

Data Preprocessing

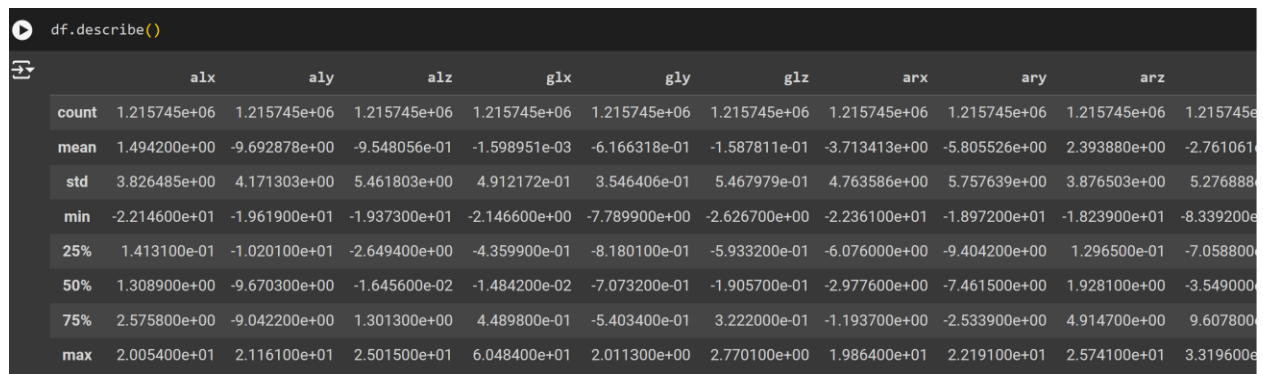
Handling Missing Values: Missing values were checked using `df.isnull().sum()`. The specific handling strategy was not detailed in the snippet.

Dealing with Duplicates: Duplicate entries were identified using `df.duplicated().sum()` and were presumably removed.

Data Splitting: Data was split into training, validation, and test subsets using sklearn's `train_test_split`, with a distribution aimed at creating training, validation, and test sets.

Statistical Summary

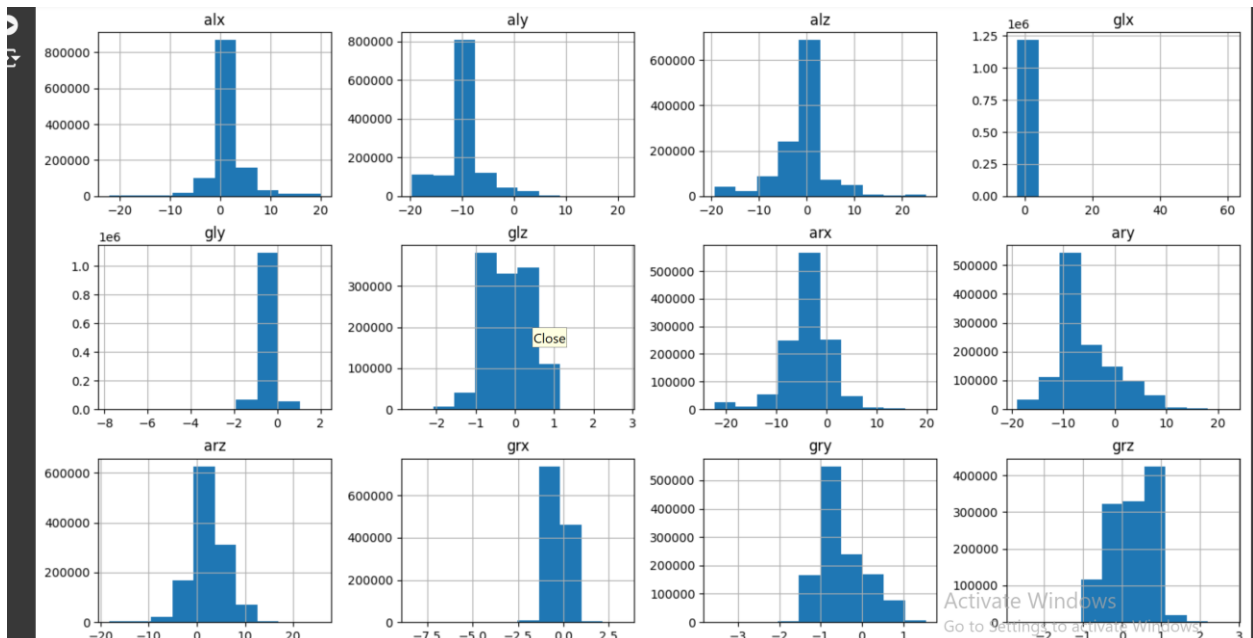
Basic statistical details using `df.describe()` to understand the central tendency and variability of the data.

A screenshot of a Jupyter Notebook cell. At the top, there is a play button icon and the code `df.describe()`. Below the code is a table representing the output of the `describe()` method. The table has 11 columns: 'count', 'alx', 'aly', 'alz', 'glx', 'gly', 'glz', 'arx', 'ary', and 'arz'. The rows represent different statistical measures: 'count', 'mean', 'std', 'min', '25%', '50%', '75%', and 'max'. The values are displayed in scientific notation.

	alx	aly	alz	glx	gly	glz	arx	ary	arz
count	1.215745e+06	1.215745e+06	1.215745e+06	1.215745e+06	1.215745e+06	1.215745e+06	1.215745e+06	1.215745e+06	1.215745e+06
mean	1.494200e+00	-9.692878e+00	-9.548056e-01	-1.598951e-03	-6.166318e-01	-1.587811e-01	-3.713413e+00	-5.805526e+00	2.393880e+00
std	3.826485e+00	4.171303e+00	5.461803e+00	4.912172e-01	3.546406e-01	5.467979e-01	4.763586e+00	5.757639e+00	3.876503e+00
min	-2.214600e+01	-1.961900e+01	-1.937300e+01	-2.146600e+00	-7.789900e+00	-2.626700e+00	-2.236100e+01	-1.897200e+01	-1.823900e+01
25%	1.413100e-01	-1.020100e+01	-2.649400e+00	-4.359900e-01	-8.180100e-01	-5.933200e-01	-6.076000e+00	-9.404200e+00	1.296500e-01
50%	1.308900e+00	-9.670300e+00	-1.645600e-02	-1.484200e-02	-7.073200e-01	-1.905700e-01	-2.977600e+00	-7.461500e+00	1.928100e+00
75%	2.575800e+00	-9.042200e+00	1.301300e+00	4.489800e-01	-5.403400e-01	3.222000e-01	-1.193700e+00	-2.533900e+00	4.914700e+00
max	2.005400e+01	2.116100e+01	2.501500e+01	6.048400e+01	2.011300e+00	2.770100e+00	1.986400e+01	2.219100e+01	2.574100e+01

Data Visualization:

Visualizations included histograms and a heatmap of correlations among numerical features to identify relationships and distribution patterns.

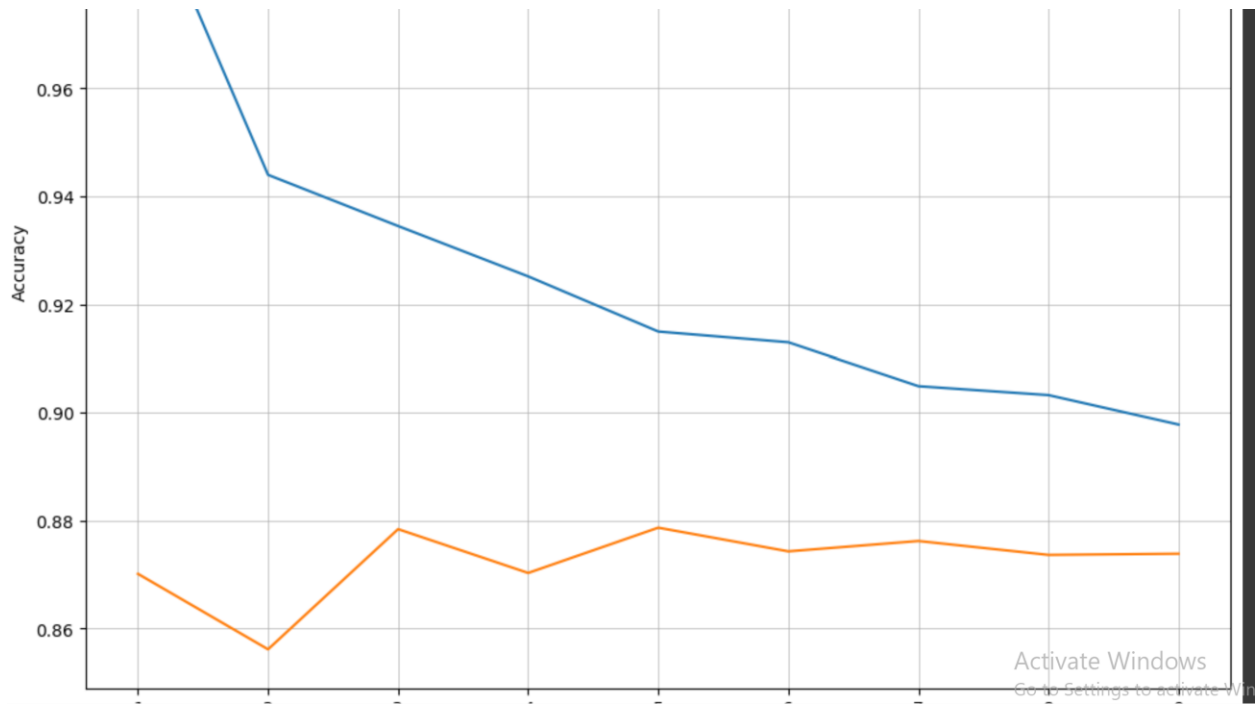


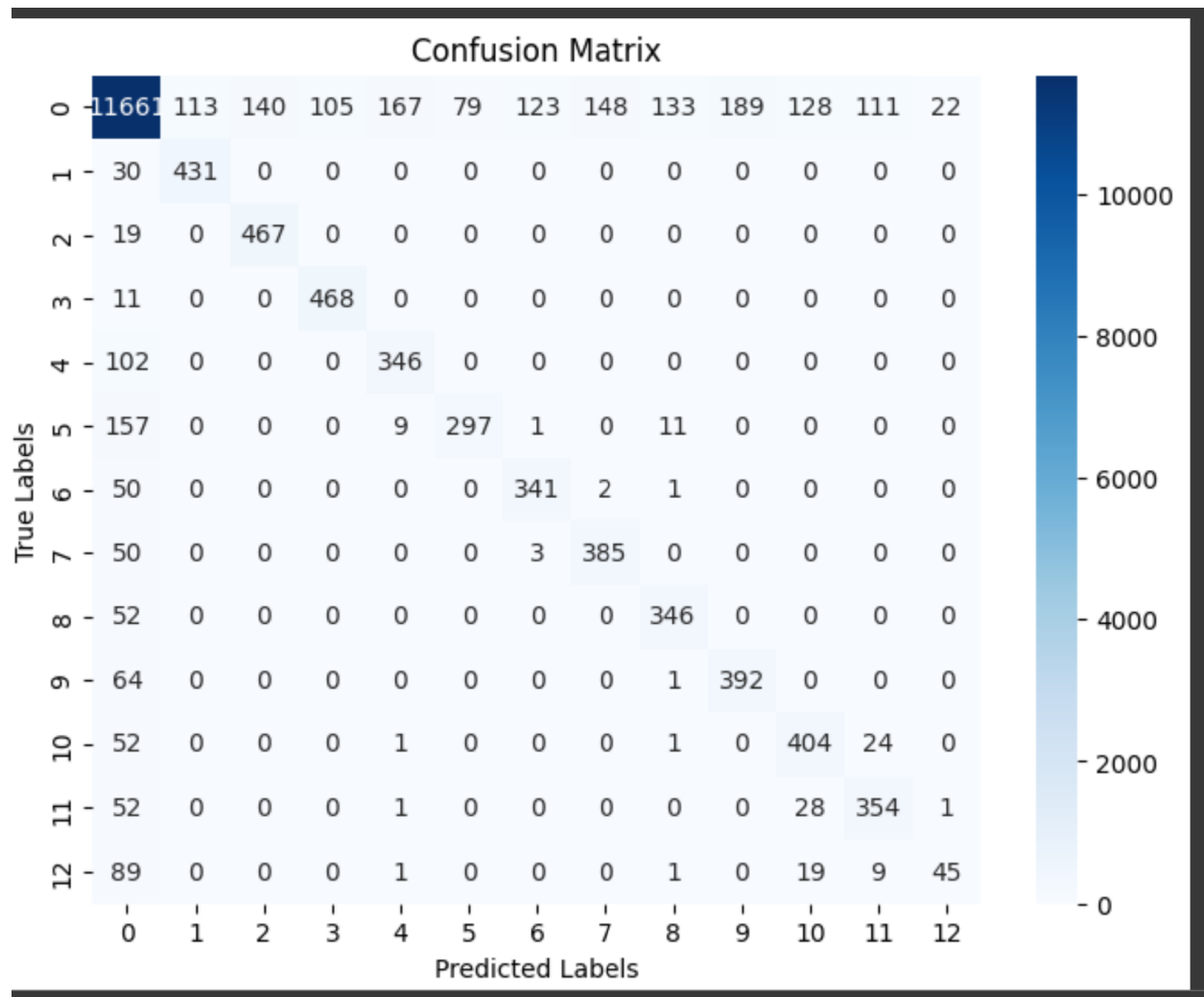
```
print("Training Accuracies:", train_accuracies)

print("Validation Accuracies:", val_accuracies)

print("Test Accuracies:", test_accuracies)
```

```
Training Accuracies: [1.0, 0.9439842070010929, 0.9345013572108436, 0.925171267082643, 0.9149598712118542, 0.9129739956052221, 0.90491298574634
Validation Accuracies: [0.873661667032244, 0.8577538933976749, 0.8748080719456021, 0.8720662425970608, 0.8767821890765519, 0.8733274840973898,
Test Accuracies: [0.8701540823600373, 0.8561715194385041, 0.8784339529527883, 0.8703185831002906, 0.8787081208532105, 0.874321434446455, 0.875
```





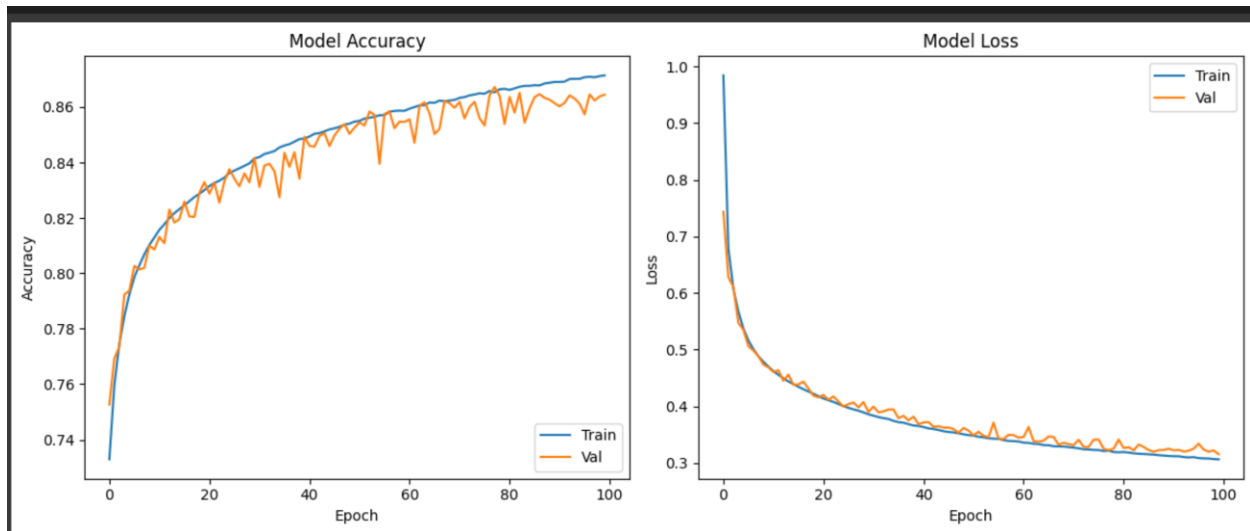
Linear Regression

Evaluation: Performance was assessed using metrics like R^2 , Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Support Vector Machine (SVM)

Model Setup: Configured with RBF kernel.

Evaluation: Validation and test accuracies were provided to assess the model's effectiveness.



Neural Network

A multi-layer perceptron model with sigmoid activations.

Training and Evaluation: The model's performance was tracked over epochs, showing training and validation accuracies and losses.

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
hist = model.fit(X_train, y_train,
                 batch_size=1024,
                 epochs=100,
                 validation_data=(X_val, y_val))
```

```
... Epoch 1/100
832/832 [=====] - 9s 9ms/step - loss: 1.3018 - accuracy: 0.7141 - val_loss: 1.2849 - val_accuracy: 0.7178
Epoch 2/100
832/832 [=====] - 9s 11ms/step - loss: 1.1729 - accuracy: 0.7236 - val_loss: 1.0629 - val_accuracy: 0.7262
Epoch 3/100
832/832 [=====] - 7s 8ms/step - loss: 1.0226 - accuracy: 0.7261 - val_loss: 0.9865 - val_accuracy: 0.7274
Epoch 4/100
832/832 [=====] - 10s 12ms/step - loss: 0.9526 - accuracy: 0.7276 - val_loss: 0.9215 - val_accuracy: 0.7295
Epoch 5/100
832/832 [=====] - 7s 8ms/step - loss: 0.8990 - accuracy: 0.7309 - val_loss: 0.8761 - val_accuracy: 0.7318
Epoch 6/100
832/832 [=====] - 10s 12ms/step - loss: 0.8580 - accuracy: 0.7327 - val_loss: 0.8372 - val_accuracy: 0.7341
Epoch 7/100
832/832 [=====] - 8s 9ms/step - loss: 0.8212 - accuracy: 0.7355 - val_loss: 0.8058 - val_accuracy: 0.7370
Epoch 8/100
832/832 [=====] - 9s 11ms/step - loss: 0.7918 - accuracy: 0.7379 - val_loss: 0.7809 - val_accuracy: 0.7389
Epoch 9/100
832/832 [=====] - 8s 9ms/step - loss: 0.7676 - accuracy: 0.7422 - val_loss: 0.7575 - val_accuracy: 0.7466
Epoch 10/100
832/832 [=====] - 9s 11ms/step - loss: 0.7457 - accuracy: 0.7468 - val_loss: 0.7357 - val_accuracy: 0.7482
Epoch 11/100
832/832 [=====] - 11s 14ms/step - loss: 0.7271 - accuracy: 0.7501 - val_loss: 0.7208 - val_accuracy: 0.7501
```

Logistic Regression

Model Setup and Evaluation: Logistic regression was used to classify activities, with performance evaluated through accuracy scores and classification reports



```
# Evaluate the model on the validation data
val_accuracy = accuracy_score(y_val, y_val_pred)
print(f'Validation Accuracy: {val_accuracy}')

print(classification_report(y_val, y_val_pred))
```



Validation Accuracy: 0.7279257740099363

	precision	recall	f1-score	support
0	0.74	0.96	0.84	130896
1	0.00	0.00	0.00	4580
2	0.00	0.00	0.00	4786
3	0.68	0.92	0.78	4556
4	0.01	0.00	0.00	4595
5	0.01	0.00	0.00	4657
6	0.05	0.01	0.01	4210
7	0.11	0.01	0.01	4404
8	0.01	0.00	0.00	4406
9	0.54	0.37	0.44	4492
10	0.40	0.08	0.14	4587
11	0.49	0.23	0.32	4613
12	0.17	0.00	0.00	1580
accuracy			0.73	182362
macro avg	0.25	0.20	0.19	182362
weighted avg	0.59	0.73	0.64	182362

