtree','gblinear']
learning_rate=[0.05,0.1,0.15,0.20]
```

```python
min_child_weight=[1,2,3,4]

# Defineing the grid of hyperparameters to search
hyperparameter_grid = {
    'n_estimators': n_estimators,
    'max_depth':max_depth,
    'learning_rate':learning_rate,
    'min_child_weight':min_child_weight,
    'booster':booster,
    'base_score':base_score
    }

# Using RandomizedSearchCV for creating model

from sklearn.model_selection import RandomizedSearchCV

# Set up the random search with 5-fold cross validation
random_cv = RandomizedSearchCV(estimator=regressor,
            param_distributions=hyperparameter_grid,
            cv=5, n_iter=50,
            scoring = 'neg_mean_absolute_error',n_jobs = 4,
            verbose = 5,
            return_train_score = True,
            random_state=42)

random_cv.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  10 tasks      | elapsed:  1.3min
[Parallel(n_jobs=4)]: Done  64 tasks      | elapsed: 14.6min
[Parallel(n_jobs=4)]: Done 154 tasks      | elapsed: 25.1min
[Parallel(n_jobs=4)]: Done 250 out of 250 | elapsed: 35.0min finished
```

[135]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBRegressor(base_score=None, booster=None,
                                          colsample_bylevel=None,
                                          colsample_bynode=None,
                                          colsample_bytree=None, gamma=None,
                                          gpu_id=None, importance_type='gain',
                                          interaction_constraints=None,
                                          learning_rate=None,
                                          max_delta_step=None, max_depth=None,
                                          min_child_weight=None, missing=nan,
                                          monotone_constraints=None,
                                          n_estimators=100, n...
                                          validate_parameters=None,
```

```
                                      verbosity=None),
                        n_iter=50, n_jobs=4,
                        param_distributions={'base_score': [0.25, 0.5, 0.75, 1],
                                             'booster': ['gbtree', 'gblinear'],
                                             'learning_rate': [0.05, 0.1, 0.15, 0.2],
                                             'max_depth': [2, 3, 5, 10, 15],
                                             'min_child_weight': [1, 2, 3, 4],
                                             'n_estimators': [100, 500, 900, 1100,
                                                              1500]},
                        random_state=42, return_train_score=True,
                        scoring='neg_mean_absolute_error', verbose=5)
```

[138]:
```
random_cv.best_estimator_
```

[138]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.1, max_delta_step=0, max_depth=2,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=8, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

The hyperparameters obtained using the above method gave the best results

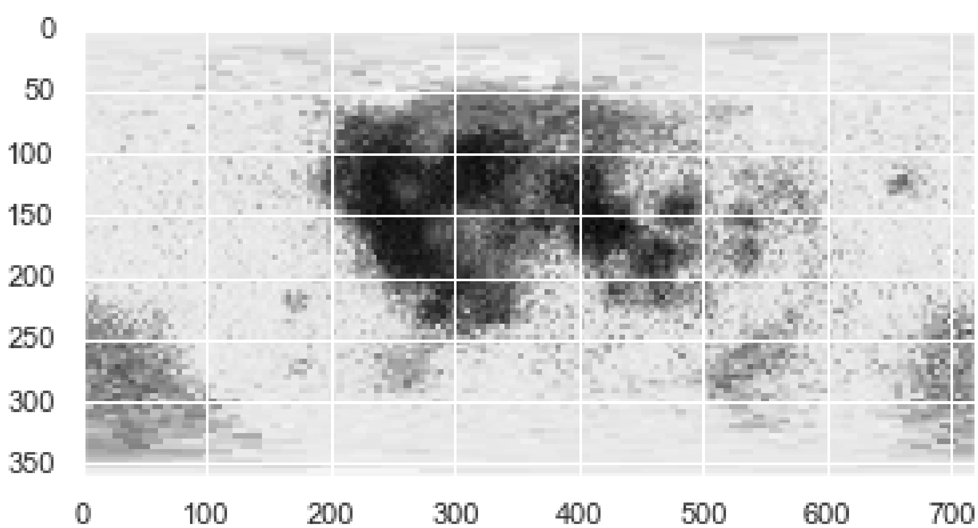
[110]:
```
regressor=xgboost.XGBRegressor(base_score=0.5, booster='gbtree',␣
 ↪colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.1, max_delta_step=0, max_depth=2,
             min_child_weight=1, missing=None, monotone_constraints='()',
             n_estimators=100, n_jobs=8, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)

regressor.fit(X_train,y_train)
# Predicting the Test set results
y_pred_train = regressor.predict(X_train)
y_pred_test = regressor.predict(X_test)
residuals  = y_test-y_pred_test
```

[111]:
```
print("About Model")
print("R:",regressor.score(X_train, y_train))
print("Adj R^2:",(1 - (1-regressor.score(X_train, y_train))*(len(y_train)-1)/
 ↪(len(y_train)-X_train.shape[1]-1)),"\n")

print("Model Evaluation")
```

```
print('MAE:', metrics.mean_absolute_error(y_test, y_pred_test))
print('MSE:', metrics.mean_squared_error(y_test, y_pred_test))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_test)))
```

```
About Model
R: 0.7903649932835797
Adj R^2: 0.7903585228176908

Model Evaluation
MAE: 0.02334789735875415
MSE: 0.0009304179266331601
RMSE: 0.03050275277140016
```

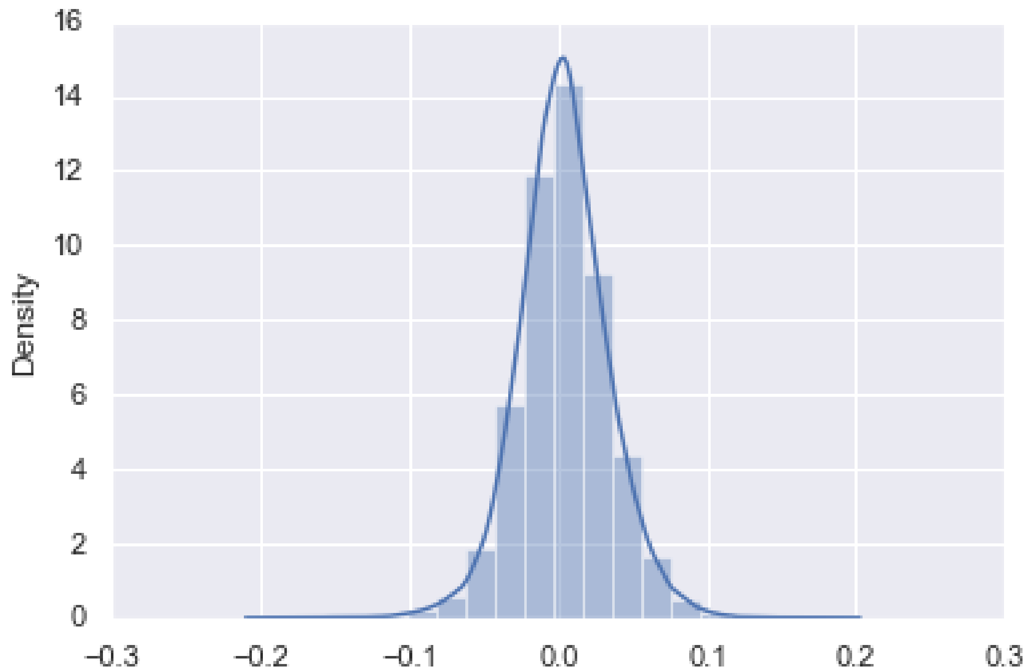
[112]:
```
y_pred_train= y_pred_train.reshape(360,360)
y_pred_test= y_pred_test.reshape(360,360)
y_img = np.concatenate([y_pred_train,y_pred_test],axis=1)
plt.imshow(y_img, cmap="gray")
plt.show()
```



[113]:
```
sns.distplot(residuals,bins=20)
```

```
C:\Users\shiva\Anaconda3\envs\tf\lib\site-
packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[113]: <AxesSubplot:ylabel='Density'>



5.1 Insights

- Looks like we have a winner here, as the MSE is the lowest obtained will now and Image also looks good on both the sides
- XGBoost is one of the most powerful ML algorithm

5.2 The MSE is 0.0009304179266331601

[114]:
```
filename = 'Best_Model_XG_boost.sav'
pickle.dump(regressor, open(filename, 'wb'))
```

5.3 5) Neural Network

Lets wrap things up by trying a Neural Network

[47]:
```
import tensorflow as tf
from tensorflow.keras.layers import Input, Dense, Activation,Dropout
from tensorflow.keras.models import Model
from tensorflow import keras
```

[162]:
```
def create_model(learn_rate=0.01):
    model = tf.keras.Sequential()
    model.add(tf.keras.layers.Dense(4))
    # model.add(tf.keras.layers.Dropout(0.2))
    model.add(tf.keras.layers.Dense(4))
```

```
    model.add(tf.keras.layers.Dense(4))
    model.add(tf.keras.layers.Dense(1))

    opt = keras.optimizers.Adam(learning_rate=learn_rate)
    model.compile(loss='mse', optimizer=opt)
    return model
```

[167]:
```
from keras.wrappers.scikit_learn import KerasRegressor
model = KerasRegressor(build_fn=create_model)
learn_rate = [0.001]
batch_size = [10,32]
epochs = [10, 50]
param_grid = dict(learn_rate=learn_rate,batch_size=batch_size,epochs=epochs)

grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=4,␣
 ↪cv=5,verbose=10)
grid_result = grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done   5 tasks      | elapsed:  3.9min
[Parallel(n_jobs=4)]: Done  10 tasks      | elapsed: 11.8min
[Parallel(n_jobs=4)]: Done  16 out of  20 | elapsed: 15.5min remaining:  3.9min
[Parallel(n_jobs=4)]: Done  20 out of  20 | elapsed: 18.7min finished

Epoch 1/10
12960/12960 [==============================] - 9s 674us/step - loss: 0.0020
Epoch 2/10
12960/12960 [==============================] - 8s 633us/step - loss: 9.6331e-04
0s -
Epoch 3/10
12960/12960 [==============================] - 8s 647us/step - loss: 9.4482e-04
Epoch 4/10
12960/12960 [==============================] - 8s 636us/step - loss: 9.3448e-04
Epoch 5/10
12960/12960 [==============================] - 8s 649us/step - loss: 9.2869e-04
Epoch 6/10
12960/12960 [==============================] - 8s 642us/step - loss: 9.2543e-04
0s - loss: 9. - ETA: 0s - loss:
Epoch 7/10
12960/12960 [==============================] - 9s 659us/step - loss: 9.2414e-04
Epoch 8/10
12960/12960 [==============================] - 8s 637us/step - loss: 9.2317e-04
0s - lo
Epoch 9/10
12960/12960 [==============================] - 8s 654us/step - loss: 9.2217e-04
Epoch 10/10
12960/12960 [==============================] - 8s 635us/step - loss: 9.1936e-04
```

```
2s - los - ETA: 1s - loss: 9.2613 - E
```

[168]:
```python
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
```

```
Best: -0.001006 using {'batch_size': 10, 'epochs': 10, 'learn_rate': 0.001}
```

After doing grid search and experimenting with the hyperparameters 'batch_size': 10, 'epochs': 10, 'learn_rate': 0.001 gave the best MSE

[48]:
```python
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(4))
# model.add(tf.keras.layers.Dropout(0.2))
model.add(tf.keras.layers.Dense(4))
model.add(tf.keras.layers.Dense(4))

model.add(tf.keras.layers.Dense(1))
opt = keras.optimizers.Adam(learning_rate=0.001)

model.compile(optimizer=opt, loss='mse')
# This builds the model for the first time:
history  = model.fit(X_train, y_train, batch_size=10, epochs=10,␣
 ↪validation_data=(X_test,y_test))
```

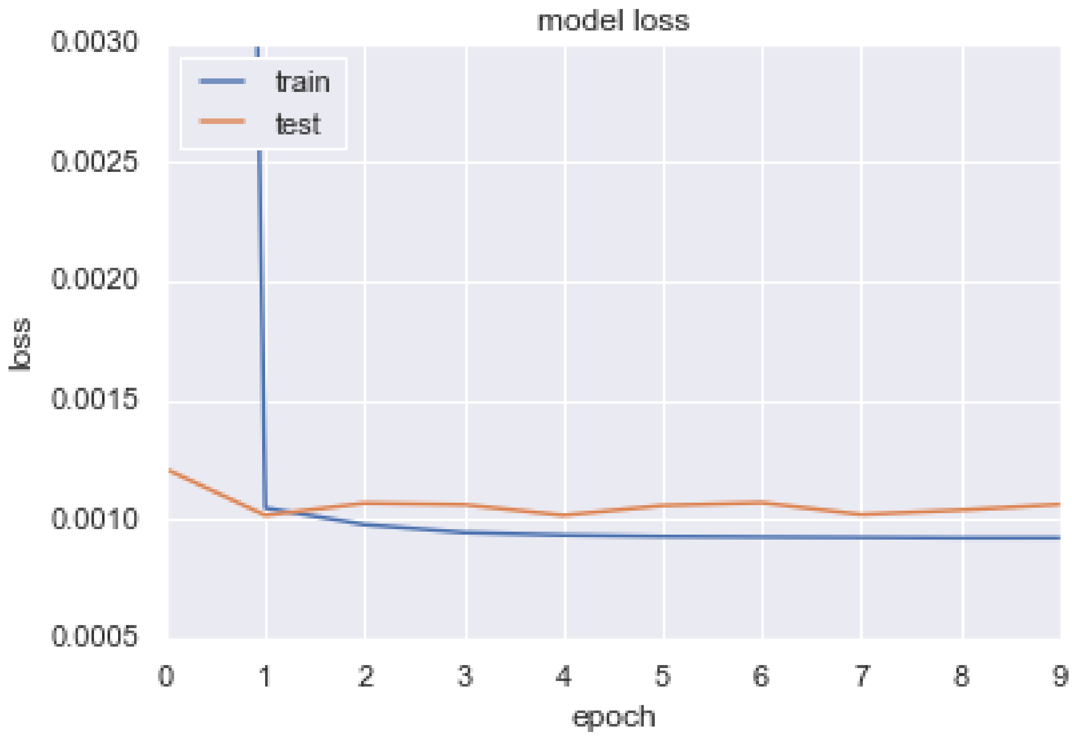
```
Epoch 1/10
12960/12960 [==============================] - 15s 1ms/step - loss: 0.0258 -
val_loss: 0.0012
Epoch 2/10
12960/12960 [==============================] - 14s 1ms/step - loss: 0.0010 -
val_loss: 0.0010
Epoch 3/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.7602e-04 -
val_loss: 0.0011
Epoch 4/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.4282e-04 -
val_loss: 0.0011
Epoch 5/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.3182e-04 -
val_loss: 0.0010
Epoch 6/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.2635e-04 -
val_loss: 0.0011los - ETA: 3s - loss: 9.2873 - ETA: 3s - -  - ETA:
Epoch 7/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.2393e-04 -
val_loss: 0.0011
Epoch 8/10
12960/12960 [==============================] - 15s 1ms/step - loss: 9.2204e-04 -
val_loss: 0.0010
Epoch 9/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.1999e-04 -
```

```
val_loss: 0.0010
Epoch 10/10
12960/12960 [==============================] - 14s 1ms/step - loss: 9.2012e-04 -
val_loss: 0.0011
```

[49]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (10, 4)                   20
_________________________________________________________________
dense_1 (Dense)              (10, 4)                   20
_________________________________________________________________
dense_2 (Dense)              (10, 4)                   20
_________________________________________________________________
dense_3 (Dense)              (10, 1)                   5
=================================================================
Total params: 65
Trainable params: 65
Non-trainable params: 0
_________________________________________________________________
```

[56]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylim(0.0005,0.003)
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



Surprisingly the training loss convereged after just 2-3 epochs, this may have to do with the hyperparameters

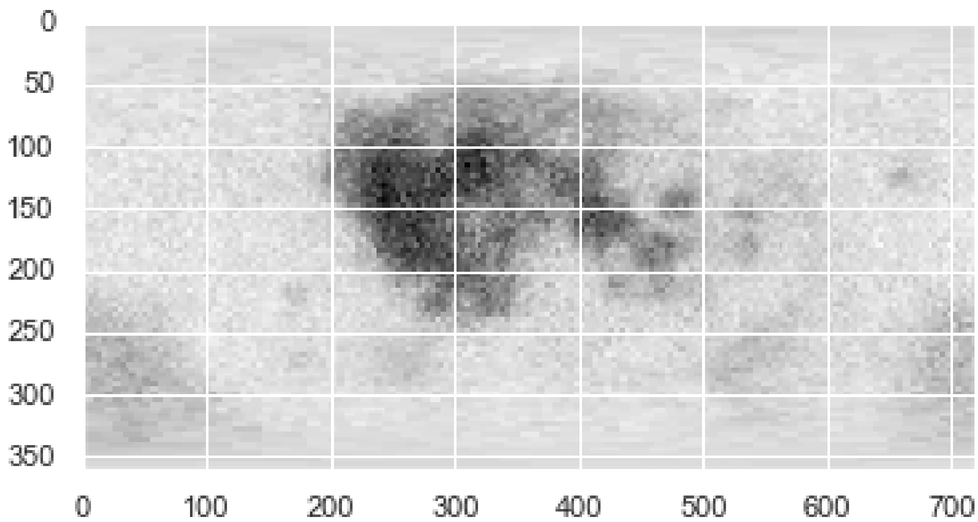
[115]:
```
y_pred = model.predict(X_test)
y_pred_train = model.predict(X_train)
y_pred_train = y_pred_train.flatten()
y_pred_test = model.predict(X_test)
y_pred_test = y_pred_test.flatten()
residuals  = y_test-y_pred_test
```

[116]:
```
print("Model Evaluation")

print('MAE:', metrics.mean_absolute_error(y_test, y_pred_test))
print('MSE:', metrics.mean_squared_error(y_test, y_pred_test))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_test)))
```

```
Model Evaluation
MAE: 0.025004365150974633
MSE: 0.0010610954305026602
RMSE: 0.032574459788347374
```

[117]:
```
y_pred_train= y_pred_train.reshape(360,360)
y_pred_test= y_pred_test.reshape(360,360)
y_img = np.concatenate([y_pred_train,y_pred_test],axis=1)
```

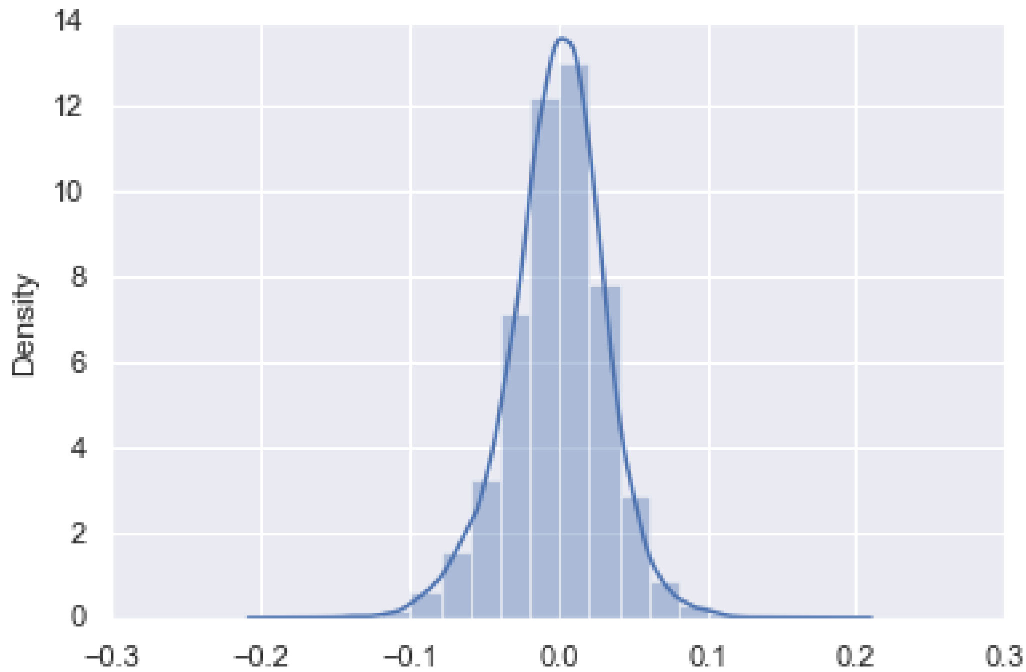
```
plt.imshow(y_img, cmap="gray")
plt.show()
```



[118]:
```
sns.distplot(residuals,bins=20)
```

```
C:\Users\shiva\Anaconda3\envs\tf\lib\site-
packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[118]: <AxesSubplot:ylabel='Density'>



5.4 Insights

- Surprisingly even after tuning and experting with a bigger and deeper nn ,the results were still poor.
- This may have to do with the less no. of input features and also lack of computional resourecs for doing a extensive grid with more hyperparameter tuning

5.5 The MSE is 0.0010610954305026602

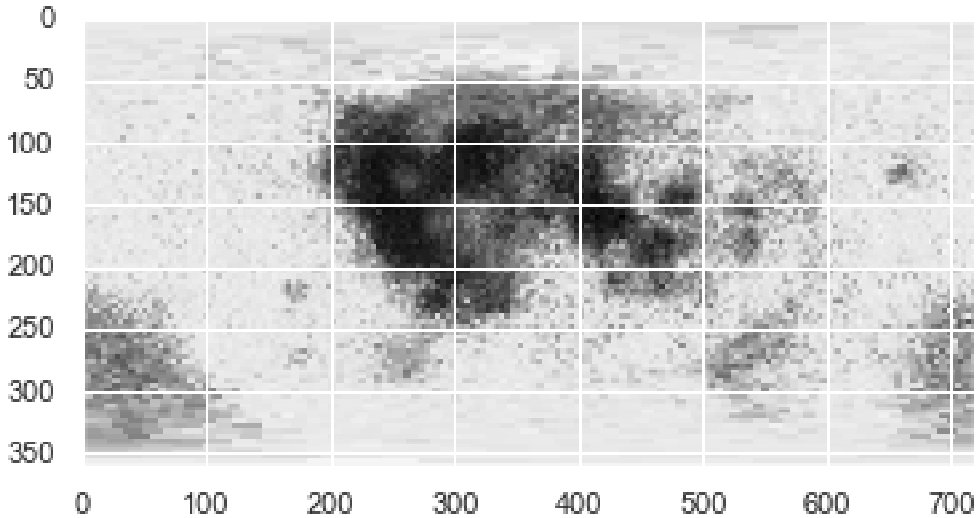
6 Final Results and Insights

The best image and lowest MSE obtained was with the tuned XGBOOST model

[76]:
```
filename = 'Best_Model_XG_boost.sav'
loaded_model = pickle.load(open(filename, 'rb'))
y_pred_train = loaded_model.predict(X_train)
y_pred_test = loaded_model.predict(X_test)
residuals  = y_test-y_pred_test
print('MSE:', metrics.mean_squared_error(y_test, y_pred_test))

y_pred_train= y_pred_train.reshape(360,360)
y_pred_test= y_pred_test.reshape(360,360)
y_img = np.concatenate([y_pred_train,y_pred_test],axis=1)

plt.imshow(y_img, cmap="gray")
```

```
plt.show()
```

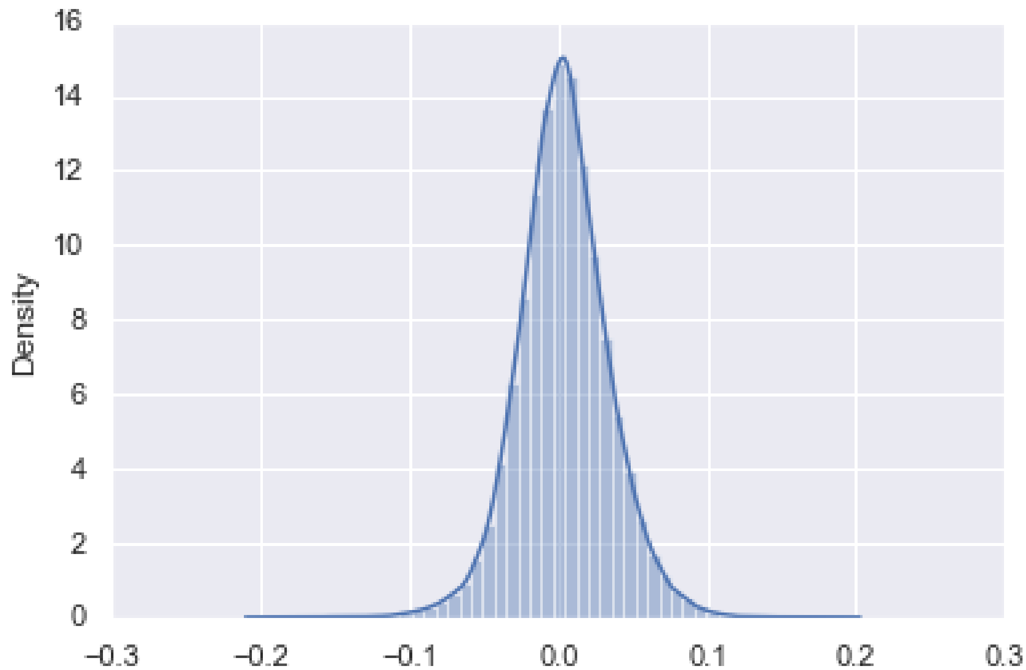
MSE: 0.0009304179266331601



[77]:
```
sns.distplot(residuals,bins=20)
```

```
C:\Users\shiva\Anaconda3\envs\tf\lib\site-
packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[77]: <AxesSubplot:ylabel='Density'>



7 Insights

- Best results were obtained using **XGBOOST, a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework.**
- Neural Networks surprisingly didnt perform as well as expected even after basic hyper parameter tuning , but there maybe a scope of improvement.
- Only having 4 features for prediction may also be a reason that most models fail to perform well.

```
[ ]:
```