Understanding Image Advertisements and Predicting Sentiment

Github Link: https://github.com/coderjolly/processing-ads

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***Abstract*—Image based advertisements are still one of the best ways to promote products but it is painstakingly difficult to personalize the content for the target audience and covey the sentiments. This study tries to compare three backbone deep learning architectures namely, ResNet 50, MobileNetv3 Large and EfficientNet B3 on an image advertisement dataset to classify the underlying sentiments being perceived by the consumers. Transfer learning is used to mitigate the small dataset problem.**

EfficientNet performed the best overall but the performance was still very poor. Grad-CAM visualizations confirmed our understanding of this model and helped us gain more confidence on the performance of the model.

***Index Terms*—CNN, advertisement, image, Grad-CAM, deep learning, transfer learning, Efficientnet, Mobilenet, Resnet, multilabel, image classification**

I. Introduction

In today's data centric world, companies are looking to improve their processes with the ever increasing amount of data we generate. With this data, comes along user profiling and understanding consumer emotions. The expansion of online visual content and social media has led to a surge of interest in the large-scale social multimedia analysis. For a long time image advertisements have been a prevalent part of our daily lives. From billboards to social media ads, companies have been constantly vying for our attention through visually appealing images. Traditionally, only a few subject matter experts understood how an advertisement would be perceived by consumers. However, with the rise of convolutional neural networks, it is now possible to predict the emotions that these consumers face when they look at these images. So, pondering over the platitude, 'A picture says a thousand words' becomes necessary.

Tech giants like Facebook and Google have produced enormous wealth by advertisements. 97.5% of the $116.6 billion revenue generated by Facebook [1] and 70.9% of Google's revenue [2] came in from broadcasting advertisements. Attracting customers to a product and producing a certain emotion is a vital aspect of using advertisements on television, social media and billboards. Selection of ads by hand is a physically tedious and onerous job where provision of image based advertisements or videos becomes highly difficult and subjective via handpicking. So, automatic advertising techniques such as the contextual advertising method was developed which aims to find the most relevant advertisements for a content that would annoy customers the least.

The components that contribute to the effectiveness of these advertisements are intricate and are being analyzed in marketing science and consumer psychology. A particular focus of this research has been on comprehending the emotions and sentiments conveyed by visual media content, which has become increasingly popular for both academic and industry purposes. Sentiment analysis is primarily the process of identifying and extracting opinions, emotions, and attitudes expressed in text. However, with the increasing use of visual media in advertising, a need for sentiment analysis on images has come up. Sentiment labels are used to annotate images with positive, negative or neutral sentiments. These annotations are used to train machine learning models to predict the emotions that an image is likely to evoke in viewers. Powerful emotions conveyed by images and videos can amplify the message conveyed in the content, making it more impactful and capable of influencing the audience more effectively. But sometimes, advertisements aren't able to hold viewers interest as the product shown doesn't necessarily incline to the viewers choices or viewers actually skip watching advertisements that aren't able to garner their attention, which is where a positive or a negative connotation comes into picture pertaining to sentiment of an advertisement.

In this study, we try to identify emotions that people felt when they looked at image advertisements using convolutional neural networks. Due to the small size of data and similarity to ImageNet, transfer learning was used to train the model. This report is organized as follows: Section 2 discusses similar works in the literature, section 3 describes the dataset and the methodology used in this study, section 4 presents the results with the experimental setup and section 5 concludes the report with some suggestions for future work.

II. Related Works

In order to create an effective advertisement, researchers take into account a ton of ideas to reach a balance of emotion and the type of message to convey. Common sense in humans dictates that the red color symbolizes stop when used in traffic related series and symbolizes blood when used in medical related settings but, computers have no way of knowing this information. Advertisements use different types of visual rhetorics like the color red to convey their message and invoke emotions in the consumer. To fathom these rhetorics it is required to discern the objects in the advertisement and then decode this rhetorics from all these objects [4] [5]. Caption generation is one of the use cases where a summarization about the image is required. Different studies try to understand [6] [7] which objects are being portrayed in an image, how they are portrayed and answering the main question: why are they being portrayed. For instance, if an advertisement is meant to target a young audience, it can be designed with bright colors and positive sentiments to appeal to that demographic. On the other hand, an ad meant for an older audience may be designed with muted colors and neutral sentiments. By predicting the sentiments that an advertisement is likely to evoke, companies can tailor their ads to specific audiences, increasing their chances of success.

Exploring objects or generic nouns such as cat or trees have been a marvel of machine vision but the association of sentiments correlating to the visuals remains a challenging and seemingly insurmountable task. The difficulty of this endeavor stems from the significant emotional distance between the low visual characteristics and the high-level sentiment that adjectives convey. To fill this gap between visual characteristics and sentiments, Borth, Damian et al. [8] proposed an alternative method that represents sentiment-related visual concepts for an intermediary representation. They have coined the term Adjective Noun Pairs (ANP) like ”sprawling trees” or ”sleepy cat” which are used to corroborate the adjective of nouns, further used to identify nouns. ANPs, despite not conveying emotions or sentiments explicitly, can still be effective indicators for identifying emotions portrayed in images, as they were identified based on a high correlation with emotion tags present in web photos. In their study Borth, Damian et al. [8] trained binary SVM classifiers on these ANPs for whole images. To further enhance the classifiers, the authors Chen, Felix et al. [9] included the localization of object-based concepts and the semantic similarity between these concepts in their work.

DeepSentiBank [10] shows significant efforts to interpret emotion from images using a model trained on web images that are tagged with multiple sentiments. Hussain, Zhang et al. [11] went on to apply DeepSentiBank on advertisements and reached a conclusion that to a detector for natural images (DeepSentiBank) couldn’t be applicable for advertisement images. Besides DeepsentiBank, Vedula & Sun et al. [12] developed an advertisement recommendation system using sentiments in multimedia content. Using deep learning techniques, image and video analysis together, has garnered a great amount of attention at Youtube for contextual understanding in video advertising [13]. But, compared to other forms of media such as publishing or billboards, which are less personalized, a great deal of work lies in interpreting advertisements media due to their extensive use of visual rhetoric as coined in Hussain, Zhang et al. [11].

An advertisement demands much in depth analysis due to the fact that they intend to persuade people to either buy or use a perticular product or, to make people aware of a social cause. The motive to persuade people is deeply imbibed inside an advertisement, where sometimes it is portrayed via simple tone or sometimes via sarcasm. In order to understand this underlying sentiment, only appearance isn’t enough. Therefore, to personalize the experience with ads, it is imperative to not only understand its topic, but also the emotion it conveys. Zhang, Luo et al. [14] introduced a framework that amalgamates multiple modalities together for envisioning topic and sentiment related predictions to further conceptualize advertisements.

III. Dataset

We have used a publicly available dataset developed by the combined efforts of Hussain et al. at the University of Pittsburgh with over 64,000 advertisement images and over 3,000 video advertisements. The authors used Amazon Mechanical Turk workers to tag each advertisement to its respective topic (eg. category of the product the advertisement targets) and what sentiment it conveys to the viewer (eg. how plants/trees play a vital role in sustenance) followed by what method it uses to imbibe that message (eg. the presence of trees or plants might be depicting life). The approach used to gather and annotate this data was influenced by the research in Media Studies, an academic field that examines the content of mass media messages, with input from one of the research paper authors [11] who had formal education in the field. The data is accessible at http://www.cs.pitt.edu/ kovashka/ads/.

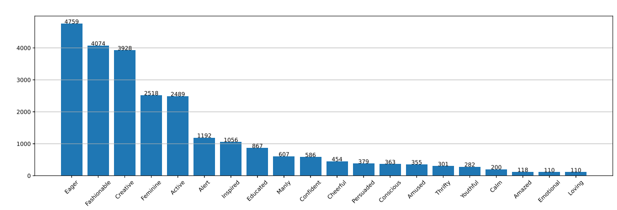


Fig. 1: Sentiment Label Distribution

IV. Methodology

Before training, the images were analysed to come up with a pre-processing pipeline to denoise the images and improve their quality as most of the images were highly compressed.

A. Bilateral Filter

For improving the quality of the images, a smoothing filter for images had to be employed. So, a bilateral filter was used to reduce noise while preserving edges in a non-linear manner.

This filter works by calculating a weighted average of intensity values from surrounding pixels to replace the intensity of each pixel. The weight of each pixel is determined using a Gaussian distribution and it preserves sharp edges. The weights used in the filter are not solely based on the distance between pixels, but also take into consideration differences in radiometric properties such as color intensity and depth distance [15].

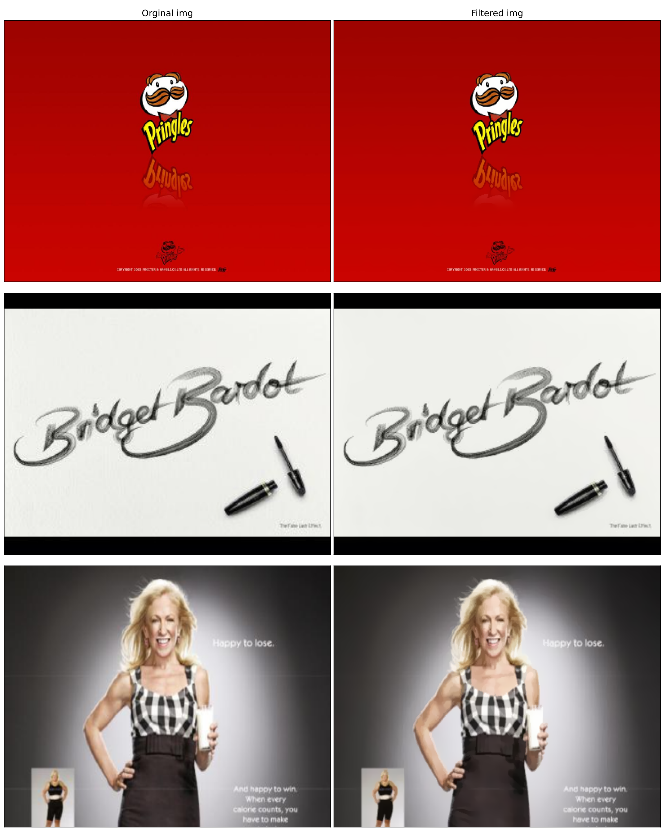


Fig. 2: Bilateral Filter applied on Ads

A bilateral filter is controlled by three parameters sigma(s), responsible for spatial region which smooths larger surfaces as we increase the spatial parameter. Sigma(r) which tends to act like a Gaussian filter when it increases as the Gaussian range widens and d, which is the diameter of each pixel neighbourhood. It is quintessential to know that all other filters smudge the edges, while Bilateral Filtering retains them. When weights are multiplied together and if one of the weights is close to zero, no smoothing occurs. This can be demonstrated by using a large spatial Gaussian with a narrow range Gaussian, which results in limited smoothing despite the filter having a large spatial extent. The range weight ensures that the edges are preserved.

As shown in Fig. 2, after applying different values of d, sigma(s) and sigma(r) on different images, it was determined that the pixel diameter of 9 along with sigma(s) and sigma(r) being 9 gave the best results. Following that, the bilateral filter has been applied twice merely because of the fact that applying bilateral filters in iterations enhanced picture quality even more. Fig. 2 depicts a significant change in the filtered image when compared with the original image. The original image had color banding or posterization, an ugly artifact that can be seen in digital images around objects. This has been notably reduced [16] and the final image is better than previous one. Another remarkable change that was witnessed was the compression artifacts, a distortion of media in images which is caused by lossy compression of media was also removed in the final image corroborating the efforts.

B. *Pre-processing Techniques*

Pytorch provides various functional transformations that can be applied using the torchvision.transform module. They accept both PIL images and tensor images, although some transformations are PIL-only and some are tensor-only [17]. As these transformations require a parameter such as a factor by which an image can be transformed, therefore they cannot be applied to all images owing to the fact that all images are different.

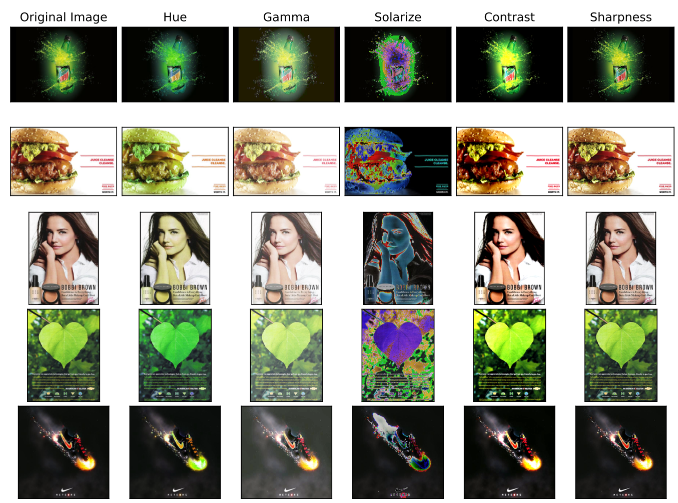


Fig. 3: Pytorch Preprocessing Techniques

For example, a Hue transform accepts an image along with a parameter, hue_factor that ranges from [-0.5 to 0.5]. 0.5 and -0.5 give complete reversal of the hue channel in HSV space in positive and negative direction respectively whereas 0 means no shift. The same level of factor cannot be expected from other techniques such as sharpness or contrast etc. Hence, this parameter cannot be kept constant for all images as it will have a variable effect or appeal on different images. In the Fig. 3, five random images have been selected and functional image processing techniques like hue transforms, gamma transforms, solarize transformations, sharpness, etc have been applied to reach a conclusion that all images bearing uniqueness in their characteristics respond differently to functional transformations applied.

Even though brightness and contrast change show a potent outcome, a specific parameter cannot be kept for all images So, this processing approach has been handled in data augmentation section where functions like AutoContrast and

AutoBrightness have been applied. Histogram equalization, a popular technique for improving the contrast of images visibly failed to work for colored images. This technique was employed on a colored image which distorted colors and features such that it could not be considered as a viable pre-processing technique.

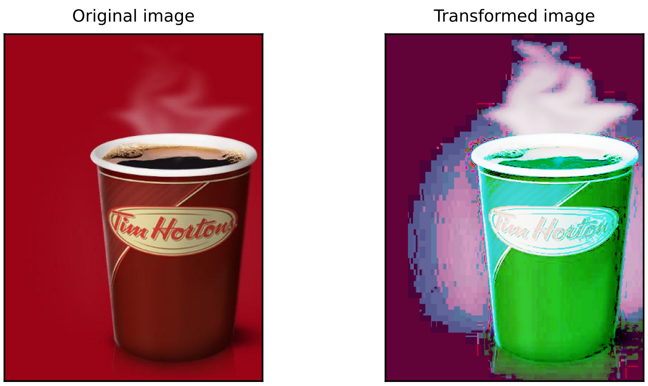


Fig. 4: Histogram Equalization on Colored Image

Fig. 4 shows the aftermath of histogram equalization on a colored image in detail where the image has been completely distorted in it's entirety and is difficult for any feature to be mapped.

C. Data Augmentations Techniques

Data augmentation plays a crucial role in the training of deep learning models as they aren't able to converge the network to an optimal solution if the size of training data is small because of the huge number of parameters needed to be tuned by the learning algorithm. It requires enormous amounts of data merely because of the fact that the deep learning algorithms start off with a poor initial state where weights are completely random and then optimization occurs using some gradient based optimization algorithm. There are various ways to augment data using the PyTorch library such as RandomHorizontalFlip, RandomAdjustSharpness, etc that produce images with any random factor while training the network. Data augmentation also helps in creating images that may be a possible in the real world but are not depicted in the dataset properly. For example, a coffee mug might be perfectly straight in one image but it could be a tilted by 15 degrees in another image. RandomRotation helps generate such images. In Fig. 5, 6, 7, 8 and 9 data augmentation being used in this study has been visualized. RandomHorizontalFlip, RandomRotation to a maximum of 30 degrees, RandomColorJitter, RandomAutocontrast with factor of 5 and lastly RandomAdjustSharpness with sharpness factor as 2 has been used.

D. Model Architectures

(I) Different backbone architectures were chosen to ensure that different types of Convolution blocks were tested for the

Fig. 5: Data Augmentation using RandomHorizontalFlip

Fig. 6: Data Augmentation using RandomRotation

advertisement data. Other selection criteria included the *number of parameters* and *GFLOPS*, important to keep track of the total training and evaluation time, and the *top 5 classification accuracy* on the ImageNet 1K benchmark dataset. Finally, the following three backbone architectures were chosen:

ResNet 50: A residual learning CNN with 50 layers that are made possible by skip connections. Without these skip connections, training such a deep network is not possible due to the vanishing gradient problem. The 50 layer variant was chosen to decrease training time while not compromising on the accuracy. This architecture had the highest trainable parameters, FLOPS and number of layers [18].

MobileNet V3 Large: This model uses depthwise separable convolution from MobileNet V2 along with squeezeexcitation blocks in residual layers from MnasNet. This makes it really quick to train while still performing at par with other architectures. This architecture had the lowest trainable parameters and FLOPS among the three selected. Howard et al. Reference [19] also used network architecture search to find the most effective model. The large configuration was chosen to not compromise on the prediction accuracy.

EfficientNet B3: This model uses compound scaling to scale the model by depth, width and resolution. The B3 version

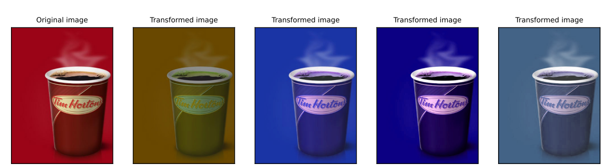


Fig. 7: Data Augmentation using ColorJitter

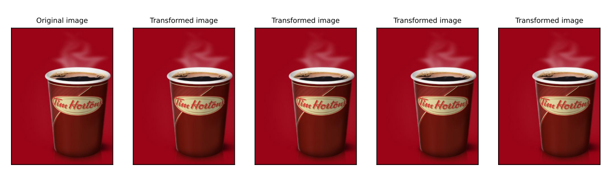


Fig. 8: Data Augmentation using RandomAutocontrast

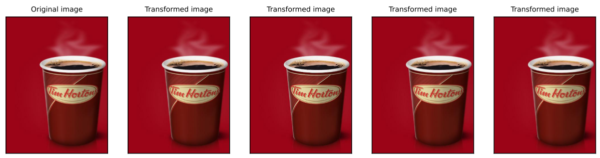


Fig. 9: Data Augmentation using RandomAdjustSharpness

TABLE I: Shortlisted Backbone Architectures.

Arch.	Params (Mil.)	Layers	GFLOPS	Imagenet Acc.
MobileNet V3 Large	5.5	18	0.22	92.57
EfficientNet B3	12.2	29	1.83	96.05
Resnet 50	25.6	50	4.09	95.43

was chosen to have faster training without compromising on the accuracy. Reference [20] This architecture performs the best among the selected on the Imagenet benchmark dataset while having half the trainable parameters of Resnet50.

E. Optimization Algorithm

The Adam optimizer [21] is an adaptive learning rate optimization algorithm which was chosen as the optimizer for this study as it converges faster by integrating benefits of the RMSProp algorithm and momentum technique. It is also robust to hyperparameters but, requires tweaking of the learning rate depending on the task at hand. For this study, a learning rate of 0.01 and the original author recommend settings for $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$ were used for the first and second order moment estimate as defined in (1) and (2) where β_1 and β_2 control the decay rates.

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t \tag{1}$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2 \tag{2}$$

Further, the Cosine annealing [22] learning rate scheduler was used to reduce the learning rate as the training progressed down to an end point of 0.001. This would help us reduce the learning rate as training progressed, preventing us from overshooting the minima.

V. Results

A. Experiment Setup

First, training data with labels that were low in count were removed. Out of the 30 available labels, only the top 20 were chosen. Next, images where the label was categorised by only one person was discarded as it was observed that many of these images were incorrectly labeled.

Then, the advertisement images were pre-processed using the bilateral filter described in IV before resizing them to the size - 384 * 384. The data was split into train, test and validation set in the 0.6:0.2:0.2 ratio and was stored in separate directories according to the defined PyTorch dataloader. Then, the mean and standard deviation of the dataset was calculated using the training dataset. All images were normalized before training using the dataloader with this calculated mean and standard deviation.

The dataset used in this study presented the the multiclass, multilabel classification problem. Thus, to make the model predict multiple labels, a sigmoid layer had to be added before the loss function to get 0 or 1 prediction for all the classes of the data. To achieve this, the BCEWITHLOGITSLOSS function of PyTorch was used as it combines the Sigmoid layer and the binary cross entropy loss function in one single class. This makes theses operations more numerically stable than their separate counterparts [23].

The backbone architectures and their pre-trained weights were obtained directly from the torchvision library and the final classification layer was modified for our dataset of 20 classes. The pre-trained weights were chosen to be the IMAGENET1K_V2 weights and only the last classification layer was fine-tuned. The rationale behind performing this type of shallow-tuning was that the Imagenet data is very similar to the advertisement images in our dataset. Additionally, the size of the selected dataset is small so deep-tuning might not work well.

The batch size was fixed to 32 for all the models. While training, the best model by validation loss was saved to prevent the usage of overfit models for the test set analysis. The actual and predicted results from each epoch was also stored to calculate the F1 scores at each step of training. While calculating the F1 score, macro averaging was used to get an average score across classes.

Initial training runs of the multilabel data produced a zero F1 score due to its highly imbalanced nature. To mitigate this, class wise weights were calculated and used with the loss function. This improved the F1 score quite considerably.

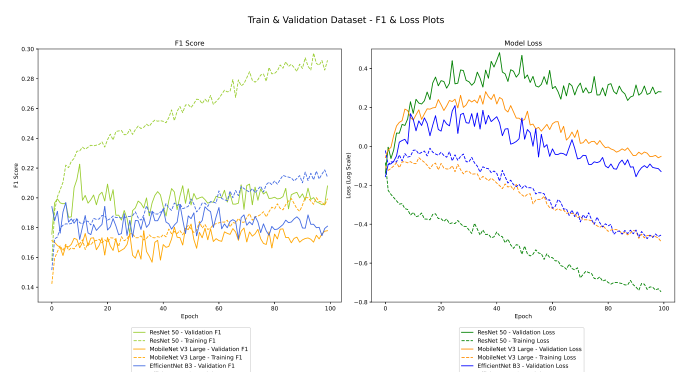


Fig. 10: Training & Validation, F1 & Loss plots for the three models.

Finally, the best models from each of the three training runs validation loss were used to get the test set metrics that are displayed in II. Per epoch training and validation F1 score and loss are provided in Fig. 10. Next, the best model which in this case was the EfficientNet B3 model was used to do further analysis like visualizing the trained filters and using

Grad-CAM to understand which areas of the image the model focused on to generate the predictions.

B. Training Results

From Fig. 10 it is clear that going from a smaller architecture to a bigger architecture, makes the model start to overfit earlier. The MobileNet model took the most number of epochs to reach the minima. The EfficientNet model performs the best for our dataset. However, all three models performed poorly. This shows that the compound scaling of EfficientNet gives good results for the advertisement dataset. The reason for poor performance overall could be due to a number of reasons. The dataset had a high number of classes but the number of examples per class was very low. Moreover, there was a high class imbalance problem. After looking at the images and the labels more closely, it was noticed that many images were poorly labeled and the labels contained quite a few synonyms.

TABLE II: F1 (higher is better), time per epoch in seconds (lower is better), and number of epochs to reach the best validation loss and F1 (lower is better) for the 3 models that were trained.

Model	*F1*	*Time*	*F1 Epochs*	*Loss Epochs*
MobileNet V3 Large	0.168	**80s**	50	98
EfficientNet B3	**0.189**	153s	**5**	90
Resnet 50	0.179	89s	10	**0**

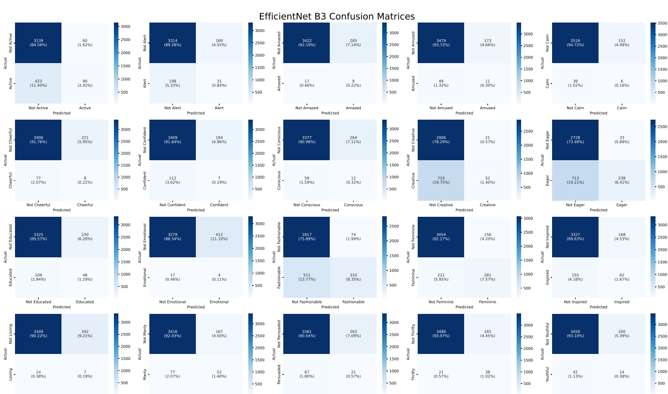


Fig. 11: Confusion Matrix for the EfficientNet model.

Looking at II it can be seen that the MobileNet architecture was the fastest to train per epoch. It took less time per epoch but, if number of epochs required to converge is considered, it does not train the fastest. The lowest validation set loss for ResNet was at epoch 0. This means that the model started overfitting right after the first epoch in terms of the loss. However, it took 10 epochs to converge on the F1 score. EfficientNet model performed the best in terms of the overall F1 score on the test set. Another surprising observation is that the EfficientNet model takes the longest to train per epoch even though the number of trainable parameters is nowhere close to ResNet.

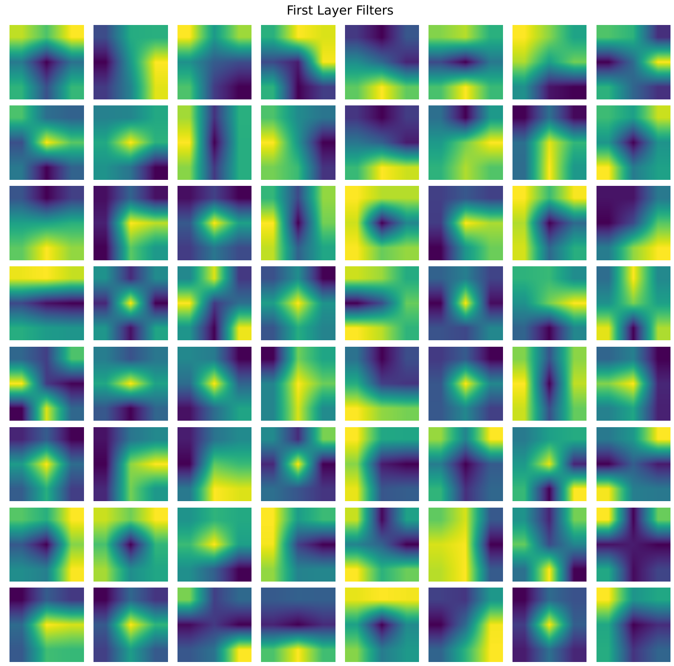


Fig. 12: Filters of the first layer.

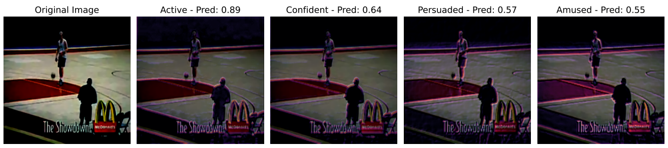
Surprisingly, MobileNet isn't as fast to train as expected when compared to ResNet even though it has five times the learnable paramenters. This could be due to two reasons, 1. depthwise convolutions are not optimized in the version of PyTorch and CUDA used and 2. training is getting CPU bound due to the data augmentation before each training run which would take the same amount of time for all the models.

In Fig. 11 it can be seen that the model classifies the labels Fashionable, Feminine, and Eager the best which are the classes that have the most number of training examples. This shows that if we increase the training dataset size, the models could improve a lot.

As the EfficientNet B3 model produced the best F1 score on the test set, it was used to generate the GradCAM visualizations to understand the model output. In Fig. 13 we can see that in the first layer of the network the model identifies prominent edges of the image. We can confirm this by looking at the filters of the first layer in Fig. 12. Most of the filters look like they identify edges and corners. In the middle layer of the network, the model is looking at many different features but isn't looking at the most relavant features for that label. On the other hand, in the final layer of the network, the model looks only at the relavant features of the image depending on the current label. For example, here it is focusing on the player playing football for the 'Active' label.

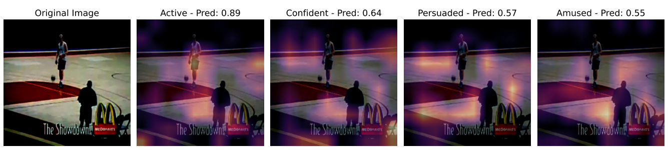
In Fig. 14, the model focuses on the picture of the woman for the 'Feminine', 'Fashionable' and 'Cheerful' labels.

In Fig. 15 We can see that the model correctly looked at the text 'Free' and classified the image as Thrifty however the actual label of persuaded was also in the top 4 predictions. This shows us that the model performs much better if we



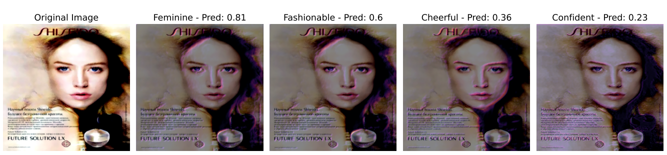
(a) First Layer Activations

(b) Middle Layer Activations



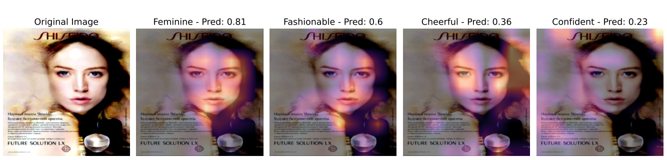
(c) Last layer Activations

Fig. 13: GradCAM visualization for an Advertisement using the Efficientnet Model. Actual label - Eager



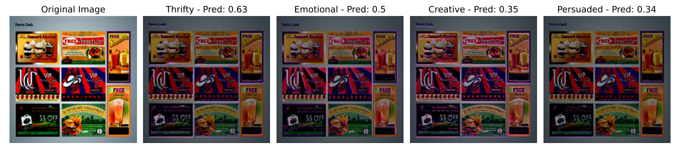
(a) First Layer Activations

(b) Middle Layer Activations

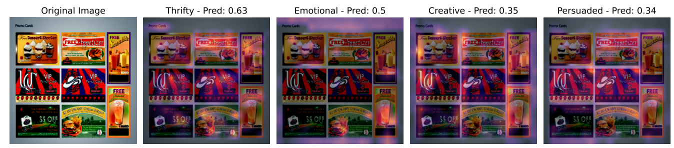


(c) Last layer Activations

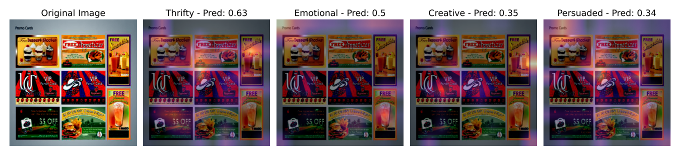
Fig. 14: GradCAM visualization for an Advertisement using the Efficientnet Model. Actual label - Fashionable, Feminine, Persuaded



(a) First Layer Activations



(b) Middle Layer Activations



(c) Last layer Activations

Fig. 15: GradCAM visualization for an Advertisement using the Efficientnet Model. Actual label - Persuaded

look at the images and generated outputs. The labels of the selected dataset are not completely correct making it difficult to evaluate the actual performance of the models. Visually looking at the gradcam visualizations and the predictions it is clear that the model is performing much better than what the F1 scores show.

VI. Conclusion

Understanding how humans perceive image advertisements could help improve the quality of these advertisements. Training a neural network model to predict the emaotions felt by humans towards different images is easy buy collecting the data is much more difficult. The low performance of the models in this study can be attributed to the low quality of the labels along with a lack of available training data. Even though the convolutional layers of the EfficientNet model were not fine-tuned, it was observed that the model could find relavant features in the image depending on the label. This shows that transfer learning is a powerful tool to train models and reduce turn-around times. Transfer learning enables the use of deep learning models even when the amount of available data is very less.

To improve the performance of the models, a number of things can be tried. Improving the labels of the available dataset can improve the models quite a bit. Additionally, getting more data would help the training effort by allowing the models to find patterns better. A long text description of how people feel when looking at different images could be an interesting take on this problem. Later, this text could be pre-processed using NLP models to create labels.

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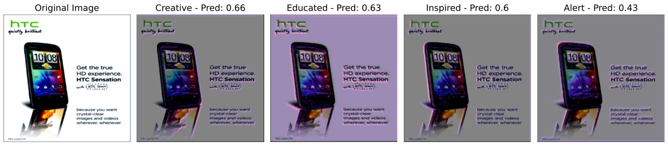

(a) First Layer Activations

(b) Middle Layer Activations

(c) Last layer Activations

Fig. 16: GradCAM visualization for an Advertisement using the Efficientnet Model. Actual label - Creative

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