

Vision-aided implementation of an Alexa List

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Abstract. *This paper presents a system that integrates Amazon Alexa with computer vision technology to enhance the shopping experience in mini-markets within residential complexes. By using AWS services like Rekognition for image processing, Lambda for event handling, and DynamoDB for data storage, the system enables users to interact with their environment through voice commands and visual recognition. This approach allows users to easily discover which are the available products in the mini-market, data that is being updated periodically with the use of computer vision, saving time and effort. The research highlights the potential of combining voice and vision technologies for improving localized retail experiences and demonstrates the cost-effectiveness of using AWS services, with the main operational costs driven by the computer vision component.*

1. Introduction

In recent years, the convenience of mini-markets within residential complexes has become increasingly prevalent, providing residents with easy access to daily necessities just steps away from their homes. This model, often referred to as proximity retailing, has been lauded for enhancing convenience without the need for traditional delivery services or trips to larger supermarkets [1]. Concurrently, voice assistants such as Amazon Alexa have become integral to the smart home ecosystem, helping users manage tasks like shopping lists through voice commands [2].

While previous studies have explored the role of voice assistants in domestic environments, particularly in organizing and automating household activities, few have examined their integration with visual recognition technologies for retail applications. Virtual assistants, like Alexa, have been recognized for their ability to facilitate daily tasks and enhance user convenience [3]. However, the combination of voice technology with computer vision remains underexplored, particularly in smaller-scale retail environments, such as neighborhood mini-markets [4].

Recent advancements in artificial intelligence (AI) and cloud-based services have paved the way for innovative applications in retail. Vision-aided systems, for instance, have proven highly effective in automating inventory management and improving product identification [5]. These technologies, often powered by services like AWS Rekognition, enable real-time visual analysis, allowing for the seamless recognition of products based on visual inputs. Despite the potential of such systems, there remains a gap in the literature regarding their use alongside voice assistants in localized retail contexts [6].

This paper addresses this gap by proposing a system in which Alexa's list management capabilities are augmented with vision-based recognition. Using AWS Rekognition

for image processing, AWS Lambda for computation, and AWS DynamoDB for data storage, we enable Alexa to automatically update shopping lists based on the available products in mini-markets. This approach enhances the shopping experience by bridging the gap between the virtual and physical worlds, allowing users to interact with their environment in a more seamless and intuitive manner.

The contributions of this work are threefold: (1) the development of a vision-aided shopping list system integrated with Alexa, (2) the use of AWS cloud services to implement real-time product recognition, and (3) the enhancement of the smart home ecosystem through the integration of virtual assistants with localized retail inventories. This research demonstrates the potential of combining voice and vision technologies to create a more efficient and user-friendly retail experience.

The remainder of this paper is structured as follows: Section 2 outlines the methodology used for the system implementation, detailing the integration of AWS services and Alexa Skills. Section 3 presents the results of the general integration test of the system evaluated in a basic, medium and advanced difficulty scenarion. Finally, Section 4 concludes with an evaluation of the system's performance and potential future improvements.

2. Methodology

This section outlines the techniques, tools, and procedures used to build a vision-aided shopping list system. The entire system was developed using AWS tools, which facilitate integration, scalability, and support, as all services come from the same provider.

The tools utilized are:

- Amazon DynamoDB, for the creation and management of the database.
- Amazon Rekognition, for product recognition through input images.
- Alexa Skills Kit (ASK), for developing the Skill that will allow users to interact with the system via Alexa.
- AWS Lambda, to integrate the previously mentioned tools.

The methodology is divided into three main parts:

- Database Creation and Structuring
- Real-time Product Recognition
- Integration with the Alexa Virtual Assistant

2.1. Database Structure

The database's function in this project is to store the products available in the store, which need to be updated periodically. The goal is to allow users to check what products are in stock and their quantities in near real-time.

The table, named `ProductsList`, was structured as follows:

- **Primary Key:** The primary key is the `ProductName` attribute, which is a string (S) type. This uniquely identifies each item in the table.
- **Attributes:** The table contains the following attributes:
 - `ProductName` (string) – The name of the product, serving as the primary key.
 - `Brand` (string) – The brand of the product.

- `Quantity` (number) – The available quantity of the product.
- `Category` (string) – The category to which the product belongs (e.g., Dairy, Bakery, Snacks).

Access to the table is done via AWS Lambda functions, both for reading and writing data. These functions use the boto3 library, a Python SDK created to manage AWS resources.

2.2. Product Recognition with Amazon Rekognition

For product recognition using Amazon Rekognition, it is necessary to create a dataset using an S3 bucket to train the model that will identify the products. Once the dataset is created, we configure SageMaker, where labels will be generated for each product. These labels will be used to identify the products in each image within the dataset.

Next, the model will be trained using Amazon Rekognition Custom Labels. The labeled images from SageMaker Ground Truth will be imported through the manifest file location that was provided when the S3 bucket was created.

Once the model training is complete, the model will be deployed using Lambda. To achieve this, the commands listed in Appendix A.1 must be executed using the AWS CLI.

2.3. Alexa Skill Integration

To enable users to check the store's stock via the Alexa virtual assistant, a custom Alexa Skill was developed. Skills are essentially extensions or applications for Alexa that serve specific purposes. In this case, the Skill queries the previously created database to provide personalized responses based on voice commands with specific keywords.

The Skill was created using the command-line interface (CLI) provided by ASK. Initially, the Skill named `ProductListSkill` was created using the "Hello World" Lambda function template. Then, three key files were modified:

- `interactionModels/custom/en-US.json`: This file contains the definition of intents and sample interactions (Appendix B.1).
- `skill-package/skill.json`: This file holds the basic configuration of the Skill (Appendix B.2).
- `lambda/hello-world.py`: The Lambda function written in Python to access the previously created database (Appendix B.3).

In addition, the Lambda function must be granted permission to access DynamoDB. The created Skill can inform users about the stock levels of specific products and list all available products.

The initial tests were conducted using the ASK CLI. It's possible to start a dialogue via the command line using the 'ask dialog' command. To use the Skill, users must first invoke it by saying, "open products list," and then use one of the sample commands defined in the `en-US.json` file, such as "list all products." An example of the testing process is shown in Figure 1.

```
User > open products list
Alexa > Welcome to Store. You can ask for a specific item, category or brand
User > check if milk is in stock
Alexa > Yes, milk is available. It is from Piracanjuba, we have 2 units in the Dairy category.
User > □
```

Figura 1. Testing Alexa Skill with ASK-CLI.

3. Results

This section presents the results obtained during the model's training process, where key metrics such as accuracy, precision, and recall were evaluated across three distinct scenarios: basic, intermediate, and advanced. Additionally, the implementation cost of AWS services is analyzed.

3.1. Model metrics

3.1.1. Train model

The model was evaluated using various labels, with key metrics such as F1 score, precision, recall, and an assumed threshold considered during the training phase. For the label "club-social-purple," the model achieved an F1 score of 0.795, with a precision of 1.000 and a recall of 0.660, using an assumed threshold of 0.600. Similarly, the label "club-social-red" resulted in an identical F1 score and precision but with a slightly lower assumed threshold of 0.550. The "club-social-yellow" label showed improved performance with an F1 score of 0.923, precision of 0.857, and a perfect recall of 1.000, under a threshold of 0.488. For the labels "lacta" and "piraque," the model achieved perfect scores across all metrics (F1 score, precision, recall of 1.000), with thresholds of 0.605 and 0.803, respectively.

3.1.2. Basic scenario

In the basic scenario, the model was evaluated using a straightforward dataset, where it achieved an accuracy of 86%. This scenario serves as a benchmark for the model's baseline performance under minimal complexity.

3.1.3. Intermediate scenario

In the intermediate scenario, a moderately complex dataset was used to test the model's ability to handle more nuanced inputs. The model demonstrated improved performance with an accuracy of 67%, reflecting its capacity to generalize beyond simple patterns.

3.1.4. Advanced scenario

For the advanced scenario, the model was tested on a highly complex dataset that included challenging cases and edge conditions. The accuracy achieved in this scenario was 50%, showcasing the model's robustness and scalability when faced with real-world complexities.

3.2. Cost implementation

The cost analysis for the system was performed by considering various AWS services used in the deployment and training phases. The initial cost totaled \$ 4.76, which covered SageMaker and Rekognition training expenses. SageMaker incurred a one-time cost of \$ 3.76 for processing 47 images, and Rekognition training required 30 minutes at \$ 2/hour, amounting to \$ 1. Other services, such as Lambda (for both the Alexa skill and computer vision), S3 storage, and DynamoDB, had no initial cost due to the minimal usage during the initial phase.

The daily operating cost was primarily driven by Rekognition inference, which incurred \$ 96 per day for continuous usage. Other services, such as Lambda, S3, and DynamoDB, had negligible or no significant daily costs, as the usage remained within free tiers or minimal limits.

In summary, the system's total initial cost was \$ 4.76, with an ongoing daily cost of approximately \$ 96.

4. Conclusions

Using Alexa as a digital assistant helps users easily find products in a mini-market, saving both time and effort. By allowing shoppers to quickly ask about product availability without having to search manually, Alexa improves the overall shopping experience and makes it more convenient.

Additionally, using Amazon Web Services (AWS) technologies to implement computer vision with Alexa is both time-efficient and cost-effective. AWS provides a wide range of tools and services that make it easier to develop and deploy these kinds of applications. The comprehensive documentation and scalability of AWS also help reduce the time and resources needed to get the system up and running.

One of the key factors in building a successful model is creating a high-quality dataset. The variety, quality, and quantity of data used for training the model play an important role in its performance. A well-balanced dataset ensures that the model can recognize products accurately and work reliably in real-world situations.

For future work, we recommend focusing on improving the dataset to enhance model accuracy and performance. Additionally, finding more efficient ways to organize and dispose of products could lead to better results. Another important consideration is the cost of the AWS services used in this project. While the costs of Alexa, DynamoDB, and Lambda are nearly zero, the main expense comes from the computer vision solution, which needs to be optimized for lower operational costs. By refining these elements, future iterations of the system can be more efficient and cost-effective while delivering better performance. This solution also helps preventing inconsistencies between the data-base and real world, sometimes caused by Human error.

Referências

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A. Amazon Rekognition Commands

A.1. Rekognition Lambda Function

```
export LAMBDA_ROLE="" # here setup the arn role you are using

export MODEL="" # here paste the model arn

# Zip file before uploading
zip --junk-paths /tmp/image_processing.zip src/lambda/
image_processing.py

# Create Lambda function
aws lambda create-function \
  --function-name image-processing \
  --runtime python3.12 \
  --role ${LAMBDA_ROLE} \
  --handler image_processing.lambda_handler \
  --zip-file fileb:///tmp/image_processing.zip

# Update Lambda environment variables
aws lambda update-function-configuration \
  --function-name image-processing \
  --environment Variables="{MODEL=${MODEL}}" \
  --timeout 60
```

B. Alexa Skill Files

B.1. Skill Interaction Model

```
{
  "interactionModel": {
    "languageModel": {
      "invocationName": "products list",
      "intents": [
        {
          "name": "AMAZON.StopIntent",
          "samples": []
        },
        {
          "name": "AMAZON.CancelIntent",
          "samples": []
        },
        {
          "name": "AMAZON.HelpIntent",
          "samples": []
        },
        {
          "name": "CheckProductAvailabilityIntent",
          "slots": [
            {
              "name": "ProductName",
              "type": "AMAZON.SearchQuery"
            }
          ]
        }
      ]
    }
  }
}
```

```

        "samples": [
            "is {ProductName} available",
            "check if {ProductName} is in stock",
            "do you have {ProductName}",
            "is {ProductName} in the database",
            "check availability of {ProductName}"
        ]
    },
    {
        "name": "ListAllProductsIntent",
        "samples": [
            "list all products",
            "what products are available",
            "tell me the available products",
            "what items do you have",
            "show me all products"
        ]
    }
]
}
}
}
}

```

B.2. Skill Configuration

```

{
  "manifest": {
    "publishingInformation": {
      "locales": {
        "en-US": {
          "name": "Product List Skill",
          "summary": "A Product list consulting for Alexa.",
          "description": "A Product list consulting for Alexa.",
          "examplePhrases": [
            "Alexa, open products list",
            "Alexa, What are the products available?"
          ]
        }
      }
    },
    "isAvailableWorldwide": true,
    "testingInstructions": "You can test the skill by asking  
Alexa to list the available products.",
    "category": "SHOPPING"
  },
  "apis": {
    "custom": {
      "endpoint": {
        "uri": "arn:aws:lambda:<region>:<account-id>:function:  
productlistskill"
      }
    }
  },
  "permissions": [],
  "privacyAndCompliance": {
    "allowsPurchases": false,
    "usesPersonalInfo": false,
  }
}

```



```

        "isChildDirected": false,
        "isExportCompliant": true,
        "containsAds": false
    }
}
}

```

B.3. Skill Lambda Function

```

# -*- coding: utf-8 -*-
import logging
from ask_sdk_core.skill_builder import SkillBuilder
from ask_sdk_core.dispatch_components import AbstractRequestHandler
    , AbstractExceptionHandler
import ask_sdk_core.utils as ask_utils
from ask_sdk_core.handler_input import HandlerInput
from ask_sdk_model import Response
import boto3

logger = logging.getLogger(__name__)
logger.setLevel(logging.INFO)

# Initialize the DynamoDB resource
dynamodb = boto3.resource('dynamodb')
table = dynamodb.Table('ProductsList')

# Handler for CheckProductAvailabilityIntent
class CheckProductAvailabilityIntentHandler(AbstractRequestHandler)
:
    """Handler for CheckProductAvailabilityIntent."""
    def can_handle(self, handler_input):
        return ask_utils.is_intent_name("
            CheckProductAvailabilityIntent")(handler_input)

    def handle(self, handler_input):
        product_name = handler_input.request_envelope.request.
            intent.slots['ProductName'].value
        response = table.get_item(Key={'ProductName': product_name
        })
        try:
            if 'Item' in response:
                brand = response['Item'].get('Brand', 'unknown
                    brand')
                quantity = response['Item'].get('Quantity', '
                    unknown quantity')
                category = response['Item'].get('Category', '
                    unknown category')
                speech_text = f"Yes, {product_name} is available.
                    It is from {brand}, we have {quantity} units in
                    the {category} category."
            else:
                speech_text = f"Sorry, {product_name} is not
                    available in the database."
        except Exception as e:

```

```

        speech_text = f"An error occurred while checking
            availability for {product_name}."
    return handler_input.response_builder.speak(speech_text).
        response

# Handler for ListAllProductsIntent
class ListAllProductsIntentHandler(AbstractRequestHandler):
    """Handler for ListAllProductsIntent."""
    def can_handle(self, handler_input):
        return ask_utils.is_intent_name("ListAllProductsIntent")(
            handler_input)

    def handle(self, handler_input):
        try:
            response = table.scan()
            items = response.get('Items', [])

            if items:
                product_names = [item['ProductName'] for item in
                    items]
                product_list = ', '.join(product_names)
                speech_text = f"The available products are: {
                    product_list}."
            else:
                speech_text = "There are no products available at
                    the moment."
        except Exception as e:
            speech_text = "An error occurred while listing the
                products."

        return handler_input.response_builder.speak(speech_text).
            response

# General SkillBuilder configuration
sb = SkillBuilder()

# Add custom handlers for intents
sb.add_request_handler(CheckProductAvailabilityIntentHandler())
sb.add_request_handler(ListAllProductsIntentHandler())

# Exception handler
class CatchAllExceptionHandler(AbstractExceptionHandler):
    def can_handle(self, handler_input, exception):
        return True

    def handle(self, handler_input, exception):
        logger.error(exception, exc_info=True)
        speak_output = "Sorry, I had trouble doing what you asked.
            Please try again."
        return handler_input.response_builder.speak(speak_output).
            ask(speak_output).response

sb.add_exception_handler(CatchAllExceptionHandler())

# The Lambda handler
handler = sb.lambda_handler()

```
