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Architecture for detecting advertisement types

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Abstract

Businesses often encounter difficulties in accurately categorizing advertisements based on their content, which leads to inefficiencies in targeted marketing and data analysis. An automated system is needed to detect the type of advertisement (e.g., food, beverage, clothing, etc.) from the submitted text. This paper aims to develop an automated system leveraging Amazon Web Services (AWS) to categorize advertisement types based on text input. We employed Convolutional Neural Networks (CNNs) in developing the automated system due to the significant performance of CNNs leveraging AWS. The solution aims to boost marketing efficiency and strengthen data analysis capabilities. To achieve this, we utilize Amazon Simple Storage Service (S3), AWS Lambda, Amazon Comprehend, Amazon DynamoDB, Amazon CloudWatch, Amazon CloudFront, and AWS Web Application Firewall (AWS WAF). Moreover, we follow some procedural steps in executing the task by uploading the advertisement text to an S3 bucket, which triggers a Lambda function that forwards the text to Amazon Comprehend for analysis, and the results are stored in DynamoDB, from where the results notification is sent to the user. Magazine image datasets were employed as test datasets for this approach. This work enables automatic advertisement categorization, enhanced marketing effectiveness, better data analysis and reporting functionality, an affordable solution using AWS services, and instant feedback for users. The AWS-based architecture provides a dependable solution for the automatic identification of advertisement types. By leveraging various AWS services, the system ensures efficiency, precision, and scalability, ultimately enhancing marketing strategies and data management.

Keywords: Advertisement, Amazon web services, Automated system, Business, Marketing.

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1. Introduction

Businesses often encounter difficulties in accurately categorizing advertisements based on their content, which leads to inefficiencies in targeted marketing and data analysis [1]. An automated system is needed to detect the type of advertisement (e.g., food, beverage, clothing, etc.) from the submitted text. At present, it is difficult to detect the type of advertisement from print and digital media, which have been the major sources for marketing goods and products by companies and organizations, gaining significant attention from consumers who have unrestricted access to Internet sites (e.g., TikTok, Facebook, Instagram, LinkedIn, Google, Twitter, etc.) through which the advertisements reach them [2]. This development has boosted the confidence of several companies and organizations in using the Internet for advertising their goods and products, whereby the goods and products are posted on Internet (online) sites in replica of magazine advertisements [3].

One of the major challenges confronting healthy competitive marketing among companies and organizations is the lack of an advertisement detection method by which the smaller companies and organizations can study the marketing modus operandi of the larger companies and organizations [4]. The lack of competitive marketing encourages monopoly, leaving the buyers at the mercy of the seller, who may decide to charge them any price [5]. No company or organization reveals its marketing budget to its rivals for competitive reasons [6]. However, rival companies and organizations are not relenting in investigating the marketing modus operandi of their larger competitors for the growth and sustenance of their own business through improved marketing strategies [4]. They often use manual methods to carry out this advertisement investigation, which are intended for guessing the marketing modus operandi of their competitors. Moreover, the manual methods are labor-intensive and time-consuming due to the ever-increasing number of advertisements, making it difficult for manual processing of the images.

Therefore, an automated system is needed for the timely detection of the type of advertisement (e.g., food, beverage, clothing, etc.) from the submitted text. This paper aims to develop an automated system leveraging Amazon Web Services (AWS) to categorize advertisement types based on text input. The solution aims to boost marketing efficiency and strengthen data analysis capabilities. To achieve this, we utilize Amazon Simple Storage Service (S3), AWS Lambda, Amazon Comprehend, Amazon DynamoDB, Amazon CloudWatch, Amazon CloudFront, and AWS Web Application Firewall (AWS WAF). Moreover, we follow some procedural steps in executing the task by uploading the advertisement text to an S3 bucket, which triggers a Lambda function that forwards the text to Amazon Comprehend for analysis, and the results are stored in DynamoDB, from where the results notification is sent to the user. Magazine image datasets were employed as test datasets for this approach.

This work enables automatic advertisement categorization, enhanced marketing effectiveness, better data analysis and reporting functionality, an affordable solution using AWS services, and instant feedback for users. The AWS-based architecture provides a dependable solution for the automatic identification of advertisement types. By leveraging various AWS services, the system ensures efficiency, precision, and scalability, ultimately enhancing marketing strategies and data management. Recently, scientific research has reached a significant height by exploring hybrid models, integrating Convolutional Neural Networks (CNNs) with sequence modeling techniques such as AWS. CNNs were leveraged with these models for the extraction of spatial features. We employed CNNs in developing the automated system leveraging AWS due to the significant performance of CNNs in the following areas, namely computer vision [7-10], image processing [11-13], and object detection and tracking [14-18], to mention a few. Figure 1 shows the architecture for detecting advertisement types.

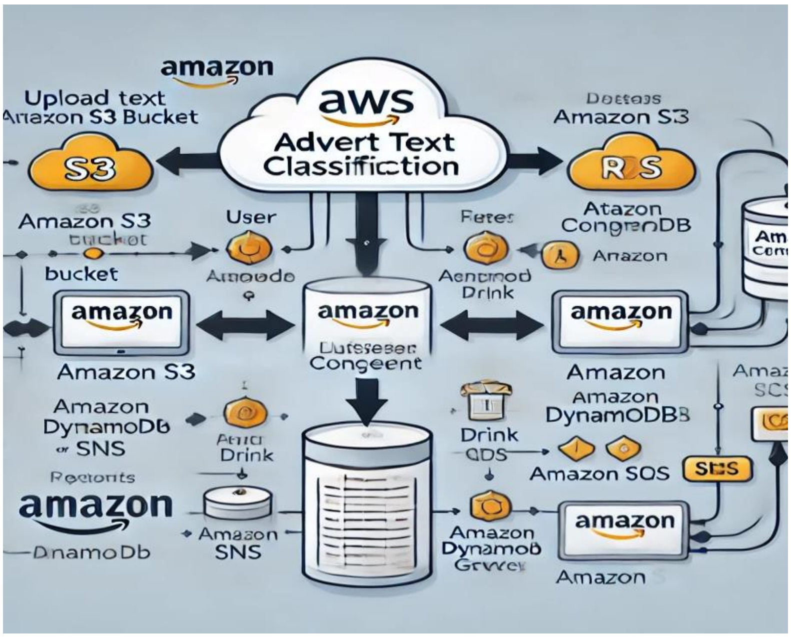

Figure 1.
Architecture for detecting advertisement types on AWS.

To the best of our knowledge, the work presented in this paper is the first of its kind in developing a scalable cloud architecture for detecting advertisement types based on text input. The contributions of this study are summarized as follows:

1. A novel cloud-based system that allows users to input texts, analyzes them to detect the type of advertisement, and returns the detected advertisement types to the user.
2. Users receive a type of advertisement detection result in real-time or near real-time with minimal processing delays.
3. The system is designed to be distributed and highly available, maintaining uptime even under heavy traffic conditions.
4. The architecture supports future enhancements, such as integrating additional advertisements or refining the model's accuracy.
5. The architecture can automatically scale in response to the number of users and the volume of uploaded advertisement types.

The paper is organized as follows: Section 2 presents the related work, which covers several methods for detecting advertisement types and non-advertisement types in social media, magazines, and newspapers. Section 3 presents the materials and methods for carrying out the experiment, including the architecture for detecting advertisement types with AWS leveraged with CNNs. The evaluation metric for validating the performance of the proposed approach and comparing it with other classifiers is also presented in this section. Section 4 presents the results. Section 5 concludes the paper.

2. Related Work

This section discusses the existing related works. It covers several methods for detecting advertisement types and non-advertisement types in social media, magazines, and newspapers. Lee, et al. [1] described the effect of content advertisements on social media and the engagement of those contents by customers using Facebook data. A total of 106,316 messages comprising 782 companies were cropped from Facebook and content-coded by combining Amazon Mechanical Turk (MTurk) and Natural Language Processing (NLP). The results obtained from the study implied that content engineering is profitable if combined with informative features that assist in obtaining instant leads with brand-personality-related content that aids in maintaining future attainment and social-media-driven branding. Bala and Verma [2], in their paper, offered their view on the trends in marketing using secondary data collected from literature and Internet sources based on happenings in the business world at the time to develop the content of the paper.

They opined that marketers and customers are all connected through WhatsApp, Facebook, etc., and new opportunities are being created for digital marketers to attract customers to their goods and services via the digital platform. According to them, having knowledge of what customers want is vital for a deeper understanding of what inspires users in content creation for a brand. Ahmed, et al. [3] undertook a study to assess the efficacy of online digital media-based advertising as a marketing tool for developing a sustainable brand. They investigated the influence of different online media channels, such as mobile phone marketing, search engine optimization, email marketing, social media marketing, and companies' websites on effective online digital media-based advertising. In addition, eight mediating variables and six moderating variables were introduced by researchers to examine the effect of exogenous and endogenous variables.

Their findings revealed results that have an unwavering impact, thereby demonstrating the positive and significant influence of the entire digital media advertising channels on the efficacy of online digital media that focuses on creating a sustainable brand. Ouji, et al. [19] presented a method for advertisement detection in a digital-based press with the aim of detecting and identifying advertisements. They introduced a robust color segmentation-based approach for controlling noise in digitization tasks. Moreover, the output from the color separation is used for visual feature computation and carrying out segmentation of layouts in pages of documents. They also presented block classification results from different pages of newspapers and magazines. Chu and Chang [20] examined the roles played by advertisements in society by analyzing the relationship between advertisements and marketing. They proposed a system for advertisement detection, segmentation, and classification from images collected from newspapers and websites to enable advertisement research.

They employed the connected components method for detecting advertisement candidates and removed non-advertisement candidates by designing rule- and learning-based filters. From the remaining advertisement candidates, visual features were extracted, and classifiers were constructed for their classification into predefined categories of advertisement. They uncovered several motivating values derived from the front pages of newspapers and magazines based on the categories of advertisements published over the years. Jiang, et al. [21] offered real-world perceptions on the approach for optimizing bag-of-visual words (BoW) performance by selecting the right representation choices. They elaborated on a soft-weighting method for assessing the significance of visual words to an image. Their experiment revealed soft-weighting as the best-performing method compared to other common weighting schemes like TF-IDF. Moreover, they also performed experiments with TRECVID datasets, from which there was an indication that BoW features alone, with the right choices of representation, already produced very competitive performance in concept detection.

Based on their empirical findings, they additionally applied their method for the detection of a dataset containing 374 semantic concepts. They released detectors, features, and detection scores to the multimedia community on several benchmark datasets. Aragües Peleato, et al. [22] presented a procedure for classifying text that was developed in the context of a project on information extraction. Based on the prototype created for the project, they processed newspaper advertisements using three main modules: (1) a classification module for associating advertisement categories, (2) a tagging module for identifying textual information units that have any relationship with the associated category, and (3) a predefined form filled with the tagged text in that category. They combined the results of classification probabilities and filling scores to generate the final classification decision. They described and evaluated the mixed classification method based on concrete experiments conducted with real data. Their findings revealed poor performance of any classification solution that depends solely on information extraction unless it is employed as a complement to the statistical approach.

3. Materials and Methods

The system proposed in this paper is developed by employing the services of AWS in terms of their applications and functions leveraged with CNNs, which significantly enable the detection of advertisement types from the submitted text with a system that notifies the users of their request status. Moreover, the experiment of the study was carried out by employing images from magazine advertisements.

3.1. Dataset

We employed South African magazines as the image dataset, such as Family magazines (Huisgenoot magazine), Business magazines (Finweek magazine and Acumen magazine), and Lifestyle magazines (Fairlady magazine, True Love magazine, and Bona magazine), as shown in Figure 2. We collected a dataset of 3,527 advertisements and non-advertisements from the magazines. A total of 3,021 images were classified as advertisements, and 506 images were classified as non-advertisements. The dataset was divided into a training dataset (80%) and a testing dataset (20%) for the proposed model training and testing. A total of 2,417 advertisement images were used for model training, and 604 advertisement images were used for model testing. Additionally, 405 non-advertising images were used for model training, and 101 non-advertising images were used for model testing. The raw images collected from the magazines were of different sizes, necessitating trimming them to equal dimensions of 100×100 pixels in width and height resolution before converting them to grayscale images for optimal computation and model training. Table 1 shows the detailed attributes of the dataset.

Table 1.
Advertisements dataset information.

Dataset	Adverts	Non-Adverts	Total Number
Training dataset (80%)	2417	405	2822
Testing dataset (20%)	604	101	705
Total dataset	3021	506	3527

Figure 2.
Sample advertisement and non-advertisement images of Family magazines (Huisgenoot magazine), Business magazines (Finweek magazine, and Acumen magazine), and Lifestyle magazines (Fairlady magazine, True love magazine, and Bona magazine).

3.2. Approach for Implementation

We employed CNNs for the extraction of advertisement features from the images of the magazines (Figure 2), which serve as text input for the AWS system, as illustrated in Figure 3. In Figure 2, the classification of the advertisements is a Herculean task due to the lack of rich visual features. We addressed this by employing three layers of CNNs, namely the convolution layer, pooling layer, and the fully connected (FC) layer. Table 2 shows the AWS services that were utilized to leverage the CNNs, which were used for feature extraction and classification.

Table 2.
AWS services utilized for detection of advertisement types.

AWS Services Utilized	Applications/Functions
Amazon S3	Storage solution for uploaded text
AWS Lambda	Serverless computing service for processing tasks
Amazon Comprehend	Tool for NLP and text analysis
Amazon DynamoDB	NoSQL database for storing results of the analysis
Amazon CloudWatch	Service for monitoring and logging
Amazon CloudFront	Content delivery network (Optional for the frontend)
AWS WAF	Web Application Firewall for improved security

The layer for feature extraction typically comprises a convolutional layer plus a rectified linear unit (ReLU) activation and a max-pooling layer [23, 24], which combine to extract meaningful features from input data, such as an image, by identifying patterns and reducing dimensionality. We employed filters, such as edge detectors, to perform the convolution process, whereby low-level edge features were extracted by convoluting the input with its corresponding filter for feature representation learning [25]. The convolutional layer was implemented using Equation 1.

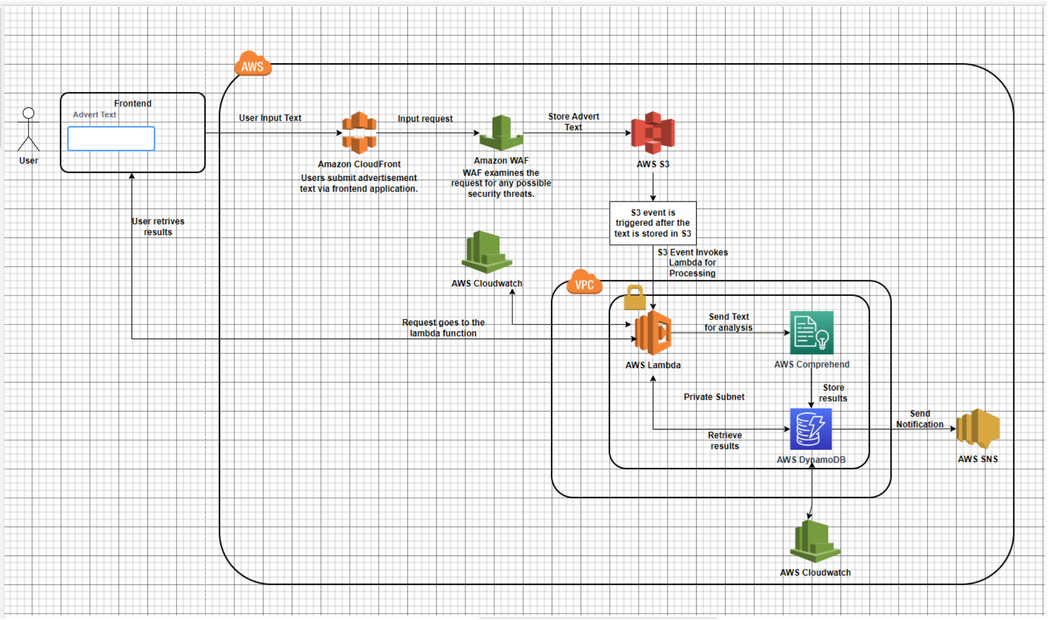

Figure 3.
Framework for detecting advertisement types on AWS.

$$Z_{ij} = \sum_{c=1}^{C}\sum_{k=-s}^{s} \sum_{l=-s}^{s} w_{klc} * x_{i+k, j+l, c} + b \qquad (1)$$

where "z_{ij}" denotes the output at position (i, j), "w_{klc}" denotes the weight at position (k, l) of filter "c", "$x_{i+k, j+l, c}$" denotes the input value at position (i+k, j+l) in channel "c", "b" denotes the bias term, "C" denotes the number of input channels, "s" denotes the filter size (half the kernel size on each side), and "*" denotes the convolution operation.

Equation 1 has some key points, which are (1) Summation over channels; this implies that the convolution is executed across all input channels by summing the element-wise multiplication of the filter weights with the corresponding input channel values, (2) Filter sliding; this implies that the filter slides across the input feature map, computing a weighted sum at each position, and (3) Bias term; this implies that each filter has a single bias value that is added to the weighted sum. The ReLU activation function was used in this work due to the following reasons: (1) The negative pixels were removed from the convolution process output using the ReLU activation function, (2) Complex patterns and relationships in data are learned by neural networks using the ReLU function, (3) ReLU only activates some neurons, making it computationally efficient, and (4) The issue of vanishing gradients is solved by ReLU. While Equation 2 expresses the ReLU activation function, Equation 3 expresses the max-pooling process. The above reasons for using ReLU were also established in [26, 27].

$$z = max\ (0, y) \qquad (2)$$

where y denotes the output of convolution process.

$$h = max\ (z) \qquad (3)$$

where z denotes convolutional layer output.

CNNs can be implemented by employing a simple approach using Numpy for carrying out feed-forward operations and back-propagation operations [28]. Low-level features were extracted using one convolutional layer with four filters. Additionally, we employed Keras [29], a Python-based high-level neural network API, to compare our proposed model with other classification models such as Support Vector Machines (SVM) [30], Multilayer Perceptron (MLP) [31], and Random Forest (RF) [32]. Several classifiers trained on labeled images for classification tasks include SVM, MLP, RF, Gaussian

Mixture Model (GMM), Hidden Markov Model (HMM), and K-Nearest Neighbors (k-NN). These classifiers are primarily applied to solve problems related to classification, such as the identification of advertisement types. Table 3 shows the procedural steps of the cloud-based approach for detecting advertisement types.

Table 3.
Procedural steps of the cloud-based approach for detecting advertisement types.

Steps	Procedure
Step 1	Create a secure virtual private cloud (VPC) to hold all application resources.
Step 2	To filter and safeguard requests, use a Web Application Firewall (WAF).
Step 3	Put API Gateway into place to provide regulated access to the application's API.
Step 4	Process and oversee advert text operations with Lambda functions.
Step 5	Use VPC Endpoint to store input and output advert text in S3 buckets for private access.
Step 6	Configure an SNS to inform users of the progress and completion of their requests.

In this paper, we employed AWS services to leverage CNNs in accomplishing the experiment for classifying advertisement types due to a lack of automated operations in existing applications and inaccurate categorization of advertisements based on their content, which leads to inefficiencies in targeted marketing and data analysis. Table 4 shows the architecture workflow for detecting the advertisement types.

Table 4.
Architecture workflow for detecting advertisement types.

Action	Workflow
User request flow	The user uses the frontend to input the CNNs extracted advert text.
	After passing security tests by WAF, the request is sent to the API Gateway. Lambda is triggered by the API Gateway to upload advert text to S3 in distinct directories.
Processing flow	Using texts from S3, Lambda calls a machine learning model to classify advert types.
	The classified result is kept in an S3 bucket called "Results bucket".
Notification flow	Lambda notifies SNS of its status following processing.
	Results are sent by SNS to the user's front-end endpoint.

We used cross-entropy as the objective function to calculate the sigmoid cross-entropy between the predicted advertisement class and the actual advertisement class.

3.3. Evaluation Metric

In this paper, we evaluated our proposed model and compared it with others using the following evaluation metrics: Equation 4 for precision (P), Equation 5 for recall (R), Equation 6 for F1-score, and Equation 7 for accuracy.

The overall accuracy is computed as follows:

$$P = \frac{True\ positive}{True\ positive + False\ positive} \tag{4}$$

$$R = \frac{True\ positive}{True\ positive + False\ negative} \tag{5}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

$$Accuracy = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{TP + TN}{TP + TN + FP + FN}\right)_i \tag{7}$$

Where TP denotes correctly identified advertisement texts as advertisements, and TN denotes correctly identified non-advertisement texts as non-advertisements, the precision and recall evaluation metrics are employed for evaluating the model's prediction accuracy.

4. Results

We compared the results of our proposed approach with the results of SVM, MLP, and RF based on Equations (4-7) and presented the results in Figure 4, which clearly shows the performance accuracy of our approach over these classifiers. With these results, it is evident that our proposed approach based on AWS services, leveraged with CNNs, has the capacity to classify advertisement types based on text input.

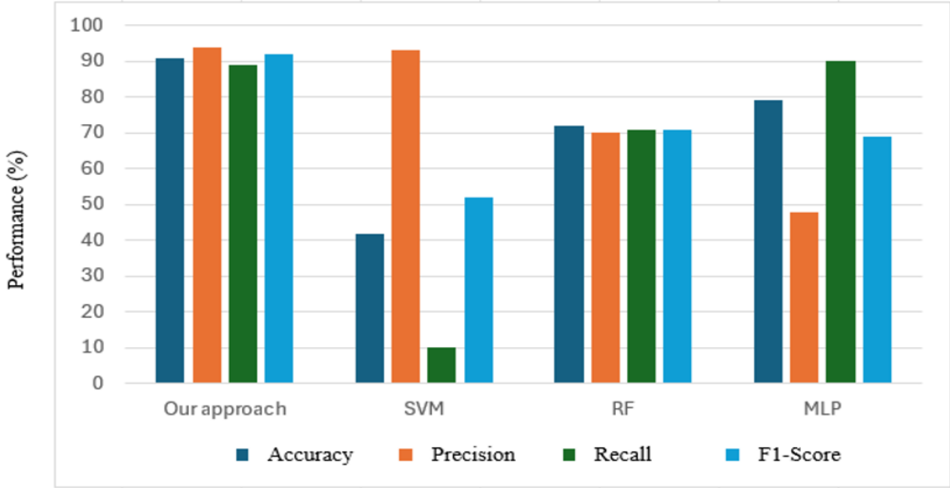

Figure 4.
Comparative results of advertisements classifiers.

Figure 4 shows the performance of our proposed approach and its comparison with other individual classifiers. For example, in terms of accuracy, our approach achieved 91% accuracy, SVM achieved 42% accuracy, RF achieved 72% accuracy, and MLP achieved 79% accuracy. In terms of precision, our approach achieved 94% precision, SVM achieved 93% precision, RF achieved 70% precision, and MLP achieved 48% precision. In terms of recall, our approach achieved 89% recall, SVM achieved 10% recall, RF achieved 71% recall, and MLP achieved 90% recall. In terms of F1-Score, our approach achieved 92% F1-Score, SVM achieved 52% F1-Score, RF achieved 71% F1-Score, and MLP achieved 69% F1-Score.

5. Conclusion

The work presented in the paper aims to develop an automated system leveraging AWS to categorize advertisement types based on text input. We employed CNNs in developing the automated system due to the significant performance of CNNs leveraging AWS. The solution aims to boost marketing efficiency and strengthen data analysis capabilities. To achieve this, we utilized S3, AWS Lambda, Amazon Comprehend, Amazon DynamoDB, Amazon CloudWatch, Amazon CloudFront, and AWS WAF. We employed South African magazines as the image dataset, such as Family magazines (Huisgenoot magazine), Business magazines (Finweek magazine and Acumen magazine), and Lifestyle magazines (Fairlady magazine, True Love magazine, and Bona magazine) for training and testing the proposed system. The experiment produced an effective solution with 91% accuracy. This work enables automatic advertisement categorization, enhanced marketing effectiveness, better data analysis and reporting functionality, an affordable solution using AWS services, and instant feedback for users. Our future work includes detecting advertisement content through a cloud-driven approach.

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