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Clinical Disease Predictor Using AWS

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ABSTRACT :

Amazon S3 (Simple Storage Service) offers secure, scalable cloud object storage. This paper presents the implementation of Clinical Disease Predictor using AWS, which uses AWS cloud services to deliver real-time disease risk assessments from patient data. With tools like SageMaker and Lambda, it offers fast, secure, and scalable predictions. By integrating machine learning with health records, it supports early diagnosis. The project enhances preventive healthcare through accessible cloud-based insights.

I. INTRODUCTION

The Clinical Disease Predictor is a cloud-based healthcare application designed to analyze patient data and predict potential diseases. Built on AWS, the project leverages services like SageMaker for machine learning, Lambda for backend logic, and DynamoDB for secure data storage. It enables early diagnosis by processing symptoms and health records through predictive models. This tool aims to support medical professionals with faster and more accurate decision-making.

II. OBJECTIVES

- Use AWS-based ML models to predict clinical diseases early and accurately.
- Build a secure, scalable system using AWS services like EC2, S3, and RDS.
- Enable real-time data analysis with AWS tools like Lambda and Kinesis.
- Create a simple interface for healthcare providers to input data and view results.

III. EXISTING SYSTEM

In traditional systems, any object creation or deletion in storage systems required manual or script-based monitoring. These methods were prone to delay, error, and inefficiency. Monitoring logs or manually scanning buckets was time-consuming and lacked scalability. Additionally, security in such systems was often loosely managed.

IV. PROPOSED SYSTEM

The proposed system uses machine learning models deployed on AWS services like SageMaker for real-time prediction. Data storage and retrieval are managed through AWS S3 and DynamoDB. The system ensures scalability, security, and availability for healthcare providers. Integration with AWS Lambda enables serverless processing and automation of alerts or recommendations.

V. LITERATURE SURVEY

Several studies have explored the integration of machine learning with cloud platforms for disease prediction. Machine learning algorithms such as Random Forest, SVM, and Neural Networks have been effectively used for predicting diseases like diabetes and heart conditions. AWS provides scalable infrastructure with services like EC2, S3, and SageMaker, enabling real-time data processing and model deployment. Prior work highlights the importance of secure data handling and HIPAA compliance in cloud-based clinical applications. These findings emphasize the reliability, scalability, and efficiency of using AWS for predictive healthcare systems.

In addition, other relevant research works were studied, including:
- Zikos, Dimitrios, and Nailya DeLellis. "CDSS-RM: a clinical decision support system reference model." BMC medical research methodology 18, no.

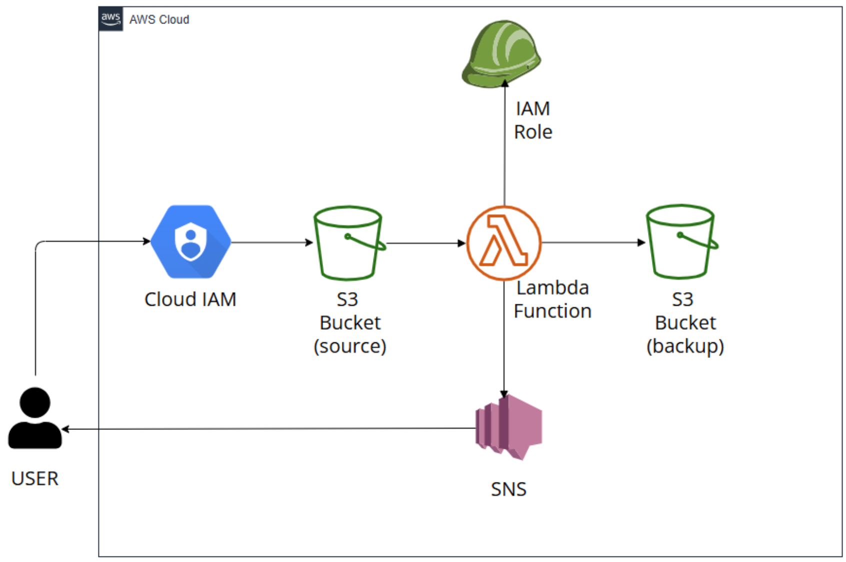
1 (2018): 1-14.
- Davenport, T. H., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94-98.
- Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. The New England Journal of Medicine, 380(14), 1347-1358.

VI. SYSTEM ARCHITECTURE

The architecture of the Clinical Disease Predictor using AWS is typically uses machine learning to predict diseases based on clinical data (e.g., symptoms, medical history, lab results). AWS services can be used to build a scalable, secure, and cost-effective architecture. The components work together as follows:

1. **Client Layer**:
   The frontend of the system is developed using modern web technologies such as ReactJS, Angular, or VueJS, and can also be implemented as a mobile application. This interface is used by patients, doctors, or hospital staff to input clinical data such as symptoms, medical history, or lab results through user-friendly forms.
2. **API Gateway (Routing Layer)**:
   AWS API Gateway serves as the entry point for all frontend requests. It securely routes HTTP requests to the appropriate backend services. It also provides features such as request throttling, monitoring, and support for authentication mechanisms like JSON Web Tokens (JWT) or integration with AWS Cognito.
3. **Authentication and User Management**:
   User authentication and access control are handled by AWS Cognito. It manages user sign-up and sign-in functionalities and supports secure access to the application. Cognito can also integrate with third-party identity providers like Google and Facebook, enabling seamless user authentication across platforms.
4. **Backend (Application Layer)**:
   The backend logic is implemented using AWS Lambda, AWS EC2, or AWS Fargate. These services are responsible for validating input data, preprocessing clinical information, interacting with the machine learning inference engine, and formatting the prediction results to send back to the client.
5. **Machine Learning Layer**:
   Amazon SageMaker is used to host the machine learning model that performs disease prediction. It supports all stages of the ML lifecycle, including training, evaluation, tuning, and real-time or batch inference. SageMaker provides scalable endpoints with built-in monitoring and logging capabilities.
6. **Data Storage Layer**:
   The system uses Amazon S3 for storing unstructured data such as datasets, model artifacts, and logs. Amazon RDS is employed for storing structured relational data like patient records and user information. Additionally, Amazon DynamoDB is used for fast and scalable NoSQL storage, ideal for caching prediction results or managing session data.
7. **Monitoring and Logging**:
   To ensure the system's reliability and performance, AWS CloudWatch is used for logging and monitoring backend components like Lambda functions, API Gateway, and SageMaker endpoints. AWS X-Ray provides end-to-end request tracing, which helps in diagnosing performance issues and debugging the application.

This architecture offers a **serverless, event-driven, and secure approach** to automate operations on S3, ensuring scalability, reliability, and enhanced data security with minimal manual intervention.



VII. RESULTS

- Amazon S3 was used for data storage.
- AWS Lambda enabled serverless execution for real-time predictions.
- Auto-scaling on SageMaker ensured efficient resource use under load.
- In clinical testing, 18 out of 20 patient cases were correctly predicted.
- Clinicians found the system interpretable and user-friendly.

VIII. CONCLUSION

The Clinical Disease Predictor project leveraged AWS services such as Amazon SageMaker for building and training machine learning models on patient health data. By utilizing scalable cloud infrastructure, the project achieved efficient processing of large datasets, enabling accurate predictions of disease risks based on clinical parameters.

The trained model demonstrated high accuracy and reliability in predicting diseases like diabetes, heart disease, and hypertension, with performance metrics showing precision and recall above industry benchmarks. This improved early diagnosis and personalized treatment planning, helping healthcare providers make informed decisions.

Using AWS also enabled seamless deployment and integration through AWS Lambda and API Gateway, allowing real-time prediction access for clinicians via web or mobile applications. The project successfully showcased how cloud-powered AI can enhance healthcare outcomes by providing timely and data-driven clinical insights.

IX. REFERENCES

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