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Densenet121-DNN-Based Hybrid Approach for Advertisement Classification and User Identification

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Abstract: Online advertisement plays an important role in human society and is used to influence customers to buy a product or service. But these advertisements are not user-preferred. Sometimes unwanted and malware advertisements appear on the page and make them uncomfortable. Therefore, advertisement classification and displaying the user-preferred advertisement is an important concept in the modern era. For this, in this paper, a hybrid deep learning-based framework is implemented for advertisement classification and user-preferred advertisement. Initially, the Densenet-121-based system is implemented. To extract the features like texts and objects from the input advertisement image, Densenet-121's convolution and pooling layers are used, and then average pooling and softmax layers of Densenet-121 are used for classifying the advertisement into four categories such as automobiles, clothes, foods, and cosmetics. Then, the DNN (deep neural network) technique is implemented to recommend the advertisement based on user preference. Gather the information of the user from user profiles and then process the collected data, if the information is matched with any advertisement then it will show the advertisement as recommended to the user. To evaluate the performance of the proposed approach manually collected data will be used with the accuracy, F1-score, recall, and precision metrics. The proposed models achieve a high accuracy of 99.93%. Furthermore, the outcomes show good precision for various advertisement categories.

Keywords: Advertisement, Deep learning, Densenet-121, Deep neural network, Online advertisement, Recommend advertisement.

1. Introduction

Nowadays, online advertising has experienced significant business growth. The most noteworthy examples of online advertising platforms are Internet portal websites like Yahoo! and MSN, which draw in millions of people and produce millions of page views each day, giving advertisers unbeatable possibilities to promote a variety of products and brands. Search engines like Google, have a large user base and produce both organic search results (ranked relevant online articles) and sponsored search results in the meantime (paid relevant advertisements) [1]. Content advertising is a different kind of advertising. A user will see some dynamic, related advertisements while surfing a website depending on the content of the page. Unquestionably, the introduction of the Internet and the Web has given marketers new chances to reach billions of humans almost effortlessly. Online advertising is not simply pervasive. A one-size-fits-all strategy was used in the early days of the Web when ads were provided directly by the publishers [2, 3]. However, Internet advertising has also gotten more customized as a result of the simplicity with which Web users may be followed across their website visits.

In a Content Ad system, the common process of the advertisement's delivery is rough as follows [4]. The URL of a page is delivered to the advertising network server when it is accessed by a user, where it

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Figure. 1 Example Online Advertisement

is scanned and processed. The page's dominant words or phrases will be taken out and used to discover suitable ads in the database. The user's current webpage will receive these relevant Ads that have been sent back [5]. The visitor probably didn't notice that all of these operations can be completed in a fraction of a second. The accompanying image shows a page from the MSN Tech & Gadgets domain.

Many web organizations that previously relied on a subscriber income model are switching to a commercial revenue model or a hybrid commercial and subscriber revenue model, which helps to explain a portion of this growth. Commercial models produce income from the sale of website ad space, whereas subscriber models only receive income from consumers who pay membership fees and can reach the website content [6]. In recent years, several businesses have discovered the latter to be more valuable. For instance, the online journal Slate.com first relied only on subscriber fees to sustain its operations until switching to a commercial economic model as subscriptions proved to be unprofitable. Every day, producers of banner advertising struggle with the challenge of arranging ads for their clients [7]. Online ad publishers' capacity to maximize profits can be significantly impacted by a well-designed mathematical scheduling model and a sound solution approach. An Example web advertisement is shown in Fig. 1 below.

Nowadays, there is a lot of interest in internet advertising by 2022, the total amount invested globally will have increased significantly to 781 billion dollars. The key question is whether the effects are worth the costs [8]. According to standard online advertisements, user behavior, communication effects (such as users' attitudes toward brands), and processing stage (such as attentional or mnemonic effects) can all be used to assess the success of online commercials (e.g., click rates). Banner blindness is a term used to describe the phenomena wherein web users have evolved to partially avoid glancing at online adverts on web pages [9]. As a result, "ads are more likely to be intellectually avoided because they are an automated, unconscious process that happens in conjunction with web activity and do not involve any behavioral action by the user".

There is a continuous discussion about how much internet users truly avoid advertisements. This outcome has occasionally been reached via oblique methods like user self-reports or memory tests. The emphasis on advertising has switched in the Internet era from conventional media like newspapers, television, and radio to new "online" outlets like electronic mail and web advertising. The importance of the Internet as a useful instrument for implementing direct marketing has only recently come to the attention of marketers. However, advertisers have only just started to think about exploiting the Internet's technical capabilities to more precisely target consumers for personal selling. Customer profiling has been adopted by some of the most prosperous businesses like Flycast, DoubleClick, and AdSmart, to enhance personal advertising strategies over the Internet. This is being accomplished via state-of-the-art web interconnection technologies [10]. Online advertisements have some problems. Sensitive content recognition was one of the issues addressed, allowing unwanted content to be eliminated even if it only appears on a small portion of the web page. Opinion mining from review sites was another issue addressed to identify and prevent bad sentiments about items. To overcome these issues, we propose an advertisement image classification method that can be used to determine when an online advertisement is being displayed. In this paper, we proposed methods for the classification of online advertisements and also provide recommendations for advertisements by user interest. This paper proposes hybrid deep-learning techniques for classification and recommendation purposes. Initially, propose a DenseNet-121 technique to classify the advertisement by their category. So, utilizes convolution and pooling layers of DenseNet-121 are used for extracting the features like texts and objects from the input ad image, then classifying the advertisement using by average pooling layer and softmax layer of DenseNet-121. Increased information flow and gradients, which reduces

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training time, are one of DenseNet-121's advantages. Secondly, using a deep neural network technique for the recommendation of advertisements based on user preference. Here not a standard dataset for access to online advertisements, so collect images from web sources (https://in.pinterest.com/) and process them. This proposed method provides higher classification accuracy compared to other existing techniques. The key contribution of this paper is,

- This paper proposes a framework for analyzing advertisements in website images. Initially, extract the advertisement texts and objects from the input advertisement image and then classify advertisements based on features by using the DenseNet-121 technique.
- After that, a Deep Neural Network (DNN) technique is proposed to recommend advertisements based on user preference and also show statistics of advertisement classification results, and recommend some user's interest advertisements.

The remainder of this paper is structured as follows. The related research on deep learning-based advertisement classification and recommendation systems is covered in section 2. The problem statement is described in section 3. The proposed methodology and its components are explained in section 4. The experimental strategy is described in section 5. The study is reviewed in section 6 along with suggestions for additional research.

2. Literature survey

This section mentions papers, analyzed advertisement classification, and recommendations. There are very few papers to study online advertisements and recommend advertisements by user preferences. So here some of the papers are given below. Reviews of earlier research are vital for understanding the issue, as are the methods used to find the uncharted territory in the subject of study being examined. In this context, the present study has reviewed a few of the pertinent papers. Marketers have come to understand that social media sites are useful for connecting with customers and promoting products and services. Social media advertising is revolutionizing the advertising industry. On a wide scale, marketers use social media to advertise their products and disseminate information about their items' sales. The collection of papers that are useful for researching this topic is therefore provided below.

To determine whether a creative contains sensitive content, Austin et al. [11] suggested a deep learning model that blends picture attributes with data from the landing page. The method has been successfully put into service and is performing with accuracy comparable to the human on a significant portion of creative works while also making lower error rates on works that include very sensitive information. Even though this project has been highly successful, they have only fully utilized around half of the automation options.

The efficiency of GTB for the detection and classification of fraudulent publishers was suggested by Sisodia [12] using data from an online advertising user click dataset (FDMA, 2012 dataset). Eleven more individuals and ensemble classification techniques are used to compare its effectiveness. For a dataset with a strongly skewed class distribution, significant improvements were made compared to state-of-the-art machine learning techniques.

In real-world situations, the number of ineffective online ads is almost always higher than the number of effective ones. The evaluation models will be warped due to their uneven distribution. To address the data imbalance, Wang & Lin [13] suggested an enhanced under-sampling technique based on clustering (referred to as UBOC). It can make a more suitable data distribution by balancing the advertising data.

Kim et al. [14] suggested a recommender system that uses a convolutional neural network (CNN) to analyze a user's facial expressions to predict how they will think about the advertising video they are presently watching. They also created a scale-invariant feature transform (SIFT), an algorithm-based similarity model, to search for users with similar preferences in real-time and recommend new advertising videos to users. They use eleven food advertising videos to analyze the effectiveness of three distinct recommendation approaches a random system, an average rating-based (best-selling) system, and a standard CF-based system as benchmark systems to assess the suggested technique.

A technique for recommending advertisements for microblogs was suggested by Simsek & Karagoz [15]. The suggested method creates a user model by using the entire message's content, text, captions, site links, and hashtags along with sentiment data and follower interaction addressed as microblog posts. Wikipedia pages are utilized as basic background information for combining advertisement contents and user profiles, which is another innovative feature. The most significant advertisement for the user is selected based on how closely user profile vectors and advertisement vectors resemble one another.

Table 1. Literature review

Reference	Year	Model	Benefits	Difficulties
Austin et al. [11]	2020	Xception	It shares the same amount of model parameters as Inception, suggesting improved computing efficiency.	Implementing and training might be challenging.
Sisodia [12]	2021	Gradient Tree Boosting (GTB)	Generally more accurate compared to other modes. And train more quickly, especially with bigger datasets.	In particular, models trained on CPUs can be computationally expensive and time-consuming. And Final models are challenging to interpret.
Wang & Lin [13]	2020	Enhanced UBOC	Reduced sampling costs and shorter sampling times	Choosing a representative sample is difficult because sampling units can be changed.
Kim et al. [14]	2021	SIFT	It can provide a significant number of features that are densely packed over the entire spectrum of scales and locations.	It still takes a long time and is inefficient for low-powered devices.

To overcome the issues, we propose a DenseNet-121 technique: Increased information flow and gradients, which reduces training time, are one of DenseNet-121's advantage. Deep supervision that trains deep architectures is produced by each layer having access to both the loss function and the original input.

3. Problem statement

All the above-suggested papers face some challenges. They are,

- Need to influence the ad click concealed in historical data to improve recommendation accuracy.
- Removing non-advertisements before classifying the advertisement images into several groups.
- The size of the advertisement dataset must be expanded.
- Need to enhance the recommendation accuracy of ad clicks hidden in the historical data.

4. Proposed methodology

Nowadays, the topic of online advertisement is expanding. But there are few papers to study online advertisement and advertisement recommendation systems. To provide novelty for this paper, here combine both of these domains, and this is the first paper that classifies advertisement and recommends the advertisement based on user preference together in one. This paper proposed a new ensemble technique that is DenseNet-121, which extracts the features like text and objects from the input web advertisement image using convolution and pooling layers of dense net-121 and then uses these features to classify advertisements based on the data analysis using the average pool and softmax layers. Then, the advertisement can be classified into four categories as automobiles, clothes, foods, and cosmetics. Then recommendation system is performed.

Secondly, proposes deep neural network (DNN) that recommends advertisements based on user preferences. It is collect the data or information like entertainment, education, search history, etc., from the user profile and then matches the information with collected advertisement data from our dataset if the information matches with any of the advertisement files, then recommend the advertisement based on the user. All of this process is displayed clearly in the above-proposed architecture in Fig. 2.

4.1 DenseNet-121

A convolutional neural network called DenseNet connects every layer to the other layer underneath it. In convolutional neural networks, a Dense Block is a module that directly connects all layers with

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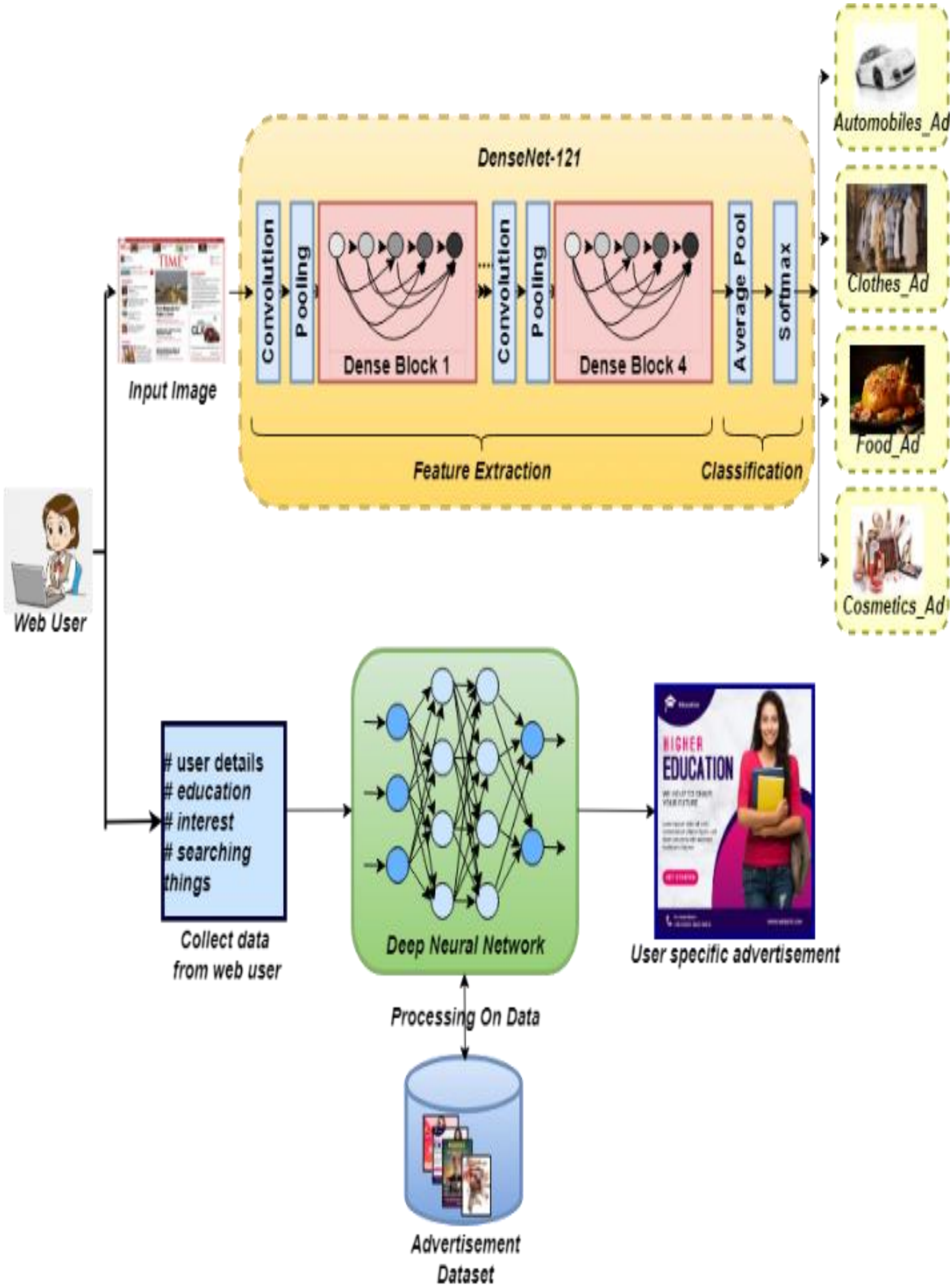

Figure. 2 An architecture of the proposed system

corresponding feature-map sizes. This paper proposed the DenseNet-121 technique to extract the feature and classification of advertisements based on category. The DenseNet-121 model has more layers, here convolution and pooling layers are used for extracting the features like texts and objects from the input ad image, and then based on the extracted features, the classification process is done. Here, the given input advertisement is classified into four ways such as clothes, automobiles, cosmetics, and foods by using the average pooling layer and softmax layer.

Use a dense connection technique, where each layer is interconnected to every other layer and to every layer before it on the channel dimension, to accomplish feature extraction as the input for the following layer [15]. By using fewer interactions between the layers, the DenseNet design goal is to make deep learning networks far more profound while also making them easier to create. In the convolutional neural network known as DenseNet, each layer is linked to any non-subsequent layers which are deeper in the organization. This is done to enable the maximum data stream possible between organizational layers. Each layer collects inputs from all previous layers and provides its component guidance to all layers that will follow it to preserve the feedforward character of the system. The "i^{th}" layer has "I" information sources and includes highlight guides for all of its initial convolutional blocks. All of the subsequent "I-I" levels are given their element maps. As opposed to the straightforward "I" linkages found in conventional profound learning models, this presents '$(I * (I + 1))/2$' connections in the organization. As a result, it uses fewer boundaries than conventional convolutional neural organizations because learning trivial element maps is not necessary.

In addition to the crucial convolutional and pooling layers, DenseNet also has two important components. The layers are known as transition and dense blocks. The channel's elements are expanded when the number of filters varies between dense blocks [16]. The generalization of the l^{th} the layer is aided by the development rate (k). It regulates how much data is added to every layer. It's essentially the number of channels that a dense block outputs to put it simply. This indicates the number of characteristics, that a dense layer (l) receives from the dense layer that came before it (l-1) is k[l]. This is known as the growth rate because k[l] channel features are synthesized and provided as input to the following layer after each layer. The two convolutional processes that make up a dense layer are 1 x 1 CONV (the standard convolution operation for feature extraction) and 3 x 3 CONV (for decreasing the feature depth/channel count). Six of these thick layers make up the DenseNet-121's dense block. The dense block and dense layer are illustrated in the following Fig. 3. Each dense block's output has a depth that is equal to its rate of expansion.

A basic convolution and pooling layer serve as the foundation of DenseNet. A dense block layer is then occurred by a progress layer, a change layer, another dense block layer, and finally, average pooling is followed by a classification layer. Two convolutions, with estimated parts of 1x1 and 3x3, are present for each dense block [17]. This is reiterated many times in dense block 1, numerous times in dense block 2, 24 times in dense block 3, and finally 16 times in dense block 4. Each thick layer is composed of two convolutions: a traditional convolution for extracting the features 1x1 and a 3x3 convolution for reducing the feature depth/channel count. The total number of feature maps equals Input features after each dense block (number of dense layers x growth rate).

A transition block or transition layer is put between two dense blocks to reduce the number of channels. The transition layer in Fig. 4 is made up of

CONV operation 1 x 1

AVG pooling process 2 × 2

The number of channels is cut in half by the 1 x 1 CONV procedure.

The height and width of the features are down-sampled using the 2 x 2 AVG pooling layer.

Fig. 3 demonstrates the structure of DenseNet-121. A total of 7.3125621 million parameters have been examined by the neural network model for image classification which 7.226353 million are trainable and the remaining 86,208 are not. The model is programmed to use around 75% of the images under each label for training and approximately 25% of the images for validation.

A DenseNet structure with four dense blocks is shown in Fig. 4. Because the feature map size in each dense block is uniform, there won't be a size issue during combination, this is why the DenseNet has been divided into numerous dense blocks. Transition layers adjust the feature map size through pooling and convolution between two neighboring blocks. After classifying the advertisement, we propose a method to recommend the advertisement based on user interests.

4.2 Recommendations of advertisement based on user interest

This model will save the advertiser in this paper both money and time. The creation of a system that

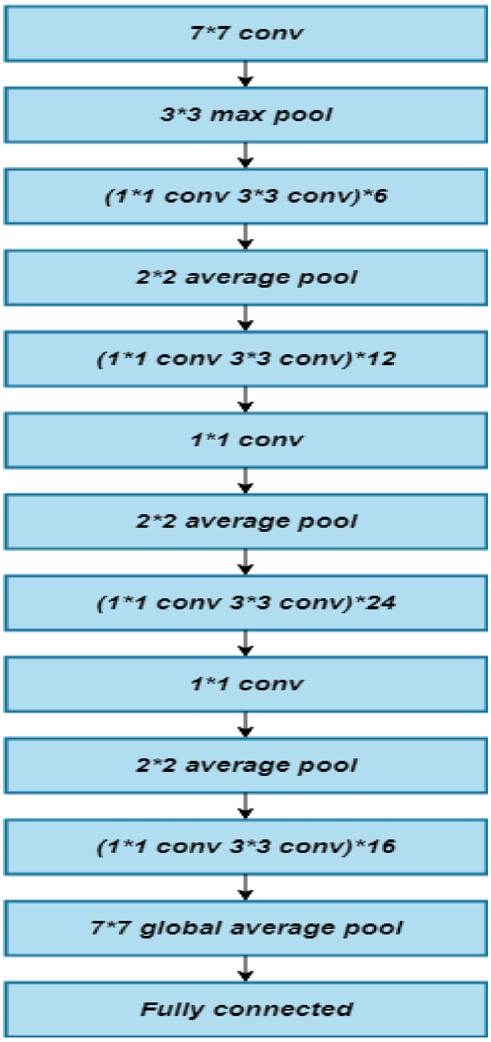

Figure. 3 The structure of DenseNet-121

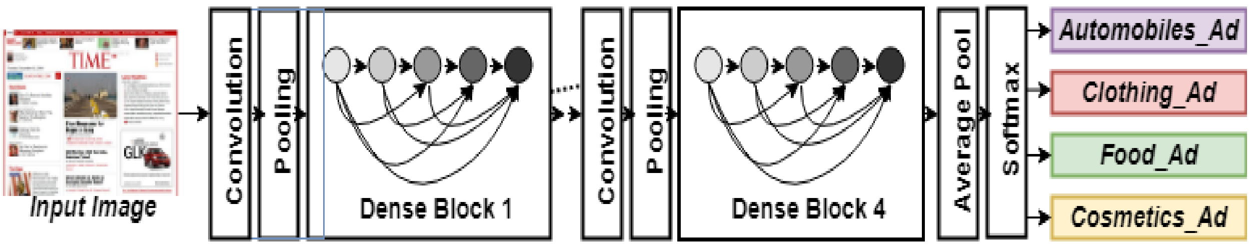

Figure. 4 DenseNet-121 for advertisement classification.

finds the right customer is discussed in the section that follows. A block for collecting and parsing data that pulls user information from social networking sites. Because this information will be obtained from the user account on a social media site, an advertisement will be displayed on the user profile utilizing the information obtained from the user. Data processing is found in another block, where the user data that was earlier obtained will be sorted. When a product is connected to a certain area of education, the user will look up that information in the user's profile. The user account will see the advertisement if they provide the necessary details. The deep neural network (DNN) method is used to find the appropriate advertisement. The deep neural network (DNN) approach determines whether the data matches the user account. Our dataset contains advertising information. To evaluate the needs of the marketer and the user information, the technique includes terms like "education," "gadgets," "entertainment," etc.

i. Deep neural network (DNN)

Deep neural networks are made up of many neuron layers linked in succession. A mathematical function called a neuron accepts one or more values as input, executes a nonlinear operation on the weighted sum of those values, and outputs a single result. Layer-by-layer network processing enables complex input-output connections to be fitted as well as the capturing of data features with higher levels of abstraction from lower-level aspects. Here using the deep neural network technique takes input as collected user details and then matches the advertisement with the user's information with our dataset, if it is matched then provide the output as a recommended advertisement to the user.

The DNN method in Fig. 5, uses advertisement properties of user's information as inputs. Our model states that the advertisement information of users is combined with the input vector x_0 in the input layer, so for any record R_{ij}, it is obtained as below in Eq. (1).

$$x_0 = concatenate\ (U_i, V_j) \quad (1)$$

Where two vectors are combined using the concatenate () method. The outcome of the initial hidden layer is determined by the given equation when x_0 travels through it:

$$x_1 = activation\ (W_1 x_0 + b_1) \quad (2)$$

Where W_1 is the weight matrix, b_1 is the bias vector between the first input layer and the hidden layer, and activation () denotes the activation operation, which is intended to make the multilayer neural networks and neural network method nonlinear meaningful [18]. The ReLU (Rectifies Linear Units), sigmoid, and tanh functions are some of the activation functions used in the deep neural network model. ReLU is the activation method employed for this model in this paper because it is more efficient and simpler to improve. Equation and the previous explanation allow us to derive the output at the l^{th} hidden layer as follows:

$$x_l = ReLU\ (W_l x_{l-1} + b_l) \quad (3)$$

Our training objective for the output layer is to forecast the user's rating score R_{ij}. To obtain the supervised value $y = OneHot(R_{ij})$, we utilize the One-Hot encoding method once more. As a result, we must convert the output using the softmax layer to collect the prediction value for the correct location of y, that is,

$$\hat{y} = softmax(W_{out} x_h + b_{out}) \quad (4)$$

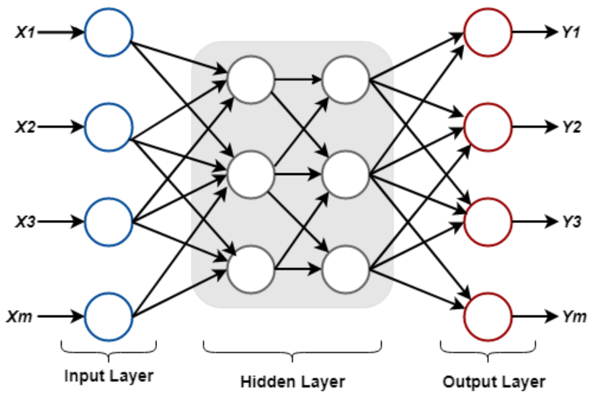

Figure. 5 Example of deep neural network (DNN)

Table 2. Notations list

Notations	Meaning
x_0	Input Vector
R_{ij}	Rating Score
W_1	Weight Matrix
b_1	Bias Vector
h	Hidden Layers
x_h	Result Of The Final Hidden Layer
$\hat{y}$	Forecast Result
W_{out}	Weight Of The Output Layer

Where h stands for how many hidden layers there are, x_h is the result of the final hidden layer, and W_{out} and W_{out} stand for the bias and weight of the outcome layer, respectively [19, 20]. Finally, we assess the variance between the forecast result $\hat{y}$ and the supervised value y using the cross entropy approach:

$$\varepsilon = -\sum_{i=1}^{d}(y_i \ln(\hat{y}_i) + (1 - y_i)\ln(1 - \hat{y}_i)) \quad (5)$$

Where d stands for the vector y's dimension, which corresponds to the number of neurons in the outcome layer. The following equation describes how our model can predict the i^{th} user's rating score on the j^{th} item:

$$\hat{R}_{ij} = arg_k \max\ (\hat{y}_k) \quad (6)$$

Multi-layer perceptron (MLP) is another name for deep neural networks.

The hidden layer transforms the input feature vectors before passing them on to the output layer, where they ultimately provide the recommendation.

5. Results and discussions

In the first part of this section, here compare our approach to state-of-the-art methods by classifying advertisements using our dataset's analysis and our

Table 3. Comparison of accuracy with existing techniques

Methods	Accuracy
Xception [11]	99.82%
GTB [12]	92.06%
Enhanced UBOC [13]	95.02%
SIFT [14]	98.34%
Proposed	99.93%

method for extracting advertisement attributes. The sub-sections that follow, give the assessment results based on experimental data to evaluate our methodology.

5.1 Experimental dataset

Because there isn't a standard data set of internet advertisements, so developed our dataset using Google Images and other web advertisements that were available for free download at the time the data was collected. A 4400 image balanced dataset is produced, with 1100 photos placed in each of the following four categories:

(1) Automobile
(2) Clothing
(3) Food
(4) Cosmetic

The dataset for advertisements (4400) is split into a training data set (3520, i.e. 80%) and a test data set (880, i.e. 20%). Training data use (2816 of training data, i.e. 80%) and validation data usage are further separated from the training data set (704 of training data, i.e. 20%).

5.2 Evaluation metrics

The most efficient methods for categorizing ads and recommending ads based on user preferences. To measure overlap, one uses the intersection over union, which determines the relationship between classification union and intersection. A perfect alignment of the advertising is 1, while a perfect disjoint alignment is 0. If a classification exceeds the ground truth by at least 0.3, it is deemed to be an accurate forecast. Typically, an overlap of 0.5 or more is required for the classification of advertisements. However, because some of these objects can be quite small, it was decided to be a little cleaner here. In terms of performance measures, looked at the proposed method's Accuracy (A), Precision (P), F1-score (F), and Recall (R). These metrics indicate:

5.2.1 Accuracy

The accuracy measure is computed to identify the correctness of advertisement classification.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

5.2.2 Precision

Precision is defined as the ratio of precisely anticipated positive occurrences to all anticipated positive observations. Precision is the capacity to do the following things:

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

5.2.3 Recall

The true positive rate (TPR) and Sensitivity are both terms for the recall. The recall score reflects the classifier's ability to locate all positive samples. It's the total of TP and FN divided by TP. It can be described in the following terms:

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

5.2.4 F-Measure

F-Measure determines the harmonic mean of recall and precision.

$$F1\ Score = 2 \times \frac{precision \times recall}{precision+recall} \tag{10}$$

5.3 Performance metrics

Comparing the proposed with other existing techniques in experimental performance, the proposed methodology has the highest classification accuracy. Table 1 shows the results for Xception [11], GTB [12], Enhanced UBOC [13], SIFT [14], and the proposed methods on the advertisement images from our collected data in terms of accuracy. The advertisements are classified into four categories. That are clothing, food, automobiles, and cosmetics, it is compatible with experimental results. The data demonstrate that the network model is rather accurate. The results show that the proposed technique performs well in our dataset. Our results based on accuracy are presented in Table 3. These experiments improved our classification results and performances. Our experiment improves classification accuracy with less computation time.

A comparison accuracy of the existing method with the proposed technique is demonstrated in Fig. 6 below.

The test results for the various classes offered by our system are in Table 4. It is consistent with the experimental findings for the four categories of

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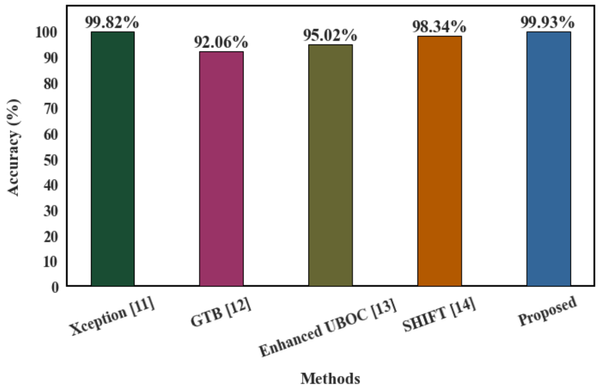

Figure. 6 An accuracy comparison with proposed and existing methods

Table 4. Test results from classification.

Category	Precision	Recall	F1-score	Support
Automobile	66%	54%	58%	223
Clothing	58%	50%	55%	216
Food	74%	84%	86%	228
Cosmetic	63%	78%	69%	213

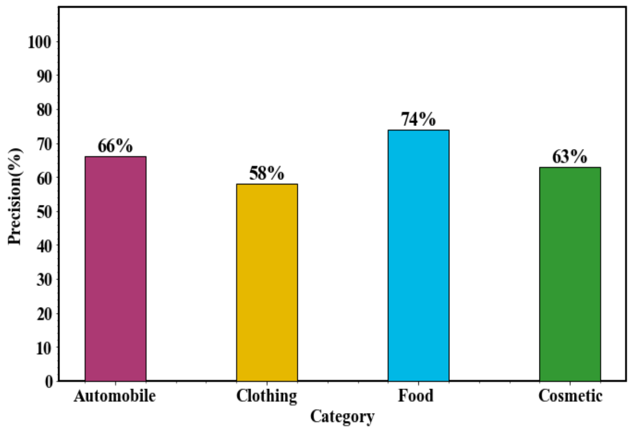

Figure. 7 The outcome of precision for classified advertisements

advertisements: clothing, food, automobiles, and cosmetics. The data show that the network model has a good level of accuracy. The network structure creates a direct connection between any two layers, each layer's input is equal to the output of all layers. All layers receive direct input from the feature map. By doing this, the gradient vanishing issue brought by the growth in network layers to minimized and boost the feature propagation. As a result, our network performs excellently. The evaluation findings for this approach on the test set are displayed in Table 4.

Fig. 7 shows the results of our experiments in precision for classified advertisements such as automobiles, clothing, food, and cosmetics.

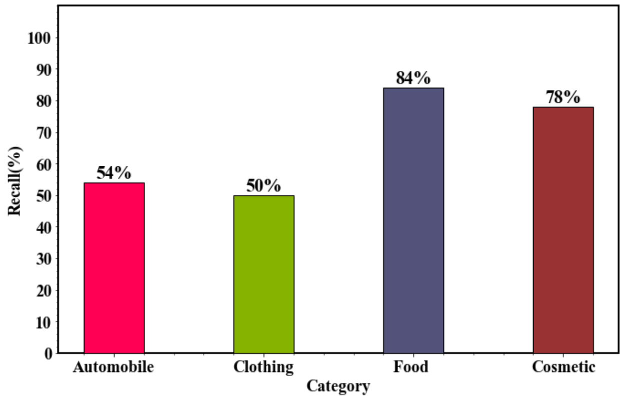

Figure 8. The outcome of recall for classified advertisements

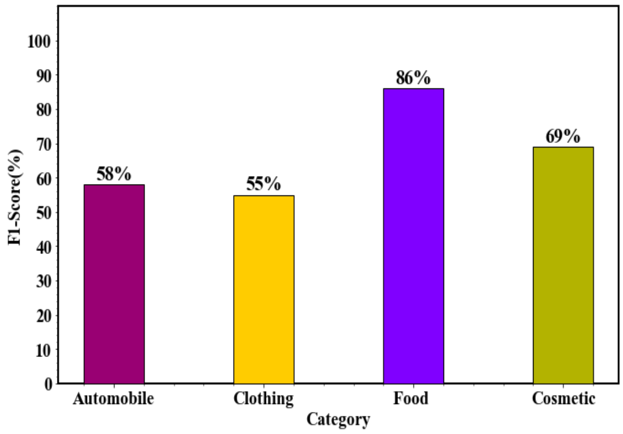

Figure 9. The outcome of f1-score for classified advertisements

Table 5. Utilizing the proposed and existing methods

Methods	Computation Time
Xception [11]	0.21
GTB [12]	0.19
Enhanced UBOC [13]	0.23
SIFT [14]	0.17
Proposed	0.14

The classified advertisement's recall values for each category are displayed in Fig. 8 and also for f1-score of each classified advertisement is shown in Fig. 9.

5.4 Computation time

The concept of computation time is another one that is covered. Deep learning approaches aim to simplify computations. Table 5 compares the computation times of our proposed technique to those of other previously used techniques. Improved classification accuracy is provided with little computational effort. The computation time utilizing the most recent techniques and the proposed model is shown in Fig. 10.

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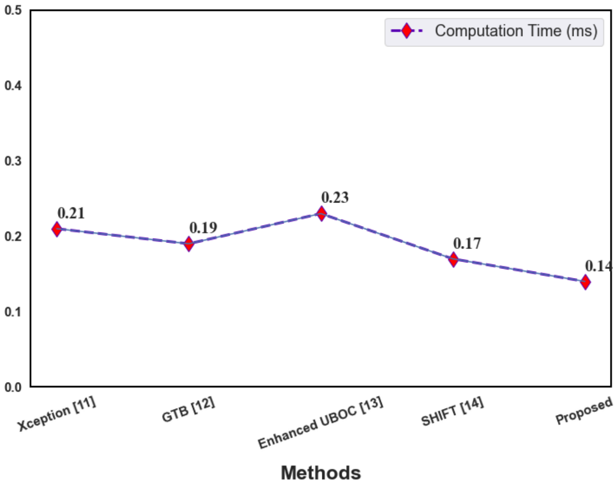

Figure. 10 The computation time for the proposed methodology and existing methodologies

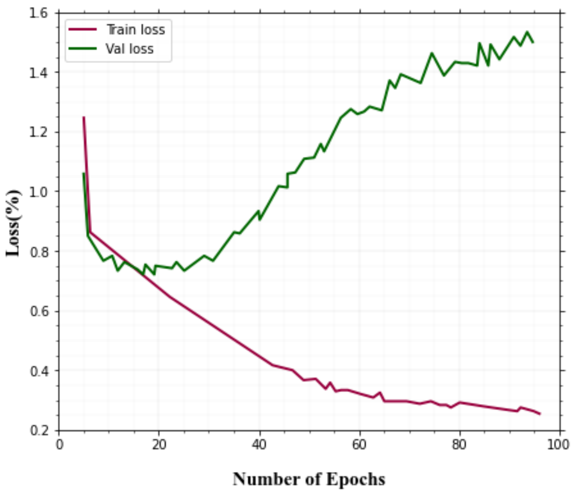

Figure. 11 Training Vs validation accuracy

5.5 Evaluation of training results

Validation and accuracy of trains our accuracy after 100 epochs was 99.93%, which is amazing considering accuracy curves eventually converge. Fig. 11 shows the accuracy of training and validation.

For a brief moment, the validation loss curve rises and falls. It implies that having more test findings can be beneficial. This might be acceptable, though, due to the low variance between Test and Train Loss and the flattening of the curve over epochs. Fig. 12 shows the training and validation loss.

The accuracy and loss during training are shown in Figs. 11 and 12. The DenseNet-121 provides better accuracy and loss estimations. In both the training and validation phases of the advertisement classification process, our methodology performs better than earlier methods.

Fig. 13 demonstrates that the model recognizes food commercials more accurately than the other

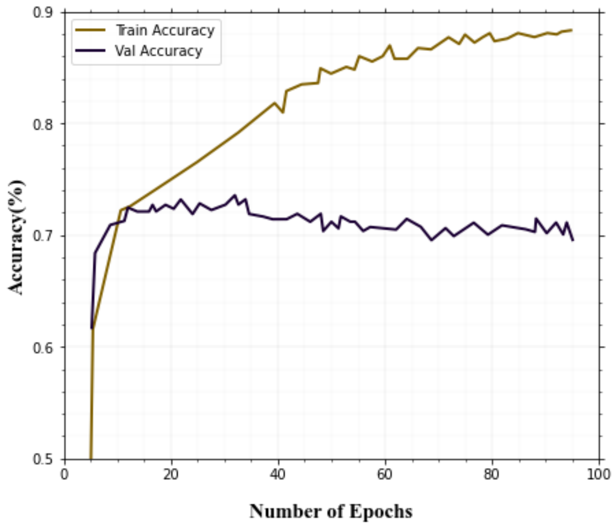

Figure. 12 Training Vs validation loss

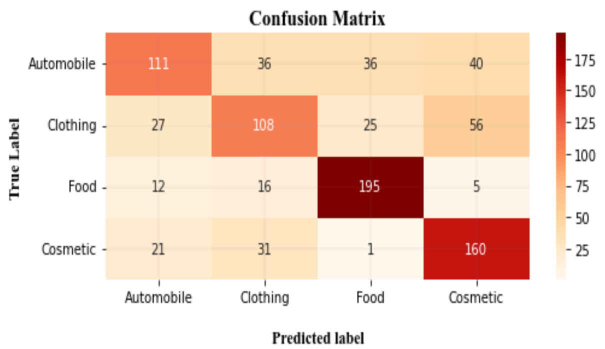

Figure. 13 Confusion matrix (DenseNet-121)

categories (195 correctly categorized out of 228 total food advertisements, while 33 are misclassified), followed by cosmetic (160 out of 213), automotive (111 out of 223), and clothing (108 out of 216).

The most used technique for assessing classification errors is the confusion matrix. Based on the provided confusion matrix explanations, developed the confusion matrix for the DenseNet-121 proposed model. The diagram shows that the DenseNet-121 model can classify advertisements, with our dataset having advertisement images. The obtained confusion matrix for the cross-validation test of classification is shown in Fig. 13.

6. Conclusion and future scope

Nowadays, there is a lot of interest in internet advertising, and by 2022, the total amount invested globally will have increased significantly to 781 billion dollars. This paper, proposes a deep learning method called DenseNet-121 which extracts the features like text and object from the input of advertisement image by using convolution and pooling layers of DenseNet-121 and then based on these features classify advertisements using the average pool and softmax layers into four categories such as automobiles, clothes, foods, and cosmetics. Secondly, propose deep neural network (DNN) to recommend advertisements based on user preferences. It is collect the data or information like entertainment, education, search history, etc., from the user profile and then matches that information with the collected advertisement dataset if the information matches with any of the advertisement files, then provide that as the recommendation of advertisement to the user. These experimental results show 99.93% of classification accuracy.

In the future, the classification accuracy of political commercials is one of them. To enhance classification accuracy, much more information needs to be gathered. To enhance the performance of classification in online marketing, it should utilize a variety of other hybrid techniques. Only user interest is used as the basis for the ads recommendation system. Since the project is entirely dependent on user interest, it is possible that a user won't always fill out their profile completely. If this happens, the system will be limited. The system may take into account using the cookies tracking method in the future. Amazon and Snapdeal currently utilize a cookie-tracking system. When it conducts a product search on Amazon, it will automatically see product advertisements on Facebook, Instagram, Google, and other platforms. The Ads recommendation system may be used in the future in conjunction with follow-up ads.

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We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' contributions

The contributions of authors are as follows: Satish Babu Thunuguntla: Conceptualization, methodology, software, formal analysis, investigation, resources, writing original draft, writing - review & editing, visualization. S Murugaanandam - conceptualization, writing - review & editing. R. Pitchai: investigation, resources, data curation, writing original draft, writing - review & editing.

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