# A Curious Case of Meme Detection: An Investigative Study

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Abstract: In recent times internet "memes" have led the social media-based communications from the front. Specifically, the more viral memes tend to be, higher is the likelihood of them leading to a social movement, that has significant polarizing potential. Online hate-speeches are typically studied from a textual perspective, whereas memes being a combination of images and texts have been a very recent challenge that is beginning to be acknowledged. Our paper primarily focuses on the meme vs. non-meme classification, to address the crucial primary step towards studying memes. To characterize a meme, metric based empirical analysis is performed, and a system is built for classifying images as meme/non-meme using visual and textual features. An exhaustive set of experimentation to evaluate conventional image processing techniques towards extracting low-level descriptors from an image is performed, which suggests the effectiveness of Haar wavelet transform based feature extraction. Further study establishes the importance of both graphic and linguistic content within a meme, towards their characterization and detection. Along-with the deduction of an optimal F-1 score for meme/non-meme classification, we also highlight the efficiency induced by our proposed approach, in comparison with other popular techniques. The insights gained in understanding the nature of memes through our systematic approach, could possibly help detect memes and flag the ones that are potentially disruptive in nature.

## 1 INTRODUCTION

Until few years ago, the most prevalent form of information exchange over the social media used to be either descriptive textual content or separate visual content, along-with additional necessary contextual information. Such communications were typically used to convey some indicative opinions about various societal, political or even generic aspects. Infact, the interaction induced by such information exchange could often be attributed to some form of social movements that keep stirring from time to time. A majority section of the millennials including normy teenagers and young adults have in the recent times started to indulge in what has now become and popularly called as meme culture. Meme, one of the popular English words [(Sonnad, 2018)], originated from a Greek word *mīmēma* which means "imitated thing". Often it is of satirical nature, which is encoded in the meme content using either graphic content, or textual messages, or even both. A lot of memes are designed to imply sarcasm, using an effective combination of image and text. Sometimes such communication entails direct or indirect association with the particular culture or community. Identification of a meme and the extent to which their diffusion may occur, is crucial for the regulatory authorities from the government and social media organizations. Hence, there are sufficient reasons to believe in the importance of addressing the problem of meme identification, from a research point of view, within the domain of computational social sciences. This paper attempts to address the inherent challenges towards detecting a meme, and presents certain approaches that are observed to be helpful towards establishing the distinguishing framework for the required task.

The last decade has seen significant research works dealing with the multimodal data, with problems ranging from scene description (Chen et al., 2015), (Krishna et al., 2016), (Young et al., 2014), (Gurari et al., 2020), (Sidorov et al., 2020) to visual question answering systems (Wang and Liu, 2017), (Hudson and Manning, 2019), (Singh et al., 2019).

Besides being challenging in nature, multi-modal tasks are inherently interesting as well, due to the fact that they are mostly rooted within the natural phenomena like the cognitive mechanism of human beings that leverages vastly disparate sources of information, towards building perception and understand-



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Figure 1: President putin with a girl,Category of image where text is in the lower half of the image (**Type-1 A Non-Meme**).

Figure 3: A Flickr8k dataset image, where caption is imposed on an image (**Type3 Non Meme**).


Figure 5: An offensive Meme on woman dressed in Hijab. It is difficult to label this as offensive until one makes the correlation between the biased emotion towards a particular religion (**A Meme**).

ing the world around them. As for the web content, multi-modality exists as the very core of the information exchange that connects people across the geographies. Many practitioners believe that multi-modality holds the key to problems as varied as natural language understanding (Xuelin et al., 2019), computer vision evaluation (Geman et al., 2015), and embodied AI (Savva et al., 2019). Multi-modal content makes the automatic detection of memes both challenging and relevant in the present day scenario, where it's volume on social media is rapidly increasing.

To acknowledge the overall complexity involved in the identification of memes from non-memes, few

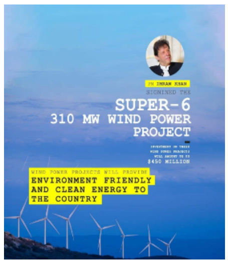



Figure 2: Poster on wind project (**Type2 Non- Meme**).

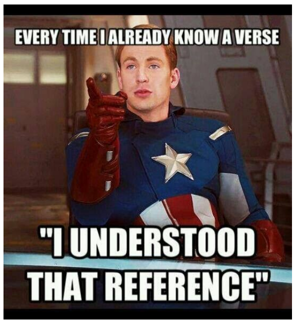



Figure 4: A image from Movie "captain America" where it shows anger.(**A Meme**).


Figure 6: A image depicting a sarcastic and funny comment on the three famous personality (**A Meme**).

samples are depicted in Fig. 4, 5 and 6. Memes can be contrasted with non-memes (normal images) having some embedded text as shown in Fig. 1, 2 and 3, where some inherent direct association between the visual cues and the textual information can be established. Therefore, Memes need to be analyzed and processed as per the requirement by leveraging different modalities it has to offer, to infer insights about the actual message intended. Few researchers have tried to automate the meme generation process (Peirson et al., 2018), while others have tried to extract their inherent sentiment (French, 2017) in the recent past. Some other work on use of multi-modal data over social media channels include (Wang and Liu, 2017). To overcome the problem of missing modality i.e. absence of the crucial multi-modal data (Baltrusaitis et al., 2017), authors of (Fortin and Chaib-draa, 2019) have provided the solution by developing multi-modal multitask emotion recognition.

The paper is organised as follows. The data set collected and used for this study is described in Section 2. Section 3 shows how image processing techniques and deep learning techniques perform while considering image as input in classifying image as meme or non-meme. A new method is proposed in Section 3.4 which detects memes. Section 3.5 tells about the basic system developed for detecting image on twitter data while Section 3.5.1 tells why the developed system is not efficient towards classifying a meme. Section 4 presents the empirical analysis conducted towards characterization of Memes in contrast with the Non-meme content. Our proposed approach towards the main task of Meme/non-meme classification considering both image and text is described in detail in Section 5. The results are reported as part of Section 6. Finally, we summarise our work by highlighting the insights derived along-with the further scope and open ended pointers in Section 7 and 8.

## 2 DATA-SET

The meme data-set is created by downloading publicly available images of different categories, such as Trump, Modi, Hillary, animated characters, etc using third-party tools and packages like Tweepy and Fatkun image batch downloader. Additionally, flickr8k (Thomee et al., 2015) data-set is also utilised towards creating the required data-set. To avoid class imbalance problems, balanced category-wise data distribution is ensured. No. of samples per category are shown in the Table 1. In this section, we describe preprocessing and annotation steps performed towards meme classification task.

Table 1: Data Distribution: Shows a distribution of web images in data-set used for this study where Non-Meme Type 1, Type 2 and Type 3 refers to Figure 1, 2 and 3 respectively.

| Category | # samples |
|---|---|
| Meme | 7,000 |
| Non-Meme (Type1) | 2,250 |
| Non-Meme (Type2) | 2,250 |
| Non-Meme (Type3) | 2,500 |
| **Total** | **14,000** |

### 2.1 Preprocessing

The images having been collected from disparate sources, are of various types such as only graphic content or even images with embedded text from different languages other than english. Whereas, a majority of the images collected from google and twitter are found to have memes with both image and text content. Thus to maintain the consistency of the data-set towards establishing a baseline setup, we have preprocessed the data with the following constraints:

- Creation of a part of non-meme data by embedding the text provided corresponding to the given images from Flickr8k(Thomee et al., 2015) data-set. This renders the content which is similar to a meme in terms of composition, but created without any intention of disseminating it online as in case with memes, hence forms a contrastive sample.
- All the images were resized to 224X224.
- Consideration of only those images which have embedded text strictly in english language.

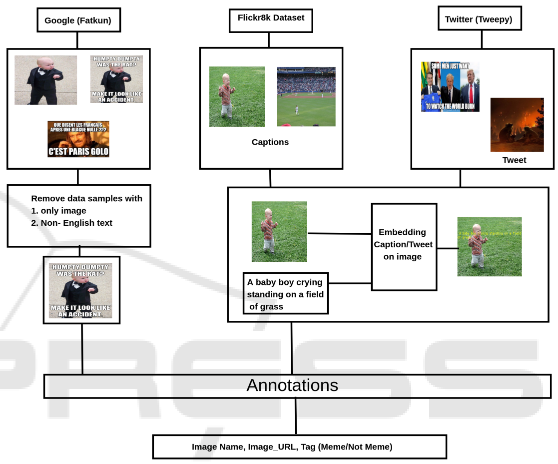



Figure 7: This shows the process of data-set creation where data samples are collected from 3 sources and pre-processed according to the defined rules. Further the images were given to AMT workers for annotation that resulted in data-set that contains image_id, image_URL and Tag.

### 2.2 Annotations

For getting the data-set annotated, we rely on people to perform manual checks for every picture present in our data-set. This is accomplished by utilizing annotations provided by the workers on Amazon Mechanical Turk (AMT), an online platform on which one can set up undertakings for workers to complete the annotation tasks and get paid for it. AMT is actively used by researchers, for eg. for getting vision related data-sets annotations (Sorokin and Forsyth, 2008). With a global client base, AMT is especially appropriate for huge scale data labeling.

As part of the annotation process, the workers are requested to provide annotation only if the background context of the image (meme) content is known. Crucial requirement for the background information is demonstrated in comprehending the information from memes shown in Fig. 4 and 5.

Table 2: Is a given image a MEME? A table that shows how annotation proceeded for each image considering the perception of each annotator towards an image. Response of 5 users is captured for 2 images and shows a confidence score. Here the left image is considered as MEME due to the high confidence score obtained as 0.8 from majority votes as Y for MEME.

| |   |   |
|---|---|---|
| User1 | Y | N |
| User2 | Y | Y |
| User3 | Y | N |
| User4 | N | Y |
| User5 | Y | N |
| Confidence score | 0.8 | 0.4 |

Although, workers are told to make an apt judgment for the response, we needed to set up a quality control framework to rely on the precision observed. With respect to this, there are two issues to be considered. Firstly, errors rate for human judgement is significantly high and not all workers adhere strictly to the guidelines. Secondly, workers don't generally concur with one another, particularly for subtle cases. Table 2 shows how user's judgment differs for labeling the images.

One possible solution towards these issues is to have various workers freely annotate a common data sample. A given picture is considered as positive only if it gets majority vote amongst the annotators. It is observed that various categories require various degrees of agreement among workers. For eg. in our scenario, while 5 workers may be more than enough for a typical "Trump" meme Table 2, $2^{nd}$ column, whereas at least 5 are necessary for getting a reliable agreement on "distorted Trump reaction" picture (a non-meme) Table 2, $3^{rd}$ column. We calculated the confidence score of each class for every data sample, which is a score for the conviction with a picture was considered to be a meme by the annotators. A confidence score of 0.6 or above formed the basis for correct label. The confidence score for a given data sample, and a category is computed using the relation below,

$$ConfidenceScore : \frac{N_Y}{N} \tag{1}$$

where, $N_Y$ is the count of *Yes's* allocated for a given image, for whether it is a Meme or not, and $N$ is set to 5 for our study. A pictorial representation of the data-set creation is shown in Fig. 7 while Fig. 5, 3 etc represents the type of data sample present in our data-set.

# 3 MEME ANALYSIS

Creating a meme involves creativity in terms of representing an emotion, phenomena or an idea, which is why it is designed to have a deeper impact on the audience, which could potentially be healthy or even dangerous. What makes it interesting from a research point of view, is that the graphic content and the text, have peculiar roles to play towards the overall impact a meme can have. Affect related information from the images has been studied by authors in (Bourlai and Herring, 2014), in which they have analysed that image also plays crucial role for tasks like sentiment analysis and emotion detection. Textual content has been studied extensively towards such tasks in the research community, and are established feature sets. In our work, we begin our investigation by exploring various feature extraction and learning techniques, towards analyzing memes using only graphic content (image processing). Different approaches studied are described in the subsequent sections.

## 3.1 Image Processing Techniques

To examine various visual characteristics like edge representation, color distribution and associated texture, following image processing techniques are explored where the classifier used is SVM.

- **HOG Features.** Histogram of oriented gradients (HOG) (Dittimi and Suen, 2018) is a feature descriptor that focuses on the structure or the shape of an object. In addition to detecting the edges, it also derives the edge direction by extracting the gradient and orientation at the semantic edges in an image. Locallized sub-regions contribute to these orientations, i.e., an image is processed in divide and conquer manner, wherein features are computed for each localised region. As an output, a histogram is generated that shows the frequency distribution of a set of continuous data. The magnitude $G_m$ and orientation (direction of edge) $G_d$ are calculated on the basis of change of magnitude in X and Y directions.

$$G_m = \sqrt{(G_x)^2 + (G_y)^2} \tag{2}$$

$$G_d = tan(\phi) = G_x/G_y \tag{3}$$

where $G_x$ and $G_y$ are change in X and Y directions respectively and $\phi$ is direction of a particular pixel.

To get the information of the edges and the corners with respect to change in intensity, we have implemented HOG technique to extract the relevant features which resulted in a 2304 dimension feature vector. These descriptors performed with a decent F1 score of 0.8 when evaluated for meme/non-meme classification problem.

- **Color Histogram.** Red, green and blue are considered as primary colors and contribute towards the 3D channel configuration of a colored image. Color Histogram (Singh et al., 2012) is used to represent the color distribution of an image considering these primary channels. Initially, it splits the image w.r.t three channels and compute the histogram for each. Finally all the obtained histograms are concatenated into what is called as flattened histogram.

  We use RGB color histogram of 8 bins to get the distribution of colors in an image resulting in a 256 dimensional feature vector. It is observed from our experimentation that color histograms do not lead to a reliable meme/non-meme classification, resulting in an F1 score of 0.56. The reason for this performance could be attributed to the possibility of non-unique color distribution present in comparison of data-points (meme/non-meme set), which is one of the commonly known limitation of this technique.

- **SIFT.** (Yuvaraju et al., 2015) Scale Invariant Feature Transform is primarily used to detect and describe the localized features in an image. It locates certain points of interest within an image, augments them with parametric knowledge called as descriptor. The entire procedure is divided into 4 sections namely: constructing a scale space, keypoint localisation, orientation assignment and key point descriptors. In case of meme, SIFT works by comparing the local features of two images from the empirical analysis of different number of match-point selection obtained from SIFT with SVM, we found the system performance gets converged to the F1 score of 0.75 after the consideration of 1500 features shown is Fig. 8.

- **LBP-Histogram.** LBP (Local Binary Pattern) (Mu et al., 2008) is used to find the texture of an image, in which the pixel values of an image are labeled by thresholding the neighbourhood of corresponding pixel and considers the result as binary outcome. We have combined it with histogram that helps in detecting the face within images. For meme classification, we have taken 768 dimension feature vectors obtained from histogram and it resulted in F1 Score of 0.49.

- **Haar Wavelet.** (Porwik and Lisowska, 2004) is used to remove noise from an image by dividing it into different sub images and then followed by performing DWT (Discrete Wavelet Transform) using a discrete set of wavelet scales and translations obeying some defined rules to get the pixel distribution in horizontal, vertical and diagonal direction. Fig. 9 shows the pixel distribution of an image, after performing Haar wavelet transform. For meme classification task, this technique is observed to outperform all the other image processing techniques with an F1 score of 0.91, due to its effective noise removal characteristic using low pass and high pass filtering.

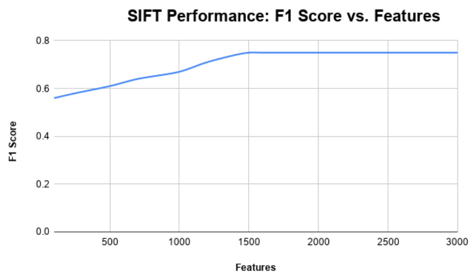



Figure 8: Shows the variation in result with varying count of features used to detect MEME. It can be observed from the graph that consideration of 1500 features is performing well and gets converged.

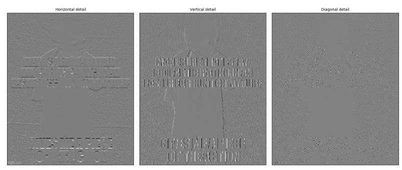


Figure 9: Shows different coefficient value obtained by applying HAAR Wavelet on an image.

## 3.2 Deep Learning Techniques

Despite low computational power, classical image feature extraction methods have limitations. For e.g. extracting specific features with limited parameters for a technique like LBP concentrates on local binary patterns and loses the edge corner information. To overcome this problem, we have performed different experiments for image feature extraction using various pre-trained deep learning models like VGG-16 (Simonyan and Zisserman, 2014), Resnet-10, and AlexNet. In spite of the effectiveness of these models for different yet closely overlapping tasks, VGG-16 is observed to have outperformed as compared to other two deep learning models, due to the use of relatively smaller receptive fields, i.e. (3x3 with a stride of 1) which can capture fuzzy interconnected pixel information unlike other models. Based on this performance, we re-trained VGG-16 with our data-set, and it is observed to outperform it's own pre-trained version. This is also tabluated in the system performance summary Table 10. This advocates the need of training a CNN freshly on a data-set, where the objective entails higher order information/feature learning, like meme/non-meme classification. Besides evaluating a purely VGG-16 based architecture, we performed several other experiments utilizing LSTM, BiLSTM and self attention based mechanism which is inspired from (Nagda and Eswaran, 2019), in that a hybrid approach comprising of CNN and LSTM, is implemented towards the task of image classification, wherein the architecture provides both semantic and sequential meaning of the information embedded in the input.

### 3.3 Takeaway from Image Processing and Deep Learning Techniques

Results shown in Table 4 signify that Haar based approach performed well in classifying an image as a meme prominently due to its noise removing property, i.e. non-salient parts of an image, or other objects that are not of significant importance by calculating horizontal, vertical and diagonal coefficients followed by application of low pass filter that results into approximate coefficients of the sub-image.

HOG also yields decent performance with an F1 score of 0.8, but it is not observed to generalize well the way Haar based model does. Also, since HOG captures edge related information where there is a change in intensity value, which might not provide distinctive characteristics towards modeling the class specific non-linearity.

SIFT is observed to be of relatively inferior performance because of its characteristics that does not lead to better classification.

LBP followed by a histogram and color histogram also show poor performance, since an image cannot be classified on the basis of the distribution of colors as well as texture of an image, as images with same color and texture can be used as a meme or non-meme depending upon the context and additional information.

To better understand the information contained in an image, we concatenated features obtained from various techniques. Results obtained indicate that the collective information of edge, corners, and removal of noise from an image obtained from HOG and Haar features performed significantly better in comparison to fusion of other features evaluated.

VGG-16 pretrained on imagnet data-set did not perform well because of the difference in nature of data-set, in terms of the passive nature of the visual content, as against particularly indicative of affect related aspects of real word ideas, in our data-set. To address this problem, we have trained VGG-16 on our data-set, which is observed to perform significantly better as compared to approaches involving different combination of deep learning techniques i.e., LSTM, BiLSTM, self-attention.

### 3.4 Proposed Method

Observed from the above section, every technique has its own advantage and disadvantage in terms of extracting various kinds of features. Like, HOG and LBP both attempts to use the same kind of information that is gradients around a pixel. The key difference between HOG and LBP is how to get the gradient information. The power of LBP stems from the fact that it uses all 8 directions for each pixel, compared to HOG which only uses 2 direction for each pixel. However, due to the coarseness of the binning employed by LBP makes it lose information compared to HOG. It is well known that HOG is great at capturing edges and corners in images unlike LBP that captures the local patterns, which makes them complimentary to each other. Similarly, SIFT works based on identifying interest points in an image. So, no sliding windows are needed to scan all regions of an image, whereas HOG uses the sliding window. These are the 2 main differences in various feature extractors. They either work based on interest point detection or rely on dense sampling techniques like sliding windows. Most importantly, the desired qualities in an feature extractor are:

- **Rotation Invariance** - should be able to identify the object, irrespective of its orientation.
- **Translation invariance** - Even if the object is moved to a different location, it should be detected.
- **Illumination invariance** - should work even if there is change in brightness and contrast in the image.
- **Scale invariance** - should work even if the image is zoomed in or out.

Indeed, features extracted from various techniques can be fused to get the in depth information embedded in an image. This motivated us to combine the various features in a form of horizontal stack followed by the application of different deep learning techniques with a combination of softmax as decision function as shown in Fig. 10. The classical feature embedding is configured in 3 different ways with a 5 X 255, 3 X 1000, and 4 X 768 dimensionality. Application of

Table 3: Comparison of VGG-16 and proposed method on different factors that shows irrespective of VGG-16 performing well, proposed method is having an upper hand.

| Comparison Factor | VGG-16 | Proposed Method |
|---|---|---|
| No. of Parameters at FC layer | 4,097,000 | 102 |
| Total Number of Parameters | 138,423,208 | 36,767 |
| No of convolution Layers | 16 | 2 |
| Total Number of Epochs | 5 | 20 |
| Training Time | 4 hours | 10 Minutes |

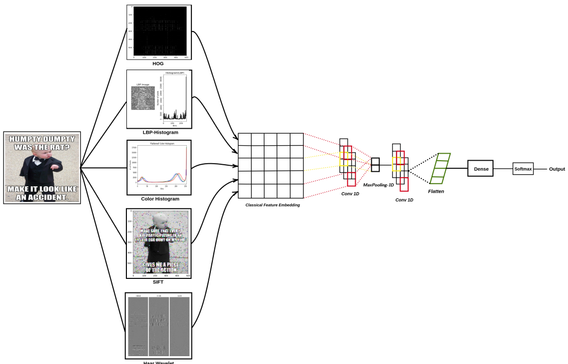



Figure 10: Shows the newly proposed method for MEME-non-meme detection that creates a classical features embedding obtained from HOG, Haar, SIFT, LBP and Color Histogram(CH )followed by the application of Deep Learning Techniques.

convolution layer on a 5 X 255 dimension embedding performed with a highest F1 score of 92.1 as it comprises of all the basic features while the least performance is shown by the implementation of convolution and LSTM on 4 X 768 feature embedding.

### 3.4.1 VGG-16 vs Proposed Method

Although the performance of proposed method is low in comparison to VGG-16, but considering computation, configuration and no. of parameters, proposed method has an upper hand which can be seen in Table 3. The combination of other techniques like LSTM, BiLSTM and attention with convolution performed well in our method in comparision to VGG-16.

## 3.5 Analysis on Twitter Data and a Real Time System

The performance of different techniques and methods used in the prior section to classify image as meme or non-meme has performed significant enough on our data-set which is shown in Table 10. This made us to predict the posted content from social network for real-time analysis. For this we considered twitter platform as it provides free API to download data for research purpose. We have collected 1200 tweets that consist of images and asked the annotators to annotate them as meme and non-meme as explained in Section 2. We predicted the image considering only those techniques which performed well on our data-set.

Table 4: Shows result of different image processing techniques like HOG( Histogram of gradient),SIFT(Scale Invariant feature transform),LBP Histogram etc and the result obtained from concatenating the classical features while other section shows the results obtained from Deep Learning Techniques like Convolution, BiLSTM and self attention.

| **Image Processing Techniques** | |
|---|---|
| *Features + SVM* | *Accuracy (F1 Score)* |
| HOG | 0.8 |
| **Haar Wavelet** | **0.91** |
| SIFT | 0.75 |
| LBP_histogram | 0.49 |
| Color_histogram | 0.56 |
| **Concatenation of features obtained from different Image Processing Technique** | |
| *Feature Combination* | *Accuracy (F1 Score)* |
| haar, lbp,hog,colorhist, sift | 0.5 |
| haar , lbp, hog, colorhist | 0.5 |
| haar, lbp, hog, sift | 0.49 |
| haar, lbp, colorhist, sift | 0.5 |
| hog, lbp, sift, colorhist | 0.49 |
| hog, lbp, sift | 0.49 |
| hog, lbp, colorhist | 0.5 |
| hog, lbp, haar | 0.49 |
| hog, sift, colorhist | 0.5 |
| hog, sift, haar | 0.8 |
| hog, colorhist, haar | 0.5 |
| lbp, haar, colorhist | 0.49 |
| lbp, haar, sift | 0.49 |
| haar, sift, colorhist | 0.49 |
| **haar, hog** | **0.88** |
| haar, sift | 0.79 |
| haar, colorhist | 0.49 |
| haar, lbp | 0.48 |
| lbp, hog | 0.49 |
| lbp, colorhist | 0.49 |
| lbp,sift | 0.49 |
| hog, colorhist | 0.49 |
| hog, sift | 0.73 |
| sift, colorhist | 0.5 |
| **Deep Learning Techniques** | |
| *Architecture Details* | *Accuracy (F1 Score)* |
| VGG-16 (Pretrained) + softmax | 0.68 |
| **VGG-16 (trained with our data-set) +Softmax** | **0.94** |
| Vgg-16 + lstm | 0.61 |
| Vgg-16 +bilstm | 0.65 |
| Vgg-16 _ Bilstm+attention | 0.65 |

Table 5: Results obtained by the newly proposed method where 5X255 corresponds to the consideration of the features obtained from all the techniques while 3X1000 corresponds to the consideration of Haar, HOG and SIFT features only. It clearly shows that combination of features obtained from all the techniques provides best result and outperformed the other existing classical techniques.

| Architecture Details | Classical Feature Dimension | | |
|---|---|---|---|
| | 5X255 | 3X1000 | 4X768 |
| **convolution layers** | **0.92** | 0.88 | 0.88 |
| convolution+lstm | 0.82 | 0.8 | 0.79 |
| convolution+bilstm | 0.82 | 0.87 | 0.88 |
| convolution+bilstm+self attention(mul,addtive) | 0.85 | 0.81 | 0.80 |

Out of all techniques it can be observed that Haar has performed well which is shown in Table 6. We further analysed the data-set and the techniques performance in predicting different types of memes and non-memes, details are shown in Table 7. The inference from the error analysis table shows that classical method is unable to perform good to detect Type 2

Table 6: Performance of the system on real time data of 30 samples taken from twitter. Scores obtained from different techniques that shows HAAR model classified the data appropriately in comparison to other techniques.

| S. No. | Models Description | Features | F1 score(Accuracy) |
|---|---|---|---|
| 1 | Image Features+Svm | **Haar** | **0.85** |
| 2 | | Hog | 0.78 |
| 3 | | Sift | 0.75 |
| 4 | Image Embedding +Conv | image embedding | 0.68 |
| 5 | Deep Learning Model | vgg-16 | 0.56 |
| 6 | | vgg-16+bilstm+selfattention | 0.67 |

Table 7: Shows the Error Analysis considering different types of MEME and non-meme and the performance of the different techniques in classifying the image.

| Techniques | Not a MEME (600) | | | MEME (600) |
|---|---|---|---|---|
| | *Type1* | *Type2* | *Type3* | |
| Classical method | 140/200 | 20/200 | 160/200 | 396/600 |
| Deep Learning Method | 80/200 | 80/200 | 20/200 | 400/600 |

non-meme while Deep Learning techniques did not performed well in detecting Type 3 non-meme.

We developed a basic system that detects meme from the real time tweets of a particular topic such as #Modi, #Trump, #covid etc. From the result of the system we have observed that it has failed to identify different meme and non-meme categories. The details of inference is explained in Section 3.5.1.

#### 3.5.1 Why It's Not Working on Real Time Data

There are some noteworthy points that could be a reason why the system is not working on real time data:

- Same image with different tweets results in meme or non-meme. This can be clearly observed from image of trump in Table 2 as if we tweet as ”trump at a conference” then it will be considered as non-meme while if tweet is ”Excuse me ! Excuse me! I am telling a Lie” then it falls in the category of memes.
- The context or background knowledge of visual and textual information of the multimodal data should be known.
- It can be observed from Fig. [5,6,4] that in the majority of the cases, visual and textual cues provide different emotions and information embedded in an image in case of memes.

Authors in (Bourlai and Herring, 2014) have analyzed corpus of tumblr post for sentiment analysis and have shown that images convey more emotions than plain text. It follows that analyzing images along with text in multimodal environments should improve the performance and result in greater accuracy of emotion analysis. Considering this, we will further analyse the data sample considering both image and text for detection of memes.

## 4 EMPIRICAL CHARACTERIZATION OF MEMES

To analyse the difference between meme and non-meme, we have performed different experiments considering various associativity measures, between original textual information extracted using OCR ($text_{ocr}$) and output of the scene description network ($scene_{text}$). The scene description network (Vinyals et al., 2015) VGG-16 (Simonyan and Zisserman, 2014) pre-trained on imagenet dataset (Russakovsky et al., 2014), is used to generate the caption or scene description from an image, whereas to extract the textual content from meme we have used off the shelf optical character recognition (OCR) API. Different metrics towards this are computed and considered towards examining the association between visual and textual content, represented by $scene_{text}$ and $text_{ocr}$ features respectively. Observations are depicted in Table 8 with multi modal images (Meme/Non-meme), their type, OCR extracted content $X$ and generated text $Y$ as different details, whereas analysis of association metric values (Semantic similarity, Cosine similarity, Pearson correlation and Euclidean Distance) is tabulated in Table 9.

- **Textual Content:** we have performed OCR extraction on the dataset using google vision API to get the text embedded over an image that was not wholly correct. Therefore, AMT workers were asked to provide the correct text against the OCR extracted text.
- **Visual Content:** We have used image captioning model VGG-16 (Simonyan and Zisserman, 2014) pre-trained on imagenet dataset(Russakovsky et al., 2014) to generate the caption or scene description from an image.

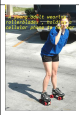
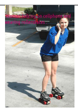
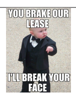
For analyzing various images to distinguish meme from a non-meme, similarity and distances that are demonstrated below calculated on the sentence embedding of the OCR extracted text and the generated text as scene description:

- **Semantic Similarity.** It is defined as the inner product of the encodings, obtained from text that gives a contextual relation between the two embeddings.
- **Pearson Correlation.** It is used to find the dependency of one text over other.
- **Cosine Similarity.** It is used to depict how similar is one text with other.
- **Euclidean Distance.** It is used to define how the two texts are distinct.

From Fig. 8 and 9 it can be shown that non-memes depicted in S.No. [1,3] have high semantic similarity scores with less euclidean distance and high pearson correlation between generated text and OCR text. Similarly, images that are memes with S.No. [2,4,5] have low semantic similarity scores, with high euclidean distance and low pearson correlation between generated text and OCR text and can be verified from Table 9. For analysing the similarities in two text for a specific image, heatmaps are generated as shown in Fig. 11 and 12. This analysis shows that a meme and non-meme are opposite in nature as there is almost no relation between the textual and visual content in case of meme unlike non-meme. An additional interesting point can be observed from Table 8, that items with S.No. [4 and 6], S.No. [3 and 5] are similar i.e. with same scene description but vary when text is induced on it. This attempts to rationalise the above mentioned point that a non-meme image consists of a correlation between image and the embedded text.

Analysis of meme is very different from other active areas involving interactions of image and text based modalities like image captioning (Aneja et al., 2017) and scene description (Vinyals et al., 2015). In these tasks, there is high correlation between visual and textual content (Klein et al., 2015), which is different in case of meme analysis. On closely observing Fig. [5,6,4] , various forms in which a meme can be expressed are clearly demonstrated, with very little or even no semantic relation between what is being shown and what is superimposed as text unlike in case of non-meme images shown in Fig. [1,2,3].

Table 8: Depiction of differences in Memes and Non-memes, with highly similar OCR and captioned texts for Non-memes, as against total dissimilarity for Memes.

| S.no | Image/Meme | Type | OCR Extracted Text | Genrated Text |
|---|---|---|---|---|
| 1 |  | Non-Meme | X: Good morning | Y: Sunshine with river flowers and mountains |
| 2 |  | Meme | X: It's going to be hard but hard doesn't mean impossible | Y: Handle of a Cycle |
| 3 |  | Non-Meme | X: A young adult wearing roller blades holding a cellular phone to her ear | Y: A girl wearing roller blades holding a cellular phone to her ear |
| 4 |  | Meme | X:Make Sure that every kid participating in an easter egg hunt on my turf gives me a piece of the action | Y: A small kid standing and pointing something. |
| 5 |  | Non-Meme | X:Woman talking on cell phone and wearing roller skates | Y: A girl wearing roller blades holding a cellular phone to her ear. |
| 6 |  | Meme | X:You Break our Lease I'll Break your face | Y: A small kid standing and pointing something. |

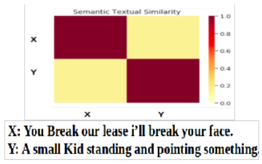



Figure 11: S.no 6.

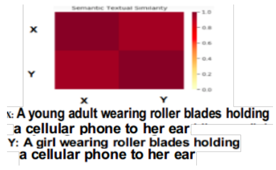



Figure 12: S.no 3.

Table 9: Observations from association evaluation, using Semantic, Cosine similarities, Pearson coefficient and Euclidean distance.

| S. No. | Semantic sim | Cosine sim | Pearson Correlation | Euclidean distance |
|---|---|---|---|---|
| 1 | 0.40 | 0.29 | 0.29 | 1.1 |
| 2 | 0.0 | 0.14 | 0.14 | 1.3 |
| 3 | 1.0 | 0.94 | 0.94 | 0.33 |
| 4 | 0.20 | 0.21 | 0.21 | 1.25 |
| 5 | 0.76 | 0.76 | 0.76 | 0.27 |
| 6 | 0.2 | 0.14 | 0.14 | 1.3 |

# 5 MEME APPROACH

To detect a MEME, we have performed experiments considering image, text and both as input. For the task, we have taken 80% of the data-set for training and remaining 20% for testing. The methods used for extracting the visual and textual features are demonstrated in the subsequent sections.

## 5.1 Visual Feature Extraction (m1)

Visual features are extracted using a pre-trained CNN like VGG-16 (Simonyan and Zisserman, 2014). After evaluating and assessing the performance of alternatives like ResNet-50 (He et al., 2015) and AlexNet (Krizhevsky et al., 2012) for feature extraction from an image, it was established that VGG-16 can learn better features at both abstract and fine-grained level (Russakovsky et al., 2014).

Towards this, following steps are involved in the process of feature extraction:

- Step 1: To maintain uniformity in image dimensions, we have resized them into 224×224×3 from a given original image $I$, the resized image $X_i$ is fed into VGG-16 as input for feature extraction.
- Step 2: Extracted feature $Y_i$ from VGG-16 for the given image is then flattened.
- Step 3: Flattened output $Y_{i'}$ is fed to a fully connected network using a dense layer and finally sigmoid based activation is used to compute the output $Y_{out}$. The network is optimized using binary cross entropy $BCE$ loss, which is defined as,

$$BCE = -(y\log(p) + (1-y)\log(1-p)) \tag{4}$$

where y is ground truth and p is predicted output of the input data.

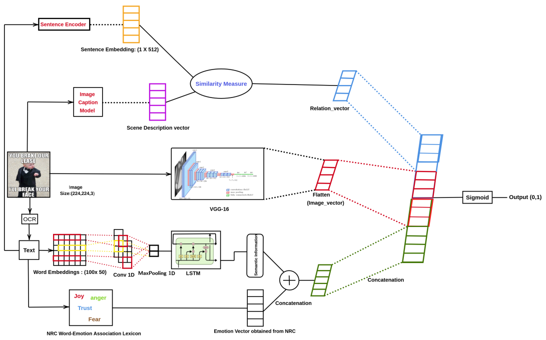



Figure 13: Meme Classification.

## 5.2 Textual Feature Extraction (m2)

To understand the text associated with an image and to get the insights of the contextual relation between the different words used in the textual content, we have used 100-Dim Glove word embeddings (Pennington et al., 2014) $embeddings(text)$, and vocab matrix of size 50 $\times$100 is obtained from such processing. Textual embeddings $x_i$ are then given as input to CNN having 64 filters of size 1$\times$5, and Relu as activation function, to extract the required *textual features*.

$$x_i = embeddings(text) \tag{5}$$

$$y_{i,k,j} = \sum_{i,k,j} w_{i,j,k}(x_{i+i',j+j'}) \tag{6}$$

To reduce the dimension size of the features generated by CNN layer, we have used maxpooling of size 2X2 $y_{i',k'j'}$. The output from this is given as input to LSTM where we get a *semantic feature* vector $s_t$.

$$y'_{i,k,j} = \max\{0, y_{i,k,j}\} \tag{7}$$

$$y_{i',k',j'} = maxpool(y'_{i,k,j}) \tag{8}$$

$$h_t, s_t = LSTM(h_{t-1}, s_{t-1}, y_{i',k',j'}) \tag{9}$$

## 5.3 Emotion Feature

To get the emotion feature from OCR extracted text $t_{ocr}$. We have used NRC emotion dictionary developed by (Mohammad, 2018) to understand the influencing capacity of each word towards different emotions, using values from 0 to 1. If the score for a word is close to 1, it is more likely to contribute towards the emotion associated with the text via various implied affects like anger, joy, trustworthy emotions etc. Similarly, if the score of word is 0, the word is less likely to influence overall emotions defined. We call the features computed as intensity vector $emotion_{vector}$.

Finally we concatenate semantic feature vector $s_t$ obtained from Section 5.2 and emotion feature vector $emotion_{vector}$, which carries encoded information of emotion content. This results in $text_{vector}$ for given image.

Table 10: Performance of web image classification : Model M3 performs well due to the addition of emotion and relation embedding.

| Modal | Precision | Recall | F1 Score |
|---|---|---|---|
| m1:Image | 0.94 | 0.96 | 0.94 |
| m2:Text | 0.81 | 0.79 | 0.80 |
| **m3:Image+Text+emotion+relation embedding** | 0.99 | 0.98 | 0.98 |

## 5.4 Relation Embedding

From Section 4 we have seen that correlation exists between the image and text in the case of non-meme. Whereas in the case of meme, this correlation decreases. In relation embedding, parameters like semantic similarity, cosine similarity, euclidean distance, and pearson correlation are computed, between the text generated via scene description network and the one extracted using OCR. We call this representation as relation vector $relation_{vector}$ of dimension $1 \times 4$.

### 5.4.1 Classifier (m3)

Finally to build a classifier with a hybrid structure as shown in Fig. 13, we concatenate all the feature vectors extracted from sub networks i.e. $Image_{vector}$ from Section 5.1, $text_{vector}$, $relation_{vector}$ and pass this concatenated vector to a sigmoid layer. The loss function employed for optimization uses binary cross entropy. This is how we built a classifier that classifies a given multi-modal web image as a meme/non-meme.

# 6 RESULTS

As shown in Table 10, we have developed three different models out of which model m3 has performed well, compared to the other 2 models. Out of three, we can acknowledge that model m2 has not performed as good as others because it was unable to capture the emotional feature due to the indifference towards the inherent user perspective. The requirement is reinforced by the fact that the perception of emotional state varies from person to person. This results in information loss in text classifier m2 i.e. the model isn't able to learn relevant features when trained over text. The performance of m3 is enhanced compared to model m2 due to the addition of emotion and relation feature, which are generated by calculating semantic similarity, cosine similarity, pearson correlation, and euclidean distance.

# 7 DISCUSSION

The data-set we present in this paper, is created considering the requirement of establishing a fundamental baseline system. Since there is dearth of reliable data-set resources for meme content analysis, we have ensured that any assumption made during the creation of the data-set or conducting the study, conforms to the norms as defined by the problem itself. The classification performances of different systems involving the usage of hand-crafted features and deep learning approaches presented insightful observations. Haar wavelet transform based features are observed to yield most optimal performance amongst different image processing techniques evaluated. Although the modeling of texture related information is decently done by this technique, but it is not as good as is learned by the initial convolutional layers. A novel method for identification of meme considering only image is proposed in Section 3.4 where a feature embedding using classical approaches is derived to embed varying structural and semantic information associated with an image. Although, VGG-16 trained on our data-set resulted in the best F1 score of 0.94, it has few notable limitations when compared to proposed method. The enhancements shown in Section 3.4.1, are significant w.r.t the difference in the performance observed. The performance of different techniques motivated us to analyse the real time data which was obtained from Twitter. Since Haar performed well for real time data that led us to develop a basic system that predicts the posted content on twitter as meme or non-meme, downloaded at a particular instant. Few limitations observed in this setup could be attributed to the fact that textual context provided in the memes isn't considered for this system. Section 4 shows empirical characterization of memes considering one of the key points obtained in Section 3.5.1. Besides establishing the efficacious of different techniques towards the task of Meme classification, we have also attempted to elucidate the existing correlation between visual and textual information in case of a non-meme unlike a meme. Finally, a baseline system is described that combines visual, textual and associated emotion related features with relation embedding obtained from Section 4, which resulted in 0.98 F1 score.

# 8 CONCLUSION AND FUTURE WORK

This paper reports an investigative study on the role of graphical content in an image, towards understanding a meme. The study builds on by applying different classical image processing and deep learning techniques, to evaluate their efficacious towards classifying meme vs non-meme. Due to the limitations observed in case of individual techniques, we propose an approach that represents an image by combining all the features obtained from different image processing techniques evaluated in a stack, alongwith deep learning based additional feature learning scheme. It is observed that the application of convolution operation for model training performs best with F1 score of 0.92. Our real time evaluation of the classification system shows that image (graphic content) alone is not sufficient to detect a meme on social media. Therefore we performed meme/non-meme characterization by analyzing different association metrics and deduced that in case of meme there is almost no semantic correlation between visual and textual content, yet both the modalities play a significant role in defining the higher order phenomena that the meme intends to convey. Finally a basic system is designed that detects meme and non-meme considering the combination of image, text and the emotion features which yields F1 score of 0.98. In the future, this work can be extended to:

- Understand the relationship type that exists between text and image with greater depth, which helps us generate or suggest/recommend a meme to the user.
- Understanding the meme-emotion diffusion in social networks and support social media platforms to provide the red flags for the inappropriate memes, which can potentially affect someone's mental state.

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