

Configuration Manual

MSc Research Project
MSc in Cloud Computing

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MSc Project Submission Sheet
School of Computing



Student Name: Sravanthi Challa
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Module: MSc Research Project
Lecturer: Shaguna Gupta
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Project Title: Machine Learning & PBFT Blockchain Methodology on AWS for Proteomics Analytics

Word Count: **Page Count:**

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Configuration Manual

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1 Introduction

Proteomics has transformed the study of proteins and provided an immense amount of new information about biological systems and disease states. However, proteomics data analysis is a difficult and computationally demanding task that frequently calls for advanced machine learning techniques. This configuration manual presents a thorough method of proteomics data analytics on Amazon Web Services (AWS) that makes use of PBFT blockchain technology and machine learning to overcome these obstacles.

The objective of this project is to improve protein identification and quantification accuracy by utilising machine learning, and to guarantee data confidentiality and integrity by integrating blockchain technology. For the purpose of deploying and managing the blockchain application and machine learning model, AWS offers a stable and scalable platform. The integration of these technologies has the potential to revolutionise proteomics research by facilitating more dependable and effective data analysis.

1.1 Target Audience

The purpose of this configuration manual is to assist researchers and developers who want to implement an AWS proteomics data analytics solution based on machine learning. From data collection and pre-processing to model training, deployment, and blockchain integration, it offers detailed guidance for every step of the procedure.

1.2 Prerequisites

Before proceeding with this configuration manual, ensure that you have the following prerequisites:

- Basic understanding of machine learning, Blockchain and proteomics
- Familiarity with AWS services, such as ECS, Docker, and Kubernetes
- Experience with Python

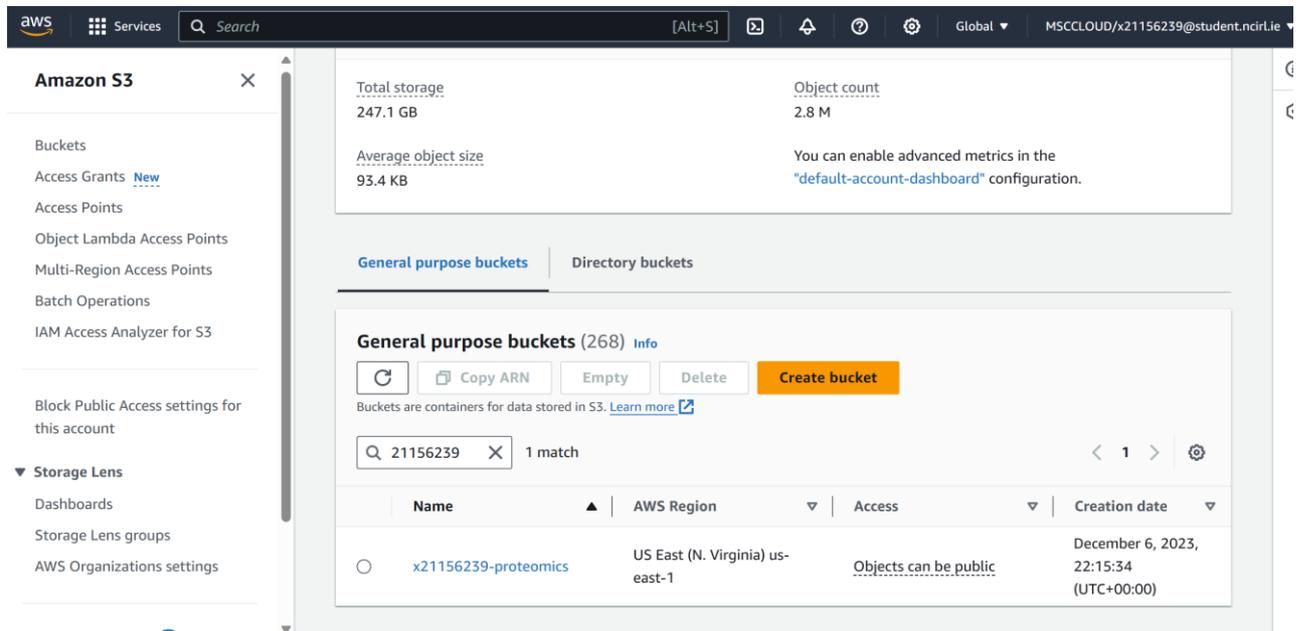
2 Data Collection and Pre-Processing

2.1 Data Collection

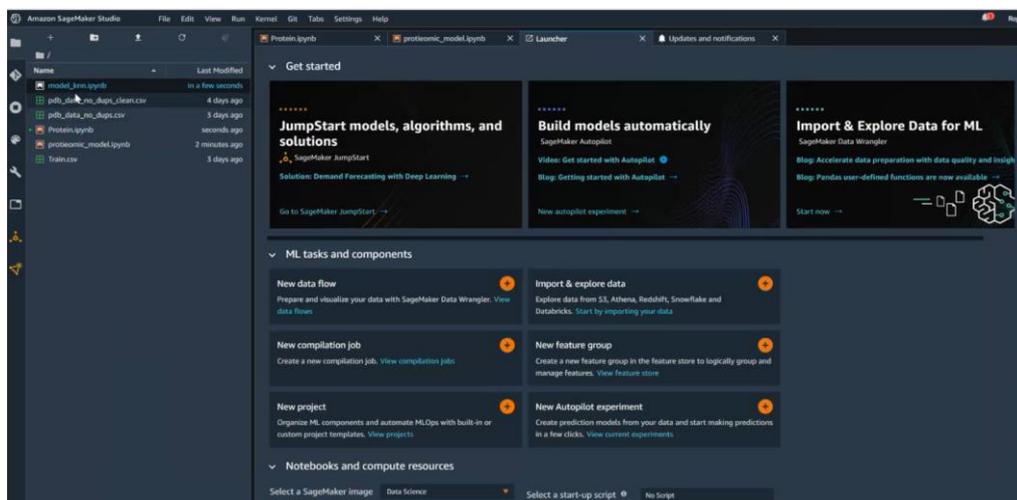
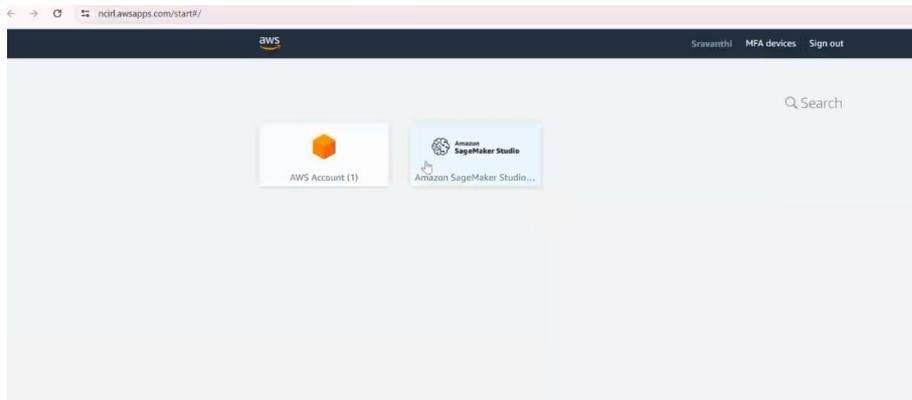
Proteomics data collection requires collecting information from a variety of experimental methods, including chromatography, NMR (Nuclear Magnetic Resonance), and mass spectrometry. These methods produce a variety of data formats, such as raw output files, chromatograms, and spectra. The data collection process is meticulous and crucial because it often involves large volumes, a variety of biological samples, and multi-dimensional features.

Data will be collected and stored in AWS S3 bucket.

1. First create AWS S3 bucket in AWS.



2. Then check whether you have access for SageMaker in AWS



- Go to SageMaker and create the machine learning algorithm file and upload PDB file. Here, the SageMaker will train the data for different models.

```

[1]: #Step 1: Import Libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.impute import SimpleImputer
from scipy import sparse as sp
from joblib import dump

[2]: #Step 2: Load and Inspect the Data

[4]: file_path = 'Train.csv'
data = pd.read_csv(file_path)
print(data.head())

structureId  classification  experimentalTechnique  macromoleculeType \
0  180D  DNA-RNA HYBRID  X-RAY DIFFRACTION  DNA/RNA Hybrid
1  181D  DNA  X-RAY DIFFRACTION  DNA
2  181M  OXYGEN TRANSPORT  X-RAY DIFFRACTION  Protein
3  182D  DNA  X-RAY DIFFRACTION  DNA
4  182L  HYDROLASE(O-GLYCOSYL)  X-RAY DIFFRACTION  Protein

residueCount  resolution  structureMolecularWeight \
0  28  1.98  6368.38
1  24  2.25  7939.35
2  154  2.07  18112.88
3  24  2.28  7637.17
4  165  1.74  18926.61

crystallizationMethod  crystallizationTempK  densityMatthews \
0  VAPOR DIFFUSION, HANGING DROP  NaN  1.78
1  NaN  NaN  2.80
2  NaN  NaN  3.69
3  VAPOR DIFFUSION, SITTING DROP  277.0  2.28
4  NaN  NaN  2.77

```

- We will be declaring the best model prediction in SageMaker in our algorithm.

```

All models saved.

[ ]: model_dir = 'content/drive/My Drive/MyModels' # Change 'MyModels' to your desired directory

# Save each model
dump(lr_model, model_dir + '/linear_regression_model.joblib')
dump(rf_model, model_dir + '/random_forest_model.joblib')
dump(gb_model, model_dir + '/gradient_boosting_model.joblib')

print("All models saved to Google Drive.")

#Step 8: Tag the Best Model

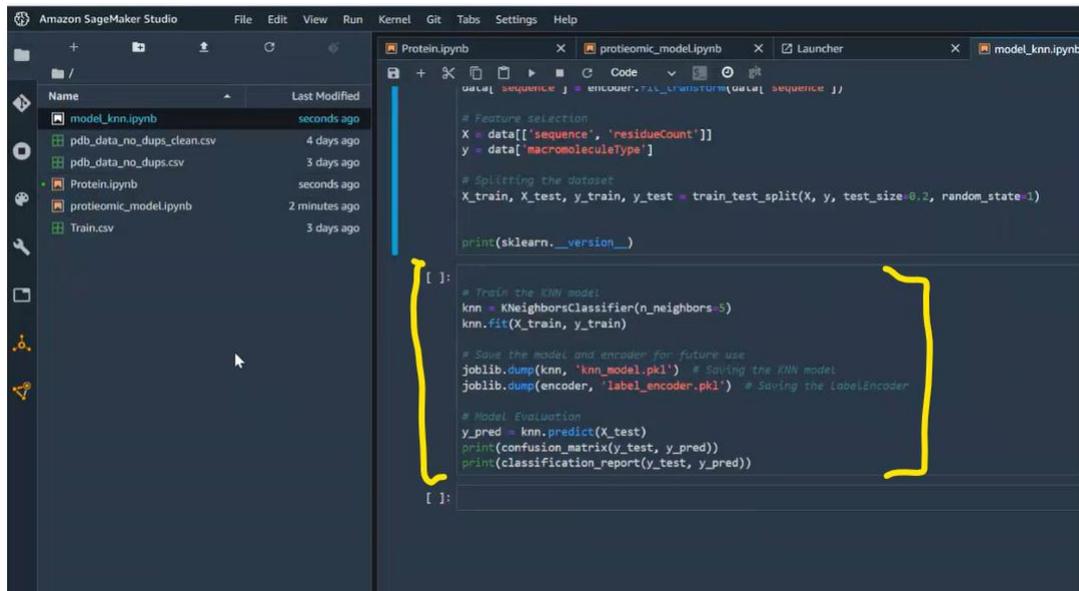
[ ]: # Determine the best model based on the lowest MAE
best_model, best_model_file = None, ""
if mae_lr < mae_rf and mae_lr < mae_gb:
    best_model, best_model_file = lr_model, 'linear_regression_model.joblib'
elif mae_rf < mae_lr and mae_rf < mae_gb:
    best_model, best_model_file = rf_model, 'random_forest_model.joblib'
else:
    best_model, best_model_file = gb_model, 'gradient_boosting_model.joblib'

# Save the best model with a special tag
best_model_tagged_file = f"best_{best_model_file}"
dump(best_model, best_model_tagged_file)
print(f"Best model saved as {best_model_tagged_file}")

Best model saved as best_random_forest_model.joblib

```

5. Write down the model training code.



```
data['sequence'] = encoder.fit_transform(data['sequence'])

# Feature selection
X = data[['sequence', 'residueCount']]
y = data['macromoleculeType']

# Splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

print(sklearn.__version__)

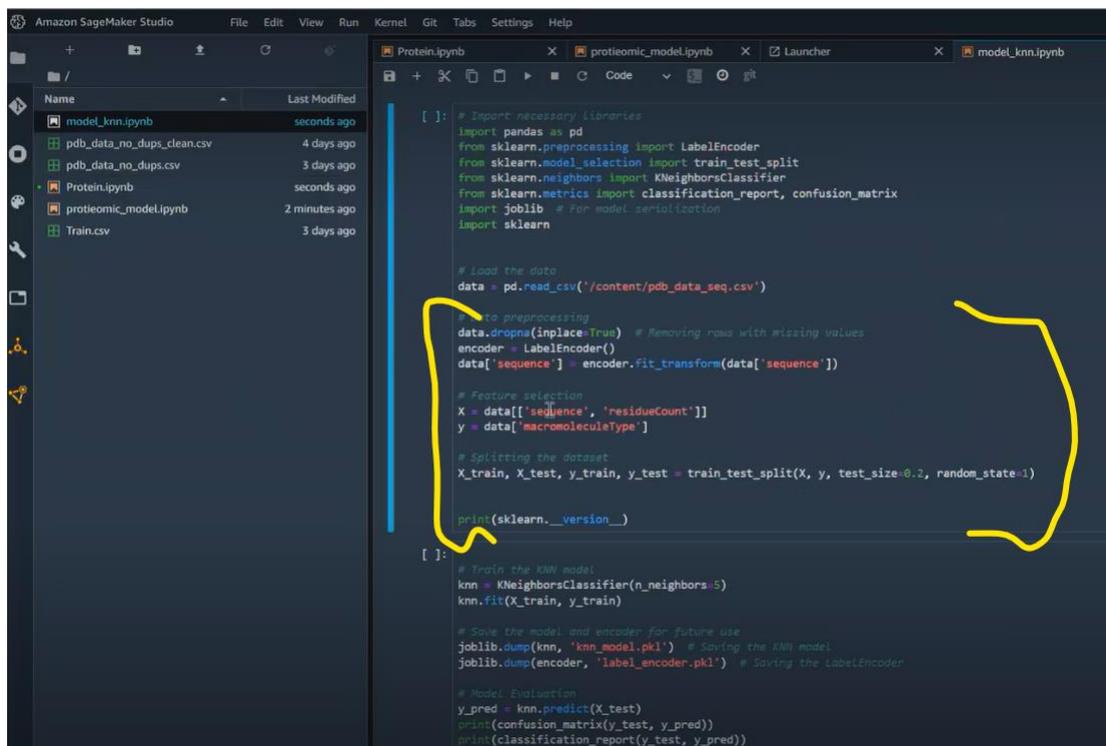
[ ]:
# Train the KNN model
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Save the model and encoder for future use
joblib.dump(knn, 'knn_model.pkl') # Saving the KNN model
joblib.dump(encoder, 'label_encoder.pkl') # Saving the LabelEncoder

# Model Evaluation
y_pred = knn.predict(X_test)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

[ ]:
```

6. Data pre-processing declaration is done, Prediction of proteins will be done by X and Y-axis data



```
[ ]: # Import necessary Libraries
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
import joblib # For model serialization
import sklearn

# Load the data
data = pd.read_csv('/content/pdb_data_seq.csv')

# Data preprocessing
data.dropna(inplace=True) # Removing rows with missing values
encoder = LabelEncoder()
data['sequence'] = encoder.fit_transform(data['sequence'])

# Feature selection
X = data[['sequence', 'residueCount']]
y = data['macromoleculeType']

# Splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

print(sklearn.__version__)

[ ]:
# Train the KNN model
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Save the model and encoder for future use
joblib.dump(knn, 'knn_model.pkl') # Saving the KNN model
joblib.dump(encoder, 'label_encoder.pkl') # Saving the LabelEncoder

# Model Evaluation
y_pred = knn.predict(X_test)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

- Based on the macromolecule, Sequence and residuecount the prediction is done. The column can be seen in the data file.

	structureId	classification	experimentalTechnique	macromoleculeType	residueCount	resolution	structureMolecularWeight	crystallizationMethod
1	100D	DNA-RNA HYBRID	X-RAY DIFFRACTION	DNARNA Hybrid	20	1.9	6360.3	FUSION, HANGING DROP
2	101D	DNA	X-RAY DIFFRACTION	DNA	24	2.26	7939.35	
3	101M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	2.07	18112.8	
4	102D	DNA	X-RAY DIFFRACTION	DNA	24	2.2	7637.17	FUSION, SITTING DROP
5	102L	DROLASE(O-GLYCOSYL)	X-RAY DIFFRACTION	Protein	165	1.74	18926.61	
6	102M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	1.84	18010.64	
7	103D	DNA	SOLUTION NMR	DNA	24		7502.93	
8	103L	DROLASE(O-GLYCOSYL)	X-RAY DIFFRACTION	Protein	167	1.9	19092.72	
9	103M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	2.07	18093.78	
10	104D	DNA-RNA HYBRID	SOLUTION NMR	DNARNA Hybrid	24		7454.78	
11	104L	DROLASE(O-GLYCOSYL)	X-RAY DIFFRACTION	Protein	332	2.8	37541.04	
12	104M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	153	1.71	18030.63	
13	105D	DNA	SOLUTION NMR	DNA	12		3350.4	
14	105M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	153	2.02	18030.63	
15	105D	DNA	SOLUTION NMR	DNA	12		3086.58	
16	106M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	1.99	18181.84	
17	107D	DNA	SOLUTION NMR	DNA	14		4744.35	
18	107L	DROLASE(O-GLYCOSYL)	X-RAY DIFFRACTION	Protein	164	1.8	18825.51	
19	107M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	2.09	18208.89	
20	108D	DNA	SOLUTION NMR	DNA	16		5650.37	
21	108L	DROLASE(O-GLYCOSYL)	X-RAY DIFFRACTION	Protein	164	1.8	18881.62	
22	108M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	2.67	18208.89	
23	109D	DNA	X-RAY DIFFRACTION	DNA	24	2.0	7747.53	
24	109L	DROLASE(O-GLYCOSYL)	X-RAY DIFFRACTION	Protein	164	1.85	18897.64	
25	109M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	1.83	18133.8	
26	10GB	TRANSFERASE INHIBITOR	X-RAY DIFFRACTION	Protein	416	2.2	47830.7	
27	10MH	TRANSFERASE/DNA	X-RAY DIFFRACTION	Protein/DNA	351	2.55	44768.42	
28	110D	DNA	X-RAY DIFFRACTION	DNA	6	1.9	2337.73	FUSION, SITTING DROP

- Sagemaker is connected to our streamlit application, and cluster is been created.

```

with Cluster("Data Collection"):
    data_collection = Storage("Data Collection")
    s3 >> data_collection

with Cluster("Pre-processing"):
    preprocessing = Custom(label="Pre-processing", icon_path="./my_resources/Preprocessing.png") # Path corrected

with Cluster("AWS SageMaker"):
    with Cluster("Modeling"):
        with Cluster("Classification models"):
            models = [
                Custom(label="KNN model", icon_path="./my_resources/random_forest.png"),
                Custom(label="Random Forest", icon_path="./my_resources/random_forest.png"),
                Custom(label="Logistic Regression", icon_path="./my_resources/logistic_regression.png"),
                Custom(label="Neural Networks", icon_path="./my_resources/neural_networks.png"),
                Custom(label="Decision Tree", icon_path="./my_resources/decision_tree.png"),
                Custom(label="Support Vector Machine", icon_path="./my_resources/support_vector_machine.png")
            ]

        with Cluster("Model Creation"):
            model_creation = Custom(label="Model Creation", icon_path="./my_resources/model.png")

        with Cluster("Testing"):
            testing = Custom(label="Testing", icon_path="./my_resources/model_testing.png")

    with Cluster("Classification Analysis"):

```

- Once we run the model training it will create a pickle file (PKL) of the that particular model in S3 bucket

Objects (6) Info

Objects are the fundamental entities stored in Amazon S3. You can use [Amazon S3 inventory](#) to get a list of all objects in your bucket. For others to access your objects, you'll need to explicitly grant them permissions. [Learn more](#)

Find objects by prefix

<input type="checkbox"/>	Name	Type	Last modified	Size	Storage class
<input type="checkbox"/>	DecisionTree.sav	sav	December 6, 2023, 22:40:29 (UTC+00:00)	8.9 MB	Standard
<input type="checkbox"/>	LinearRegression.sav	sav	December 6, 2023, 22:40:55 (UTC+00:00)	5.4 MB	Standard
<input type="checkbox"/>	NeuralNetworks.sav	sav	December 6, 2023, 22:41:14 (UTC+00:00)	42.5 MB	Standard
<input type="checkbox"/>	ProteinSeqBC.pkl	pkl	December 6, 2023, 22:33:16 (UTC+00:00)	12.2 KB	Standard

- The trained file, gives us precision, recall, f1score and support

The screenshot shows the Amazon SageMaker Studio interface. On the left, a file explorer shows various files including 'knn_model.pkl', 'label_encoder.pkl', 'model_knn.ipynb', and several CSV files. The main window displays a Jupyter notebook with a confusion matrix and classification metrics.

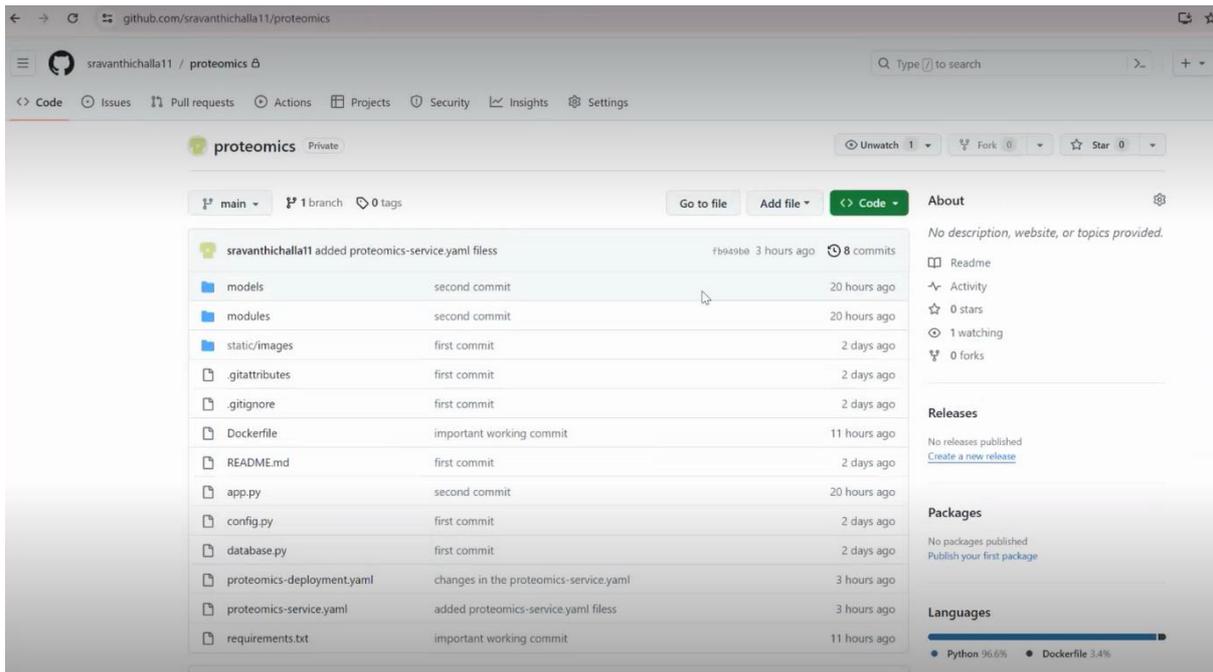
```

[ 0  0  0  0  2  1  0  0  0  48  9  0
  0]
[ 47  0  3  6  9  9  0  4  0  15  0  359
  5]
[ 2  0  0  0  0  0  0  0  0  0  0  5
  6]]

```

	precision	recall	f1-score	support
DNA	0.85	0.93	0.89	749
DNA#DNA/RNA Hybrid	0.00	0.00	0.00	6
DNA#RNA	0.44	0.28	0.34	25
DNA/RNA Hybrid	0.37	0.28	0.32	25
Protein	0.97	0.99	0.98	68964
Protein#DNA	0.83	0.78	0.80	4282
Protein#DNA#DNA/RNA Hybrid	0.62	0.41	0.49	32
Protein#DNA#RNA	0.74	0.68	0.71	534
Protein#DNA/RNA Hybrid	0.60	0.60	0.60	10
Protein#RNA	0.95	0.90	0.93	11337
Protein#RNA#DNA/RNA Hybrid	0.69	0.15	0.25	60
RNA	0.82	0.78	0.80	458
RNA#DNA/RNA Hybrid	0.40	0.46	0.43	13
accuracy			0.96	86495
macro avg	0.64	0.56	0.58	86495
weighted avg	0.96	0.96	0.96	86495

11. Create Github repository and upload all your UI code in it.



12. For creating cluster, Docker and Kubernetes setup has to be done.

Deploying Docker container to AWS and managing it with Amazon Elastic Kubernetes Service (EKS) involves several steps. Here's a step-by-step guide to help you through the process:

Step 1: Prepare Your Docker Image

1. **Build your Docker image** (if not already done):

```
```sh
docker build -t proteomics-app .
```
```

2. **Tag your Docker image** for Amazon Elastic Container Registry (ECR):

```
```sh
docker tag proteomics:latest ASIATUYJP7SUEWGX6WN.dkr.ecr.us-east-1.amazonaws.com/proteomics:latest
```
```

Replace ``<aws_account_id>`` with your AWS account ID and ``<region>`` with your AWS region.

Step 2: Push Your Image to Amazon ECR

1. **Authenticate Docker to your default ECR registry**:

```
```sh
aws ecr get-login-password --region eu-east-1 | docker login --username AWS --password-stdin ASIATUYJP7SUEWGX6WN.dkr.ecr.eu-east-1.amazonaws.com
```
```

2. ****Create an ECR repository**** (if you haven't already):

```
```sh
aws ecr create-repository --repository-name proteomicsRepo --region us-east-1
```
```

3. ****Push your Docker image to ECR****:

```
```sh
docker push ASIATUYJP7SUEWGXB6WN.dkr.ecr.eu-east-1.amazonaws.com/proteomics-app:latest
```
```

Step 3: Set Up Amazon EKS

1. ****Create an EKS cluster****. This can be done via the AWS Management Console or using AWS CLI. The CLI command is:

```
```sh
eksctl create cluster --name proteomics-cluster --version 1.28 --region us-east-1 --nodegroup-name standard-workers --node-type t3.medium --nodes 1 --nodes-min 1 --nodes-max 1 --managed
```
```

2. ****Configure `kubectl` to communicate with your cluster****:

```
```sh
aws eks --region us-east-1 update-kubeconfig --name proteomics-cluster
```
```

Step 4: Deploy Your Application on EKS

1. ****Create a Kubernetes deployment****. You need a deployment YAML file (e.g., `proteomics-deployment.yaml`) that references your ECR image. Here's an example of what this file might look like:

```
```yaml
apiVersion: apps/v1
kind: Deployment
metadata:
 name: proteomics
spec:
 replicas: 2
 selector:
 matchLabels:
 app: proteomics
 template:
 metadata:
 labels:
 app: proteomics
 spec:
```

```

 containers:
 - name: proteomics
 image: ASIATUYJP7SUEWGXB6WN.dkr.ecr.us-east-
1.amazonaws.com/proteomics-app:latest
 ports:
 - containerPort: 8501
 ...

2. **Deploy the application**:
    ```sh
    kubectl apply -f proteomics-deployment.yaml
    ```

3. **Expose the application** (e.g., using a LoadBalancer service):
    ```yaml
    apiVersion: v1
    kind: Service
    metadata:
      name: proteomics-app-service
    spec:
      type: LoadBalancer
      ports:
        - port: 80
          targetPort: 8501
      selector:
        app: proteomics-app
    ```

 Then apply this configuration:
    ```sh
    kubectl apply -f proteomics-service.yaml
    ```

4. **Access your application**. After a few minutes, get the LoadBalancer URL:
    ```sh
    kubectl get services
    ```

 Look for the `EXTERNAL-IP` of your `proteomics-app-service`.

Step 5: Monitoring and Management

- Use Kubernetes Dashboard or AWS CloudWatch for monitoring.
- Set up autoscaling if needed.
- Regularly update your application with security patches.

working ECR:

```

1. Retrieve an authentication token and authenticate your Docker client to your registry.

Use the AWS CLI:

```
aws ecr-public get-login-password --region us-east-1 | docker login --username AWS --password-stdin public.ecr.aws/y3d9e0t2
```

Note: If you receive an error using the AWS CLI, make sure that you have the latest version of the AWS CLI and Docker installed.

2. Build your Docker image using the following command. For information on building a Docker file from scratch see the instructions [\[here\]](http://docs.aws.amazon.com/AmazonECS/latest/developerguide/docker-basics.html) (<http://docs.aws.amazon.com/AmazonECS/latest/developerguide/docker-basics.html>) . You can skip this step if your image is already built:

```
docker build -t x21156239_proteomics-ecr .
```

3. After the build completes, tag your image so you can push the image to this repository:

```
docker tag x21156239_proteomics-ecr:latest public.ecr.aws/y3d9e0t2/x21156239_proteomics-ecr:latest
```

4. Run the following command to push this image to your newly created AWS repository:

```
docker push public.ecr.aws/y3d9e0t2/x21156239_proteomics-ecr:latest
```

```
Windows PowerShell
2023-12-12 15:05:10 [i] nodegroup "ng-da3678ea" has 2 node(s)
2023-12-12 15:05:10 [i] node "ip-192-168-21-193.ec2.internal" is ready
2023-12-12 15:05:10 [i] node "ip-192-168-46-223.ec2.internal" is ready
2023-12-12 15:05:12 [i] kubectl command should work with "C:\Users\jojot\.kube\config", try 'kubectl get nodes'
2023-12-12 15:05:12 [i] EKS cluster "proteomics-cluster" in "us-east-1" region is ready
PS D:\RIC_projects\proteomicssequence_final> aws eks --region us-east-1 update-kubeconfig --name proteomics-cluster
Added new context arn:aws:eks:us-east-1:323444116722:cluster/proteomics-cluster to C:\Users\jojot\.kube\config
PS D:\RIC_projects\proteomicssequence_final> kubectl apply -f proteomics-deployment.yaml
deployment.apps/proteomics-deployment created
PS D:\RIC_projects\proteomicssequence_final> kubectl apply -f proteomics-service.yaml
service/proteomics-service created
PS D:\RIC_projects\proteomicssequence_final> kubectl get services
NAME TYPE CLUSTER-IP EXTERNAL-IP
kubernetes ClusterIP 10.100.0.1 <none>
 443/TCP
 12m
PS D:\RIC_projects\proteomicssequence_final> .186.16 a2e82abd4d06b439bb30db6c6a418936-394370751.us-east-1.elb.amazonaws.com 80:30645/TCP 8s
PS D:\RIC_projects\proteomicssequence_final>
PS D:\RIC_projects\proteomicssequence_final> kubectl get svc
NAME TYPE CLUSTER-IP EXTERNAL-IP
kubernetes ClusterIP 10.100.0.1 <none>
 443/TCP
 14m
proteomics-service LoadBalancer 10.100.186.16 a2e82abd4d06b439bb30db6c6a418936-394370751.us-east-1.elb.amazonaws.com 80:30645/TCP 2m1s
PS D:\RIC_projects\proteomicssequence_final> kubectl describe svc oteomics-service
Error from server (NotFound): services "oteomics-service" not found
PS D:\RIC_projects\proteomicssequence_final> kubectl describe svc proteomics-service
Name: proteomics-service
Namespace: default
Labels: <none>
Annotations: <none>
Selector: app=proteomics
Type: LoadBalancer
IP Family Policy: SingleStack
IP Families: IPv4
IP: 10.100.186.16
IPs: 10.100.186.16
LoadBalancer Ingress: a2e82abd4d06b439bb30db6c6a418936-394370751.us-east-1.elb.amazonaws.com
Port: <unset> 80/TCP
TargetPort: 8501/TCP
NodePort: <unset> 30645/TCP
Endpoints: 192.168.0.92:8501
Session Affinity: None
External Traffic Policy: Cluster
Events:
```

## 13. Kubernetes setup

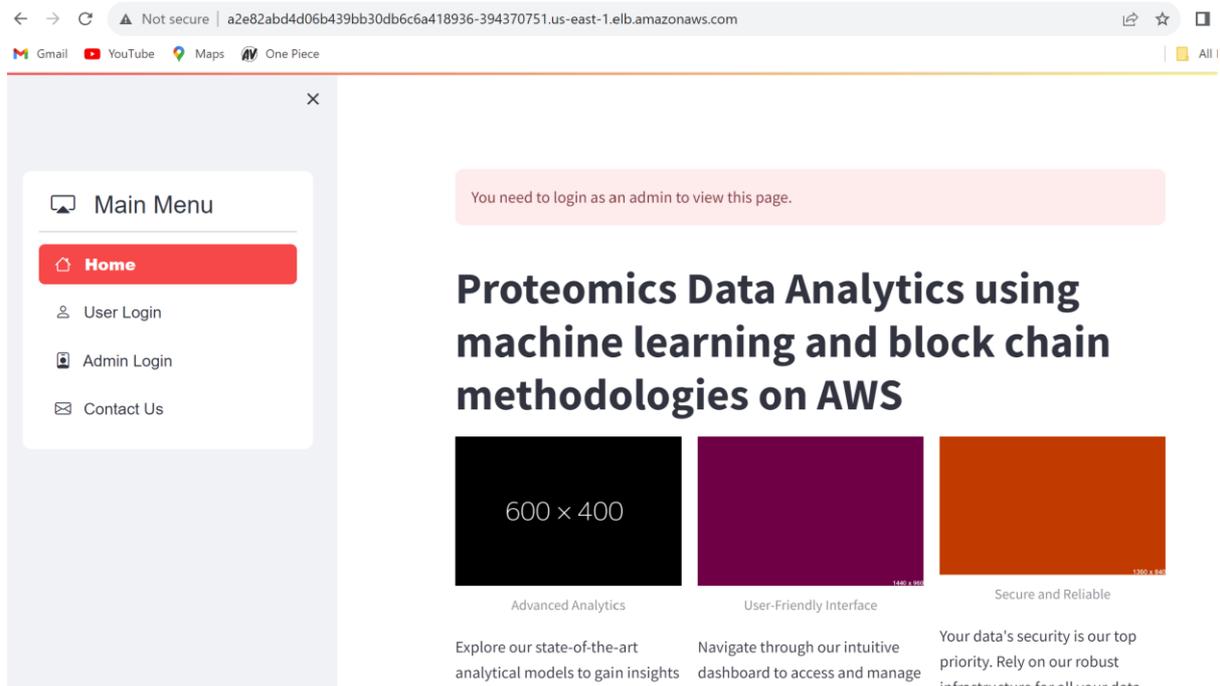
```
Windows PowerShell
d85b356ec3b5: Layer already exists
latest: digest: sha256:daf2e22fcb1e17a907287cffe8d6b83511384f897f632a7c9efa08440c79fa size: 2210
PS D:\RIC_projects\protienssequence_final> eksctl create cluster --name proteomics-cluster --region us-east-1 --managed
2023-12-12 14:49:02 [✓] eksctl version 0.165.0
2023-12-12 14:49:02 [✓] using region us-east-1
2023-12-12 14:49:02 [✓] setting availability zones to [us-east-1b us-east-1c]
2023-12-12 14:49:02 [✓] subnets for us-east-1b - public:192.168.0.0/19 private:192.168.64.0/19
2023-12-12 14:49:02 [✓] subnets for us-east-1c - public:192.168.32.0/19 private:192.168.96.0/19
2023-12-12 14:49:02 [✓] nodegroup "ng-da3678ea" will use "" [Amazonlinux2/1.27]
2023-12-12 14:49:02 [✓] using Kubernetes version 1.27
2023-12-12 14:49:02 [✓] creating EKS cluster "proteomics-cluster" in "us-east-1" region with managed nodes
2023-12-12 14:49:02 [✓] will create 2 separate CloudFormation stacks for cluster itself and the initial managed nodegroup
2023-12-12 14:49:02 [✓] if you encounter any issues, check CloudFormation console or try 'eksctl utils describe-stacks --region=us-east-1 --cluster=proteomics-cluster'
2023-12-12 14:49:02 [✓] Kubernetes API endpoint access will use default of [publicAccess=true, privateAccess=false] for cluster "proteomics-cluster" in "us-east-1"
2023-12-12 14:49:02 [✓] CloudWatch logging will not be enabled for cluster "proteomics-cluster" in "us-east-1"
2023-12-12 14:49:02 [✓] you can enable it with 'eksctl utils update-cluster-logging --enable-types={SPECIFY-YOUR-LOG-TYPES-HERE (e.g. all)} --region=us-east-1 --cluster=proteomic
s-cluster'
2023-12-12 14:49:02 [✓]
2 sequential tasks: { create cluster control plane "proteomics-cluster",
2 sequential sub-tasks: {
wait for control plane to become ready,
create managed nodegroup "ng-da3678ea",
}
}
2023-12-12 14:49:02 [✓] building cluster stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:49:03 [✓] deploying stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:49:33 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:50:04 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:51:04 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:52:05 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:53:05 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:54:06 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:55:06 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:56:07 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:57:07 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:58:08 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 14:59:08 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 15:00:09 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-cluster"
2023-12-12 15:02:13 [✓] building managed nodegroup stack "eksctl-proteomics-cluster-nodegroup-ng-da3678ea"
2023-12-12 15:02:14 [✓] deploying stack "eksctl-proteomics-cluster-nodegroup-ng-da3678ea"
2023-12-12 15:02:14 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-nodegroup-ng-da3678ea"
2023-12-12 15:02:44 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-nodegroup-ng-da3678ea"
2023-12-12 15:03:26 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-nodegroup-ng-da3678ea"
2023-12-12 15:04:00 [✓] waiting for CloudFormation stack "eksctl-proteomics-cluster-nodegroup-ng-da3678ea"
```

## 14. ECR repository creation

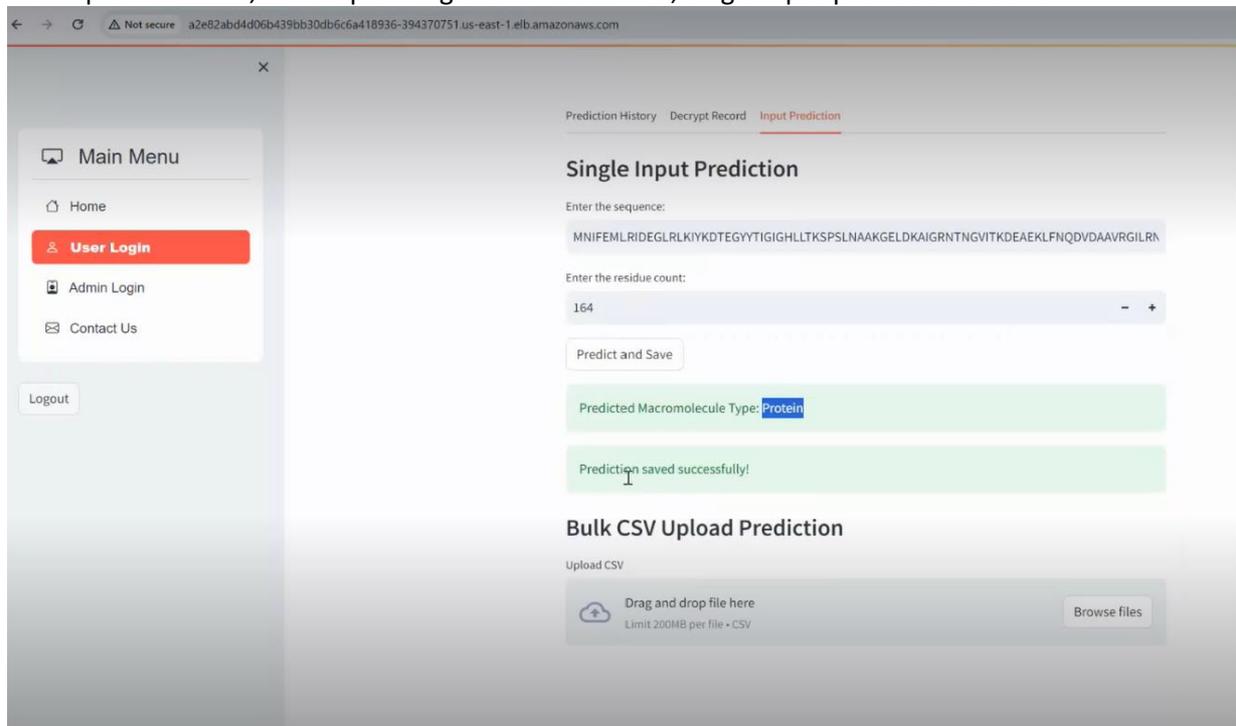
```
Windows PowerShell
+ FullyQualifiedErrorId : CommandNotFoundException
PS D:\RIC_projects\protienssequence_final> aws ecr get-login-password --region us-east-1 | docker login --username AWS --password-stdin 323444116722.dkr.ecr.us-east-1.amazonaws.com
An error occurred (UnrecognizedClientException) when calling the GetAuthorizationToken operation: The security token included in the request is invalid.
Error: Cannot perform an interactive login from a non TTY device
PS D:\RIC_projects\protienssequence_final> aws configure
AWS Access Key ID [*****PJYV]: AKIAUNTFRTZK6UXMB6V
AWS Secret Access Key [*****5PUH]: spibZLxs/HxqtEDDnYnS8UytNhdW2lhdR8zBjX
Default region name [us-east-1]:
Default output format [None]:
PS D:\RIC_projects\protienssequence_final> aws ecr get-login-password --region us-east-1 | docker login --username AWS --password-stdin 323444116722.dkr.ecr.us-east-1.amazonaws.com
Error saving credentials: error storing credentials - err: exit status 1, out: 'not implemented'
PS D:\RIC_projects\protienssequence_final> docker build -t testapp .
[+] Building 17.4s (10/10) FINISHED docker:default
=> [internal] load metadata for docker.io/library/python:3.10.11-slim-buster 0.0s
=> transferring context: 26 0.0s
=> [internal] load build definition from Dockerfile 0.0s
=> transferring dockerfile: 961B 0.0s
=> [internal] load metadata for docker.io/library/python:3.10.11-slim-buster 2.1s
=> [1/5] FROM docker.io/library/python:3.10.11-slim-buster@sha256:9c5ad55e08d36d9cbacd8348127a84c4bb69bcd34a40a4 0.0s
=> [internal] load build context 0.9s
=> transferring context: 1.92MB 0.0s
=> CACHED [2/5] WORKDIR /app 0.0s
=> CACHED [3/5] COPY requirements.txt . 0.0s
=> CACHED [4/5] RUN pip install --no-cache-dir -r requirements.txt 0.0s
=> [5/5] COPY . . 8.1s
=> exporting to image 6.2s
=> exporting layers 6.2s
=> writing image sha256:509d2883f95c39a3e12569d24d278b0db4e4cae84b7bb63d1a942b837cb36ecb 0.0s
=> naming to docker.io/library/testapp 0.0s
What's Next?
View a summary of image vulnerabilities and recommendations -> docker scout quickview
PS D:\RIC_projects\protienssequence_final> docker tag testapp:latest 323444116722.dkr.ecr.us-east-1.amazonaws.com/testapp:latest
PS D:\RIC_projects\protienssequence_final> docker push 323444116722.dkr.ecr.us-east-1.amazonaws.com/testapp:latest
The push refers to repository [323444116722.dkr.ecr.us-east-1.amazonaws.com/testapp]
027f436df88e: Pushed
54a2b6448f88: Pushed
18d16d73d580: Pushed
461f34f72d28: Pushed
adb58d7d925f: Pushed
```

## 15. After this all is done we have to create EC2 instance in AWS.

16. Open the deployed link. UI will be like below.



Now upload CSV file, After Uploading the bulk CSV data, Single input prediction is done.



The predicted sequence will be stored in prediction history tab

**User Dashboard**

Prediction History | Decrypt Record | Input Prediction

### Your Encrypted Prediction History

	id	user_id	sequence	residueCount	predictedMacromoleculeType	created_at
	2	73	1	26745	5 Protein	2023-12-11 22:38:07
	5	76	1	39720	6 Protein	2023-12-11 22:38:10
	0	71	1	43040	4 Protein	2023-12-11 22:38:05
	6	77	1	43968	6 Protein	2023-12-11 22:38:12
	3	74	1	4850	6 Protein	2023-12-11 22:38:08
	1	72	1	5896	5 Protein	2023-12-11 22:38:06
	7	78	1	82253	6 Protein	2023-12-11 22:38:13
	8	79	1	96853	6 DNA	2023-12-11 22:38:14
	9	80	1	97954	6 Protein	2023-12-11 22:38:15
	10	81	1	CGCGTATACGCG	1 DNA	2023-12-12 19:44:27

Now we will upload a small CSV file for testing, after uploading below is the view

**Bulk CSV Upload Prediction**

Upload CSV

Drag and drop file here  
Limit 200MB per file • CSV

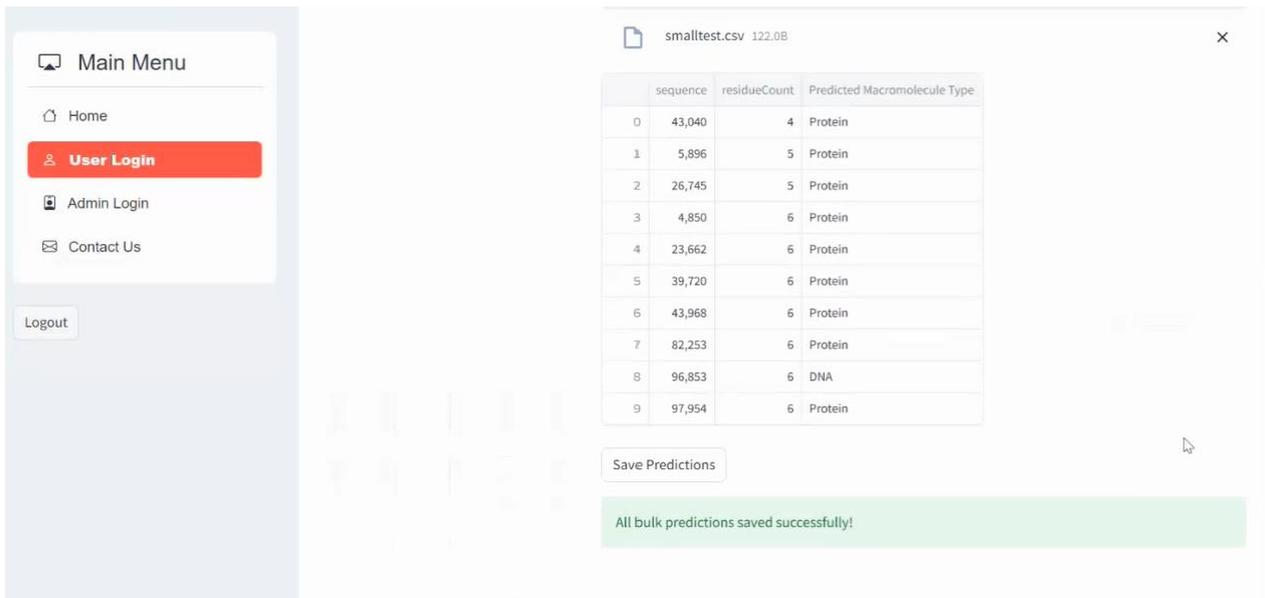
Browse files

smallest.csv 122.0B

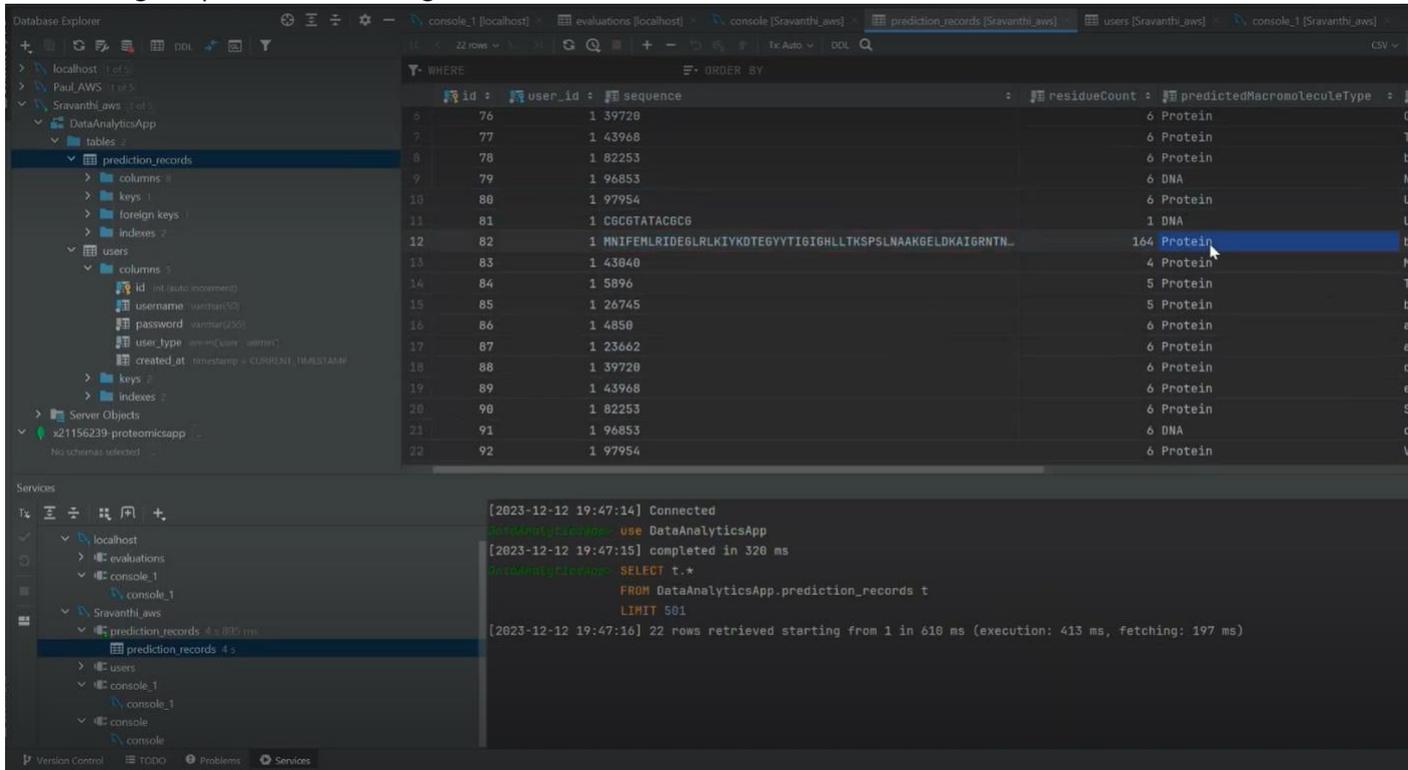
	sequence	residueCount	Predicted Macromolecule Type
0	43,040	4	Protein
1	5,896	5	Protein
2	26,745	5	Protein
3	4,850	6	Protein
4	23,662	6	Protein
5	39,720	6	Protein
6	43,968	6	Protein
7	82,253	6	Protein
8	96,853	6	DNA
9	97,954	6	Protein

Save Predictions

After saving upload save prediction

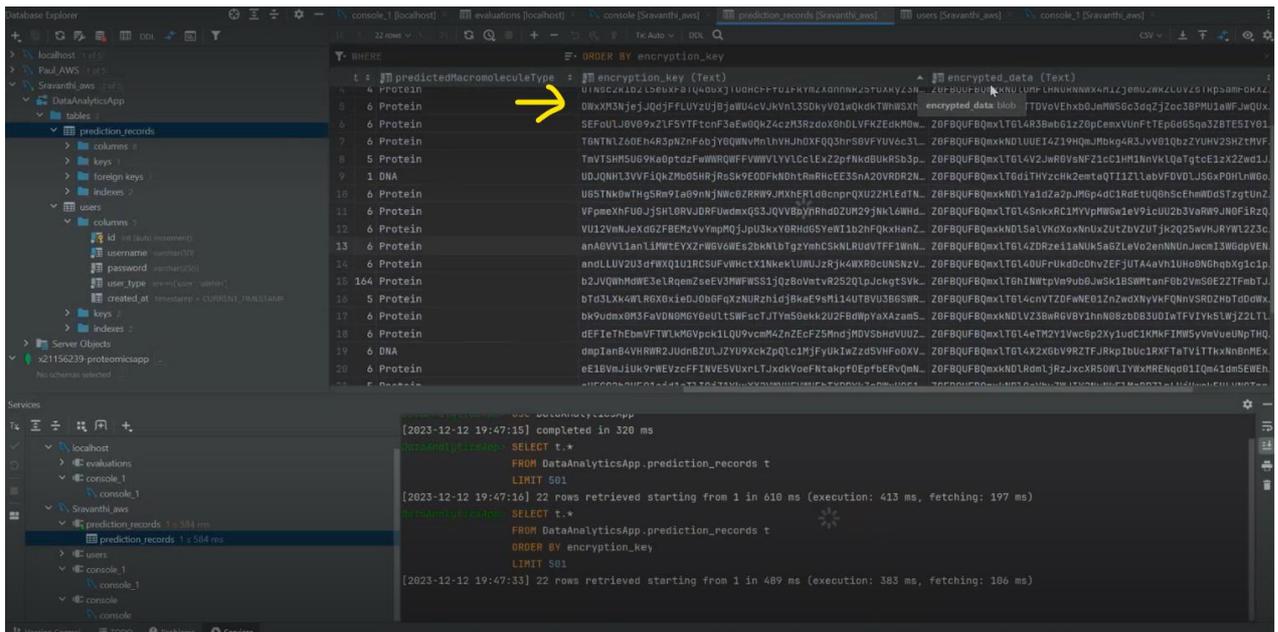


After saving the predictions, it will get stored in database

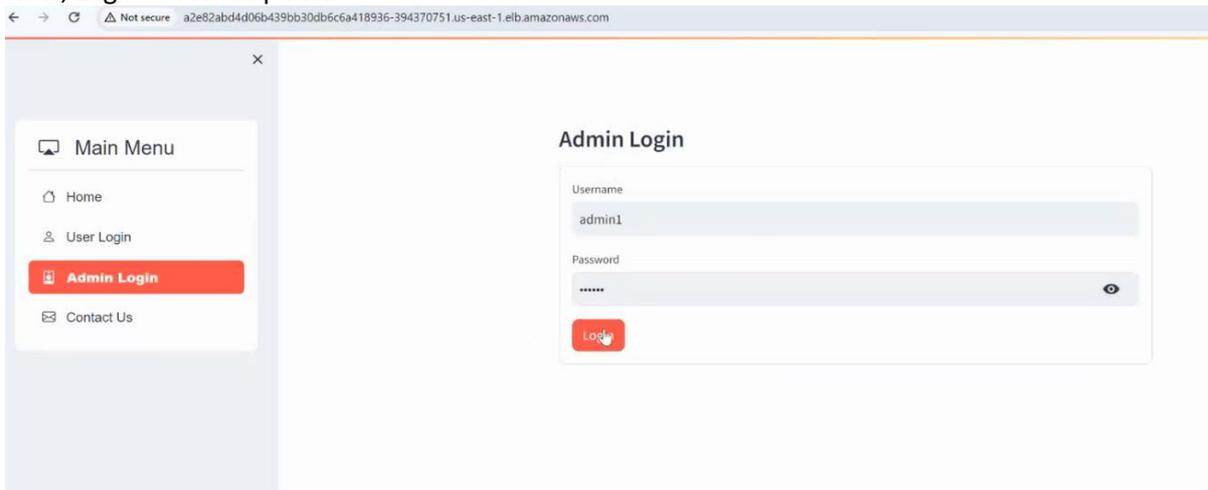


While the prediction is getting saved in database, also the data is getting encrypted due to PBFT blockchain algorithm.

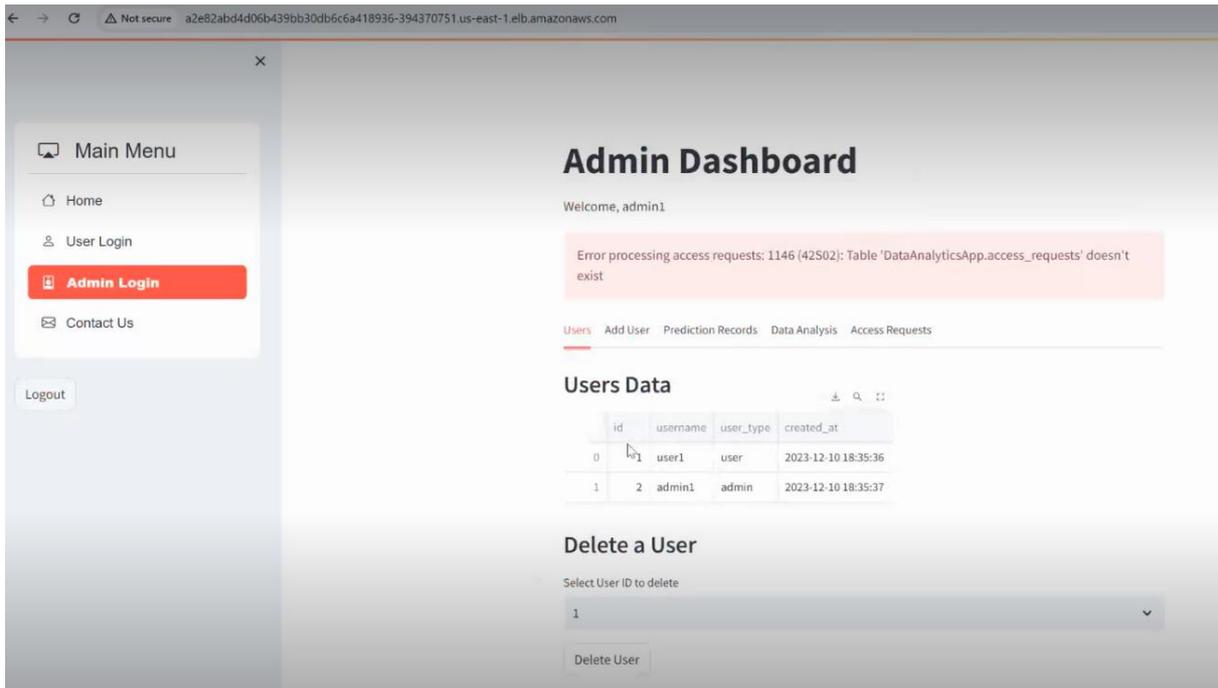
Only Admin will be having access to the encrypted key, Only when User request admin for the key, then only it can accessed by user.



Now, Login to Admin panel.



Here, we can create and delete user



On Prediction tab, we can see all the uploaded prediction data.

Users Add User **Prediction Records** Data Analysis Access Requests

### Prediction Records Data

	id	user_id	sequence	residueCount	predictedMacromoleculeType	encryption_key
	12	83	1 43040	4	Protein	77,122,89,51,98,70,112,80,81,8
	13	84	1 5896	5	Protein	84,109,86,84,83,72,77,53,85,71
	14	85	1 26745	5	Protein	98,84,100,51,76,88,107,52,87,1
	15	86	1 4850	6	Protein	97,110,65,48,86,86,108,49,97,1
	16	87	1 23662	6	Protein	97,110,100,76,76,85,86,50,85,5
	17	88	1 39720	6	Protein	100,69,70,73,101,84,104,69,98
	18	89	1 43968	6	Protein	101,108,70,88,84,109,90,52,83
	19	90	1 82253	6	Protein	83,69,70,111,85,108,74,48,86,4
	20	91	1 96853	6	DNA	100,109,112,73,97,110,66,52,8
	21	92	1 97954	6	Protein	86,70,112,109,101,88,104,70,8

Even in UI Admin can see the Encryption key. Move the table to right to view encrypted key

Users Add User Prediction Records Data Analysis Access Requests

### Prediction Records Data

	encrypted_data	created_at
12	2,70 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,89,108,86,52,84,85,104,86,87,86	2023-12-12 19:46:57
13	,70 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,86,50,74,119,82,48,86,115,78,70	2023-12-12 19:46:57
14	,81 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,99,110,86,84,90,68,70,119,78,69	2023-12-12 19:46:57
15	,7,6 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,90,68,82,122,101,105,49,97,78,8	2023-12-12 19:46:57
16	,72,5 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,79,85,70,114,85,107,100,68,99,6	2023-12-12 19:46:57
17	,81, 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,101,84,77,50,89,49,86,119,99,71	2023-12-12 19:46:57
18	,01, 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,78,106,78,83,101,88,111,122,99,	2023-12-12 19:46:57
19	,69 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,82,51,66,119,96,71,49,122,90,48	2023-12-12 19:46:57
20	,9,8 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,88,50,120,71,98,86,57,82,90,84,7	2023-12-12 19:46:57
21	,00, 90,48,70,66,81,85,70,66,81,109,120,108,84,71,108,52,83,110,107,120,82,67,49,77,89,8	2023-12-12 19:46:57

In Data Analysis tab, first upload the CSV file.

Main Menu

- Home
- User Login
- Admin Login**
- Contact Us

Logout

## Admin Dashboard

Welcome, admin1

Error processing access requests: 1146 (42S02): Table 'DataAnalyticsApp.access\_requests' doesn't exist

Users Add User Prediction Records **Data Analysis** Access Requests

### Data Analysis

Upload CSV

Drag and drop file here  
Limit 200MB per file • CSV

Browse files

merged\_pdb\_data\_ne... x

After uploading file, Visualizations will appear

Main Menu

- Home
- User Login
- Admin Login**
- Contact Us

Logout

	structre/id	classification	experimentalTechnique	macromoleculeType_x	residueCount_x	re
0	100D	DNA-RNA HYBRID	X-RAY DIFFRACTION	DNA/RNA Hybrid	20	
1	100D	DNA-RNA HYBRID	X-RAY DIFFRACTION	DNA/RNA Hybrid	20	
2	101D	DNA	X-RAY DIFFRACTION	DNA	24	
3	101D	DNA	X-RAY DIFFRACTION	DNA	24	
4	101M	OXYGEN TRANSPORT	X-RAY DIFFRACTION	Protein	154	

### Visualizations

Select Plot Type

Histogram

Select Column

classification

Number of Bins

5 20 100

Generate Histogram

# Bar Chart

