Serverless Machine Learning Model Deployment with AWS SageMaker

A Course Project Report Submitted in partial fulfillment of the course requirements for the award of grades in the subject of

CLOUD BASED AIML SPECIALITY
(22SDCS07A)

by

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Certificate

This is Certified that the project entitled **"**Serverless Machine Learning Model Deployment with AWS SageMaker**"** which is a experimental,Simulation& hardware work carried out by GUDIPUDI LOHITH KUMAR 2210030223, in partial fulfillment of the course requirements for the award of grades in the subject of **CLOUD BASED AIML SPECIALITY**, during the year **2024-2025**. The project has been approved as it satisfies the academic requirements.

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1. INTRODUCTION

In the era of digital healthcare, the ability to make quick, accurate predictions about a patient's condition is crucial for effective treatment planning and resource management. This project aims to leverage the power of machine learning and cloud computing to address this need by deploying a Serverless Machine Learning Model using AWS SageMaker. The project showcases how modern cloud infrastructure can simplify the deployment and scalability of intelligent healthcare solutions.

The core idea is to develop a predictive model that can process healthcare data—such as demographic details, medical history, hospital admission records, and treatment indicators—and output insights such as disease classification or health condition prediction. Traditional model deployment often requires managing servers, infrastructure scaling, and maintenance, which can be time-consuming and expensive. By adopting a serverless architecture, the project ensures that the machine learning model is deployed in a way that is scalable, cost-effective, secure, and easy to maintain.

The project uses a structured healthcare dataset containing anonymized records of patients. Each record includes vital features like gender, age, blood type, date of admission/discharge, medical conditions, and treatment outcomes. These features are preprocessed and used to train a machine learning model—specifically a Random Forest Classifier, chosen for its accuracy and interpretability in healthcare applications.

After training and evaluation, the model is deployed to AWS SageMaker, where it is exposed as an endpoint capable of real-time inference. To make this endpoint accessible and functional in a serverless environment

2. AWS Services Used as part of the project

1. AWS SageMaker

AWS SageMaker is the cornerstone of this project. It provides a fully managed platform that streamlines the machine learning workflow—from data preparation to model training, evaluation, and deployment. In this project, SageMaker was used to:

Train the machine learning model (Random Forest Classifier) using a preprocessed healthcare dataset.Host the trained model as a real-time endpoint that can receive input data and return predictions with low latency.

2. Amazon S3 (Simple Storage Service)

Amazon S3 acts as the central storage hub for all project assets. It was used to Store the healthcare dataset, making it accessible for preprocessing and model training.

3. AWS Identity and Access Management (IAM)

IAM ensures that all AWS resources interact securely and only with authorized entities. It was used to Create IAM roles and policies that allowed SageMaker to read/write from S3 and invoke other AWS services.Secure access for Lambda functions, ensuring they could call the SageMaker endpoint without exposing credentials.

4. Amazon CloudWatch

Amazon CloudWatch plays a key role in monitoring and observability within the deployment.

3. Steps involved in solving project problem statement

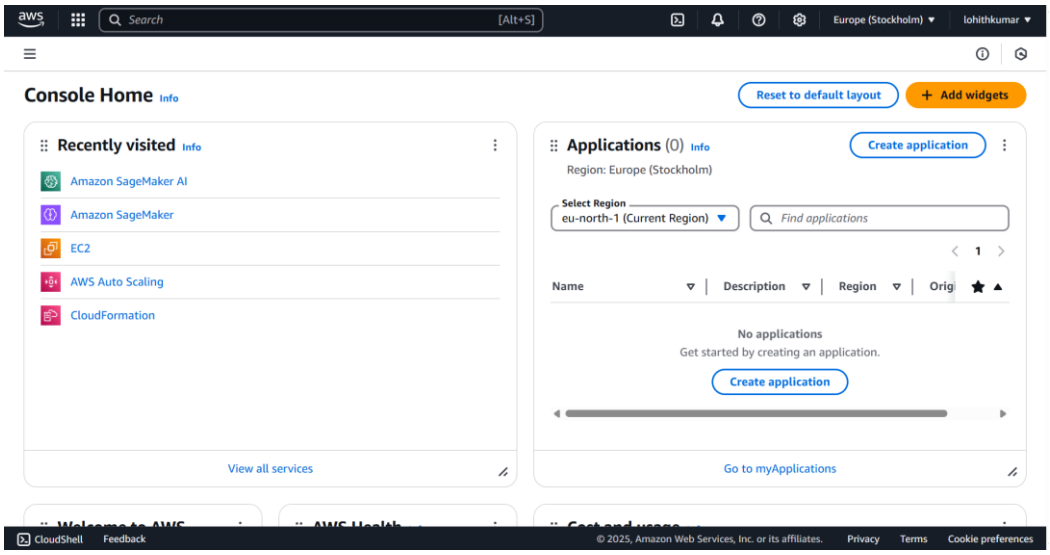
The project began with data loading and preprocessing, where the healthcare dataset was loaded using the Pandas library. Irrelevant columns such as 'Name', 'Doctor', 'Hospital', and 'Room Number' were removed to eliminate noise from the data. To maintain consistency, all column names were converted to lowercase and spaces were replaced with underscores. Additionally, duplicates were dropped, and missing values were handled to ensure data quality and integrity.

Next, in the feature engineering phase, date-related columns like 'date_of_admission' and 'discharge_date' were converted to datetime format to enable time-based computations if needed. Categorical features such as 'gender', 'blood_type', and 'medical_condition' were encoded using LabelEncoder to make them suitable for the machine learning model. Numerical features were standardized using StandardScaler to ensure uniform scale and improve model performance.

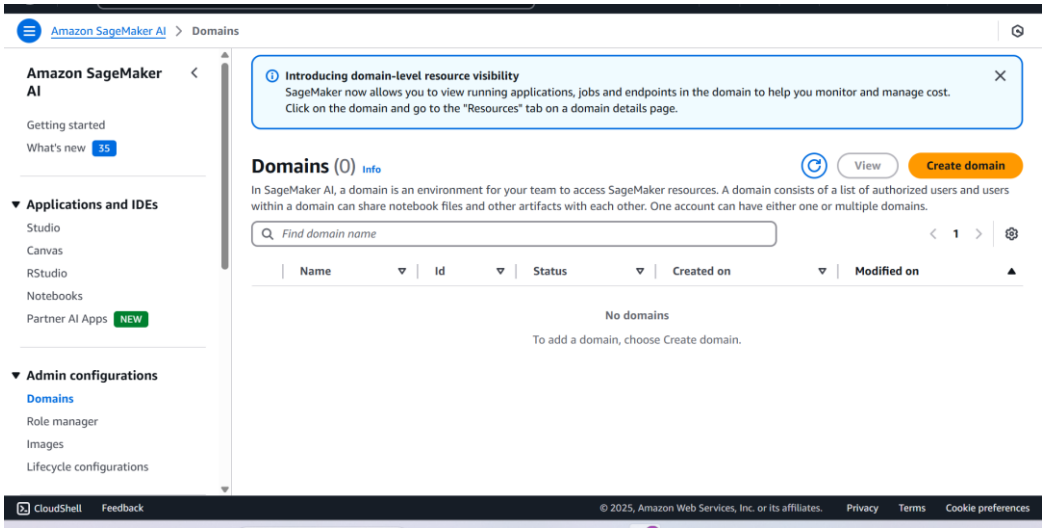
For model building and evaluation, the cleaned dataset was split into training and testing sets. A RandomForestClassifier was trained on the training data due to its robustness and efficiency in handling structured datasets. To further improve the model's performance, GridSearchCV was employed for hyperparameter tuning. The model was then evaluated using various metrics including accuracy, confusion matrix, and classification report, which provided insights into how well the model was performing on unseen data.

Finally, the model was prepared for deployment using AWS SageMaker. The trained model was serialized using joblib and the artifact was uploaded to an Amazon S3 bucket. A SageMaker endpoint was created to serve the model for real-time inference. To build a fully serverless architecture, an AWS Lambda function was configured to invoke the SageMaker endpoint upon receiving prediction requests. This Lambda function was then integrated with Amazon API Gateway, which enabled the model to be accessed securely over HTTP, completing the end-to-end deployment pipeline.

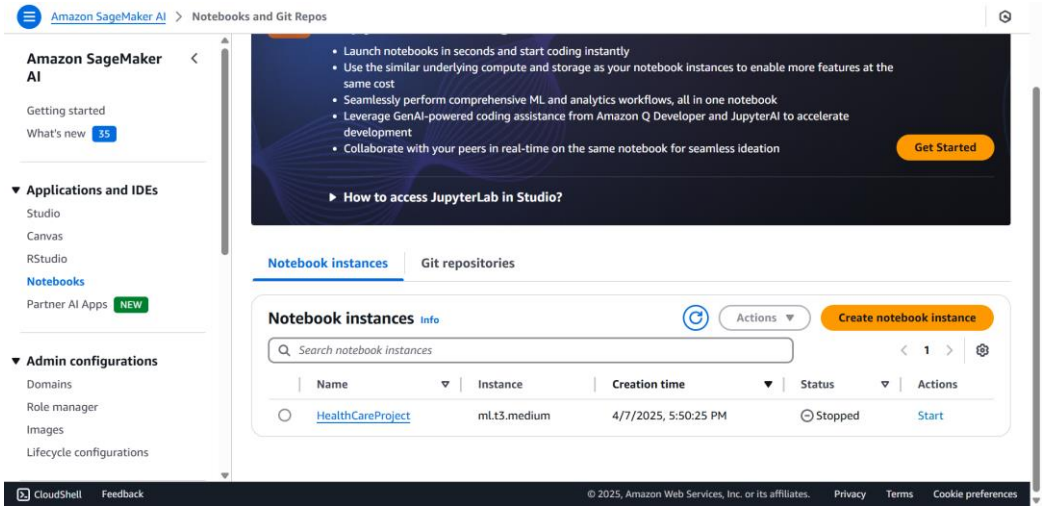
4. Stepwise Screenshots with brief description



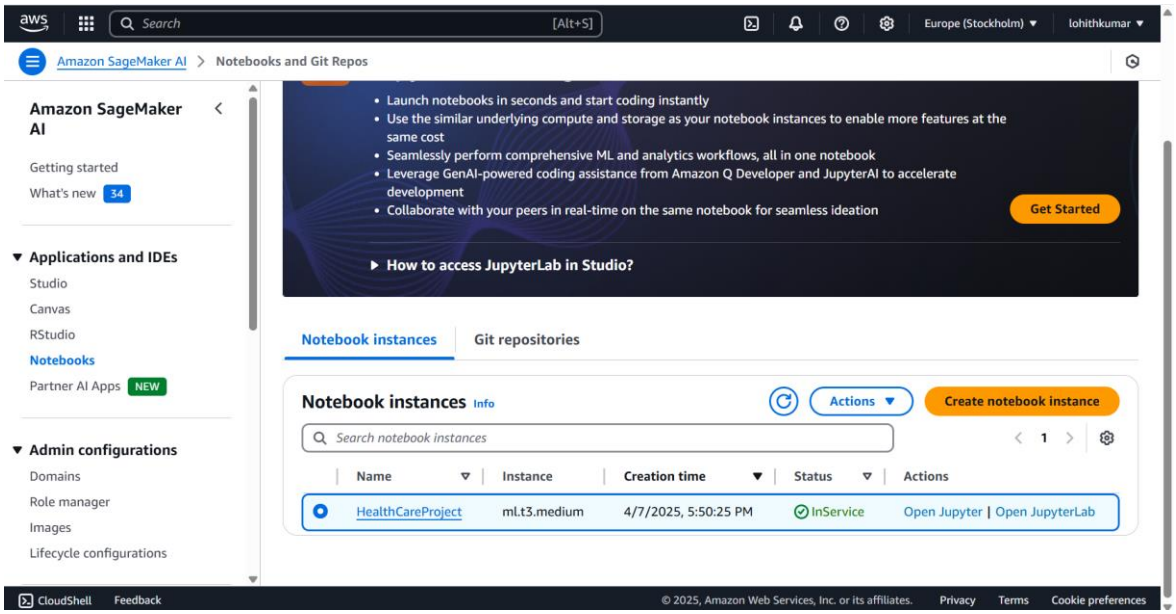
1-Login to the AWS free tier account



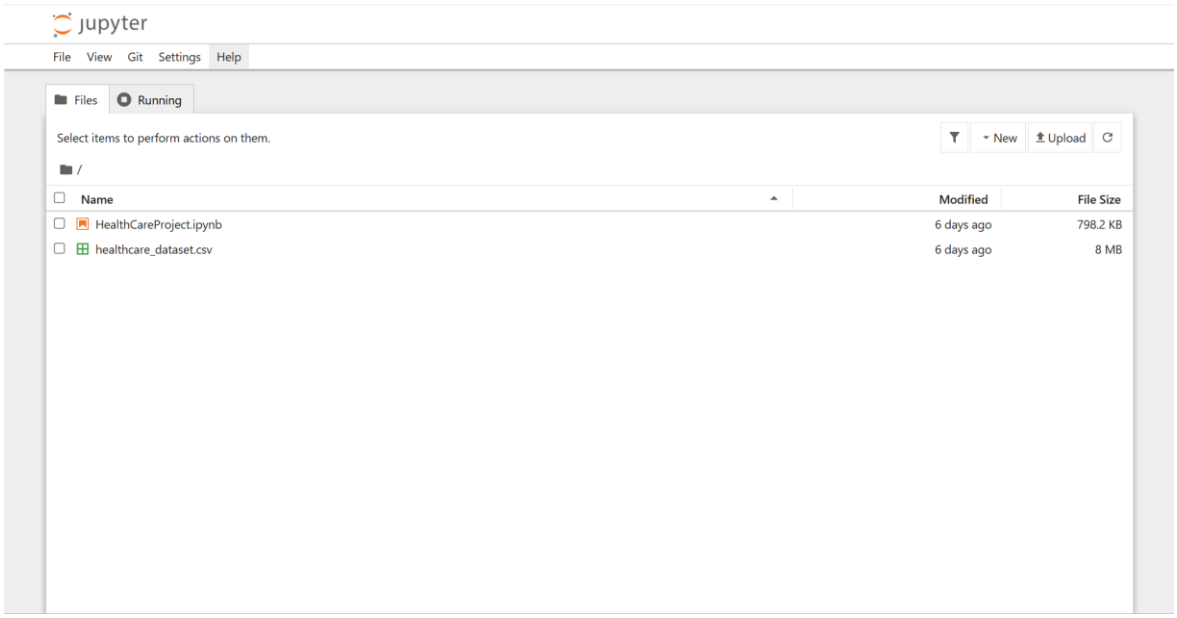
2-Search for the AMAZON SAGEMAKER AI



3-Create the notebook using the Sagemaker AI



4-Start the Services and open Jupyter notebook



5- Take the csv file and ipynb file

jupyter healthcare_dataset.csv Last Checkpoint: 6 days ago

File Edit View Git Settings Help

Delimiter: ,

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hos
1	Bobby JacksOn	30	Male	B-	Cancer	2024-01-31	Matthew Smith	Sons and
2	LesLie TErRy	62	Male	A+	Obesity	2019-08-20	Samantha Davies	Kin
3	DaNnY sMItH	76	Female	A-	Obesity	2022-09-22	Tiffany Mitchell	Cook
4	andrEw waTtS	28	Female	O+	Diabetes	2020-11-18	Kevin Wells	handez Rogers and V
5	adrIENNE bEll	43	Female	AB+	Cancer	2022-09-19	Kathleen Hanna	White-V
6	EMILY JOHNSOn	36	Male	A+	Asthma	2023-12-20	Taylor Newton	Nunez-Hump
7	edwArD EDWaRDs	21	Female	AB-	Diabetes	2020-11-03	Kelly Olson	Group Middl
8	CHrisTInA MARtinez	20	Female	A+	Cancer	2021-12-28	Suzanne Thomas	vell Robinson and Va
9	JASmINe aGullaR	82	Male	AB+	Asthma	2020-07-01	Daniel Ferguson	Sons Rich
10	ChRISTopher BerG	58	Female	AB-	Cancer	2021-05-23	Heather Day	Padilla-W
11	mIchElLe daniELs	72	Male	O+	Cancer	2020-04-19	John Duncan	Schaefer-P
12	aaRon MARtiNeZ	38	Female	A-	Hypertension	2023-08-13	Douglas Mayo	Lyons-
13	connOR HANsEn	75	Female	A+	Diabetes	2019-12-12	Kenneth Fletcher	Powers Miller, and Fl
14	rObeRt bAuer	68	Female	AB+	Asthma	2020-05-22	Theresa Freeman	Rivera-Gutie
15	bROOkE brady	44	Female	AB+	Cancer	2021-10-08	Roberta Stewart	Morris-Are
16	MS. nAtalIE gAMble	46	Female	AB-	Obesity	2023-01-01	Maria Dougherty	Cline-Will
17	haley perkins	63	Female	A+	Arthritis	2020-06-23	Erica Spencer	Cervantes-V
18	mRS. jamiE cAMPBELl	38	Male	AB-	Obesity	2020-03-08	Justin Kim	orres, and Harrison J
19	LuKE BuRgEss	34	Female	A-	Hypertension	2021-03-04	Justin Moore Jr.	Houston
20	dANIEL schmIdt	63	Male	B+	Asthma	2022-11-15	Denise Galloway	Hammond

6-Data set in my csv file

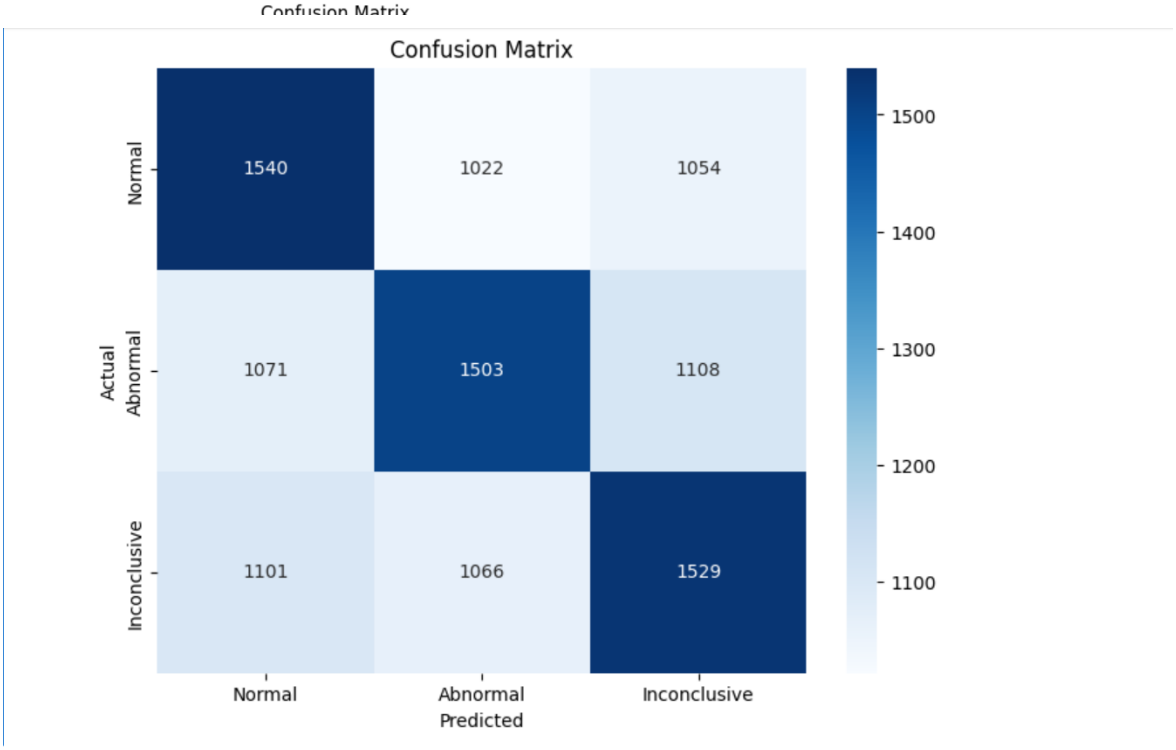
```
Best Hyperparameters: {'class_weight': 'balanced', 'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}

Accuracy: 0.41586319810805894

Classification Report:
              precision    recall  f1-score   support

           0       0.41      0.43      0.42      3616
           1       0.42      0.41      0.41      3682
           2       0.41      0.41      0.41      3696

    accuracy                           0.42     10994
   macro avg       0.42      0.42      0.42     10994
weighted avg       0.42      0.42      0.42     10994
```



7-Final output of my project

5. Learning Outcomes

This project provided a comprehensive, hands-on experience in building and deploying a machine learning solution using cloud-based infrastructure. It offered practical exposure to AWS SageMaker, enabling the training, deployment, and management of machine learning models in a fully managed cloud environment. A key takeaway was the understanding of serverless architecture, achieved through the use of AWS Lambda and API Gateway, which allowed for scalable, on-demand inference without the need to manage backend servers. The project also strengthened skills in data preprocessing and feature engineering, particularly in handling categorical and numerical features, managing missing data, and applying appropriate encoding and scaling techniques. Additionally, model optimization techniques such as GridSearchCV were employed to fine-tune hyperparameters and boost model performance. The integration of multiple AWS services—including S3, SageMaker, Lambda, IAM, and CloudWatch—enabled the development of a secure, efficient, and maintainable end-to-end machine learning pipeline. Finally, the use of CloudWatch offered valuable insights into monitoring and debugging deployed ML models, providing visibility into logs and performance metrics. Overall, the project helped solidify concepts in both machine learning and cloud computing, with a strong focus on solving real-world problems in the healthcare domain.

6. Conclusion

In conclusion, this project successfully demonstrates the end-to-end workflow of a serverless machine learning model deployment using AWS services. From data cleaning and feature engineering to model training and cloud deployment, each step was carefully executed to build a scalable and reliable prediction system for healthcare applications. The use of AWS SageMaker drastically simplified model training and deployment, while services like Lambda and API Gateway enabled real-time access in a cost-effective, serverless manner. This project not only highlights the technical feasibility of deploying ML in cloud ecosystems but also emphasizes its practical impact in domains like healthcare where fast, reliable predictions are critical. The architecture used here can be easily adapted or scaled for other industries and use cases, making it a powerful blueprint for cloud-based AI solutions.

7. References

- AWS SageMaker Documentation
- AWS Lambda Documentation
- Amazon API Gateway
- Amazon S3 Documentation
- Amazon CloudWatch
- Scikit-learn Documentation
- Pandas Library
- Healthcare Dataset