Meme Non - Meme Analysis on Twitter

submitted in partial fulfilment of the requirements for the award of the degree of

Master of Computer Applications

(2018-2021)

By

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<u>Certificate</u>

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Prabhleen Kaur

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Table of Contents

List of Symbols

S No.	Symbol	Nomenclature and Meaning
1.	CNN	Convolutional Neural Network

List of Tables

List of Figures

Abstract

Among all social networking sites, Internet memes are one of the most expressive type of content and have a huge virality factor. In the age of the internet, memes in the form of funny images, quotes, jokes, tweets have become an important social phenomenon. In this paper, we analyze memes usage on Twitter. First, we collected and curated a dataset of 776 meme and 826 non-meme images posted by users using ten different and trending hashtags from Twitter, then we manually annotated those images. Second, we developed a machine learning model that is capable of automatically classifying images as a meme and non-meme classes by discovering patterns in the data. In this paper, we perform experiments in two ways, namely, combined hashtag and one-vs-all hashtag settings by using an approach of Convolutional neural network (CNN) based models of deep learning for the classification of images. The results show that images were correctly classified with the training accuracy of 98% and testing accuracy of 90.27% .

Keywords: Machine Learning, Algorithms, Convolutional Neural Network, Memes, Twitter.

Chapter 1: Introduction

In the age of the internet, while social media is a platform for communication, memes are images or videos that represent the thoughts and feelings of a specific audience. People can share their experiences easily by using images that have a funny or relatable caption. Viewers are also six times more likely to remember and relate a message if it is a visual in the form of a meme than the plain text. People find memes very interesting because they are relatable and the audience thrives for things that they can relate to. Every time we log in to any social media platforms like Instagram, Twitter, Facebook, our timeline is covered with memes. But memes are much more than just a source of humour, they are used as a tool for political discourse, expressing public opinion, and for advertising brands. People react in different ways to everyday happenings and

it is important to understand public opinion in a crisis situation (Siemer et al. [12]). The situation caused by the virus is one of its kind. This experience has not only left people fearful health wise but is also affecting their emotional and mental state. New terms like social distancing, quarantine, remdesivir which were never heard before have become the new common. Memes are becoming a useful source of data for analyzing behavior of people on social media websites. Twitter is an online social networking and micro-blogging platform that enables users to send and read text messages called "tweets". It has a large volume and diverse collection of memes which will be helpful for training our model and will make it robust and successful in recognizing patterns. Lots of tweets flood in with every news about the everyday situation. Using these memes we can analyze various socio-economic factors that are currently prevailing and a lot more.

This paper analyzes memes usage on Twitter. A lot of memes datasets are publicly available on Kaggle (Martin et al. [11], Suryawanshi et al. [14], Barnes et al. [1], Suryawanshi et al. [13], Beskow et al. [3], Bauckhage et al. [2]). We created our own dataset because the existing memes datasets available on Kaggel are not specific to India. Also existing meme datasets have various limitations like some of the datasets do not have class labels and some do not have a balanced distribution of memes across classes so this might result in poor predictive performance specifically for the minority class. So, we did an India specific work and analyzed recent Indian memes posted by people on Twitter. Our goal is to generate insights about mass human behavior, thoughts, emotions of Indian people on a wide range of issues as it is very important to understand public opinion in the crisis situation. We created a dataset of around 1,602 images which consists of 776 meme and 826 non-meme images posted by people using ten different and trending hashtags from Twitter, then we manually annotated those images.

Second, we did classification of an image as a meme or a non-meme image using Convolutional Neural Networks (CNN) based models. We perform experiments in two ways, namely, combined-hashtag and one-vs-all hashtag settings. In combined hashtag settings, we combined all meme and non-meme images for all hashtags and we divided the dataset into training and test sets with 75:25 ratio. We successfully classified the images and achieved an average training accuracy of 98 percent and average validation accuracy of 90.27 percent and in one-vs-all hashtag settings we used meme and non-meme images for nine hashtags as training data and meme and non-meme images of one hashtag as testing data to check how good our model will perform when one of the hashtags is used as a testing data.

Chapter 2: Related Work

1. Martin et al. [11] have also collected a memes data set of Chilean users tweets, then they manually annotated those images. They developed a classification algorithm to classify images as memes, non-memes and sticker classes. They also compared several classification methods and they achieved best results using Residual Neural Network and Linear SVM with a precision of 0.73. Third, they proposed a deep learning model that was able to retrieve memes from the dataset using a text query in spanish.

2. Barnes et al. [1] have collected memes by using Pushshift API to scrape data from Reddit from various meme subreddits. The dataset consists of the post ID, image URL and the upvotes/downvotes for that particular meme. Since the dataset was initially unlabeled, they classified posts with a normalized upvotes value in the top 5% of all posts as dank meaning viral, and the rest were classified as not_dank. Their data set consists of 4019 dank posts and 76,343 not_dank posts from March 17th, 2020 to March 23rd, 2020. They proposed a content-based analysis of what makes a meme successful and whether the success of a meme can be predicted based on its content alone excluding social network factors.

3. Suryawanshi et al. [13] have constructed the multi offensive multi model meme dataset consisting of 743 memes by extending an existing memes dataset on the 2016 US Presidential Election by manually annotating the data into either the offensive or non-offensive class. Eight annotators participated in the annotation campaign and they categorised images as offensive if the image consists of personal attack, racial abuse or attack on minority Then they used this dataset to implement a multimodal offensive content classifier for memes.

4. Beskow et al. [3] created their own dataset of 25,109 images by searching images from Twitter, Tumblr, Flickr, Google Search and Instagram. They classified images on the Internet as memes and non-memes and compared their results to uni-modal approaches. They studied memes usage in the 2018 US Midterm election and 2018 Swedish election.

5. Suryawanshi et al. [14] have also collected Tamil memes dataset by asking sixteen volunteers to send them memes that they get in their social media platforms like Instagram, Facebook, WhatsApp, and Pinterest from November 1, 2019, to January 15, 2019.Then they manually annotated meme images as 1,951 troll-memes and 1,018 non-troll memes. They also included Flickr30K2 images to the non-troll class to prevent class imbalance.

6. Chagas et al. [4] have also worked on analyzing online political memes during the Brazilian 2014 elections. Their main goal was to design a taxonomic matrix that could help those researchers interested in dealing with memes.

7. Chew et al. [5] have also worked on analyzing tweets content during the 2009 H1N1 outbreak. Their study proposed the usefulness of social media to study public health. Lots of tweets flood in with H1N1 pandemic related news on Twitter. Their study included classifications, knowledge translation and sentiment analysis.

8. Yang et al. [16] analyzed various factors on which the spread of memes depends to reach Chinese communities.

9. French et al. [7] identified correlations between semantic meaning of memes and textual content on memes and trend of popular memes.

10. Kulkarni et al. [10] studied the use of internet memes as a tool of political discourse.

11. Velioglu et al. [15] proposed an approach for detecting hate speech in memes. considering visual and textual content. They used a pre-trained VisualBERT model and achieved 0.811 AUROC and an accuracy of 0.76.

12. Handayani et al. [8] studied the use of memes as a representation of social issues such as hot temperature, high traffic, poor conditions of roads, hospitals and schools with the help of social media.

13. Hu et al. [9] developed a multimodal sentiment analysis method to study the emotional state of people by using a large Tumblr social media dataset. emotional state of the user by focusing on predicting the emotion word tags attached by users to their Tumblr posts.

14. Du et al. [6] analyzed the relationship between demographics of users and the patterns of images with text memes they share. They develop an accurate classifier for identifying images with text on the internet.

15. Bauckhage et al. [2] analyzed the properties which affect the growth or decline of 150 famous internet memes. Their analysis was based on time series that were collected from Digg, Google Search, StumbleUpon and Delicious recommendation engines .They analyzed different patterns of memes shared in the different

communities and they observed that memes spread through homogenous communities rather than the Internet at large.

Chapter 3: Proposed Methodology

Fig 1 shows the flow chart for the whole project working :

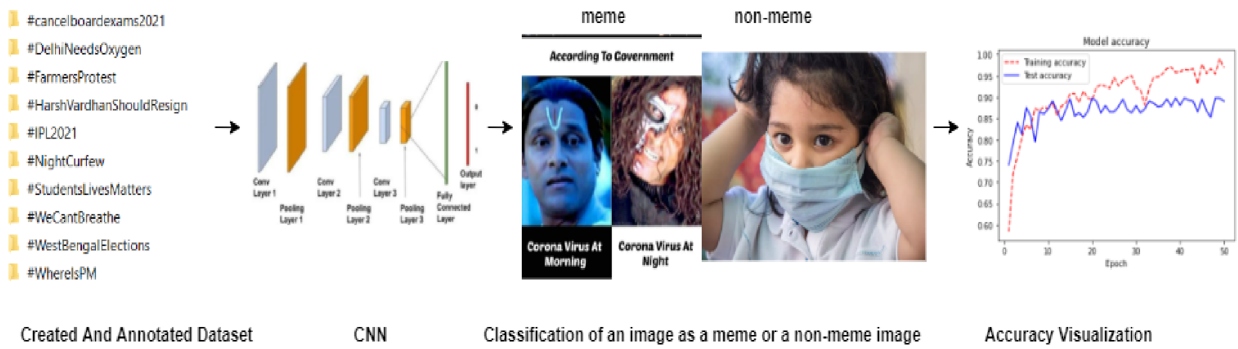


Figure 1: Flowchart explaining the proposed methodology

We have created a dataset of around 1,602 tweets containing 776 meme and 826 non-meme images using ten trending hashtags from Twitter, then we annotated those images. Then this dataset is given as input in Convolutional Neural Network (CNN), in this all the images goes through all the layers of CNN - Convolutional layer, ReLU layer, pooling and fully connected layer in training phase and develops a vector with some elements as high so we will know through the train phase that for normal which elements are high in that vector. For testing when we give a new input image it will also go through all the layers of the CNN and will develop a vector and when we will compare the sum of the corresponding high elements of this vector with that of the vector for meme and non-meme and if it matches to meme that is the sum of the new vector corresponding high level matches to meme then we classify the image as meme otherwise we classify the image as non-meme. After classification accuracy of the model is captured through graphs.

3.1 Dataset Creation

In the machine learning approach to solve problems, creating or collecting a dataset for training is considered as one of the important steps of model development. A lot of memes datasets are publicly available on Kaggle (Martin et al. [11], Suryawanshi et al. [14], Barnes et al. [1], Suryawanshi et al. [13], Beskow et al. [3], Bauckhage et al. [2]). We created our own dataset because in our work we wanted to analyze recent Indian memes posted by people on Twitter. Our goal is to generate insights about mass human behavior, thoughts, emotions of Indian people on a wide range of issues. Twitter has a large volume and diverse collection of memes which will be helpful for training our model. So, we wrote a script in python to download 1,602 tweets containing pictures from Twitter using ten trending hashtags. Names and description of ten hashtags are as follows -

NightCurfew - Delhi Government announced a night curfew in the city from 10 pm to 5 am till April 30, 2021 after the rising cases of covid with cases going over 3,500 on a daily basis to prevent social activities like weddings and night parties as these are not essential. Government does not look into these measures as a frequent option as they understand that economic activities have to remain functional but at the same time we have to prevent infection spread. Meme makers started pouring memes using # NightCurfew on Twitter after the announcement of this news.

cancelboardexams2021 - Students across the country are trending # cancelboard exams2021 on Twitter asking the Ministry of Education to either cancel the exams fully and pass all the students or conduct the exams online. The reason behind this is India is grasping with a scary second wave of covid-19. On 17th September, 2020 when India hit its first covid peak, the country had 96,424 fresh cases. However in March 2021 for the first time India had more than a lakh fresh cases despite having two vaccines Covidshield and Covaxin.

StudentsLivesMatter - This hashtag was also No. 1 trending on Twitter, through which various university students and government jobs aspirants raised concerns over appearing for upcoming semester and entrance exams.

FarmerProtests - Indian Farmers are protesting against three new agricultural bills passed by the central government. The demand of the protesting farmer's is the repeal of these three laws as these laws will benefit the corporate, but not the farmers. So people are using # FarmerProtests on Twitter to raise their voice against injustice.

WhereIsPM - The situation of the virus has worsened so much that people are not getting treatment and the beds in the hospital are also not empty. So, people are expressing their pain and anger using # WhereIsPm on Twitter.

IPL2021 - Indian Premier League (IPL) 2021 is back in India after being held in UAE last year due to the coronavirus pandemic. Millions of IPL Fans eagerly wait for IPL (T20 Cricket League) which is conducted every year. The IPL 2021 final will be played at the Narendra Modi Cricket Stadium Ahmedabad in the month of May. The eight teams will play across six venues - New Delhi, Bengaluru, Mumbai, Kolkata, Ahmedabad and Chennai.

WeCantBreathe, # DelhiNeedsOxygen - During the second wave of Covid-19, many people died not because of the virus but because of the unavailability of oxygen support as hospitals in Delhi continue to face an acute shortage of oxygen**.** People are expressing their sufferings and crying for help on Twitter using # DelhiNeedsOxygen and # WeCantBreathe in the hope of getting emergency oxygen supply for their loved ones.

WestBengalElections - The 2021 West Bengal Assembly Elections for 294 seats

took place in eight phases from 27th March, 2021 to April 29, 2021. It was an interesting fight between Trinamool Congress, Left front and BJP. The Trinamool Congress won 213 seats and a consecutive third term in the state. The chief minister, Mamata Banerjee however, lost by 1956 votes in Nandigram to BJP.

HarshVardhanShouldResign - Dr Harshvardhan is the Minister of Health and Family Welfare of India. People are crying for hospital beds, begging for oxygen, ambulances are charging high fees for a few kilometres and cremation sites are overflowing with dead bodies. So, people are expressing their anger using # HarshVardhanShouldResign as according to them he has shown less interest in protecting the people.

Steps for collecting images from tweets are given below :

1. **Registering application -** First, we need to create an app on the Twitter Developers Website and after that we will receive consumer_key, consumer_secret_key, access_token and access_token_secret which will be used to access twitter data.

2. **Accessing Data -** In order to access Twitter data, we need to use a python library Tweepy by using the command - pip install tweepy , OAuthHandler method and our configuration keys.

3. **Storing Data -** Now we will collect all tweets using trending hashtags and store them in a JSON format for analysis. Tweepy has a Cursor interface to iterate through all the tweets and store them in a JSON file.

4. **Obtaining the full path for the image -** Now we have all the tweets for a given hashtag and we want to filter those tweets which contain a media file. In order to do this we use the field *media* to get multimedia content within a tweet. After this, we can access the URL of each of the specific media attachments with *media_url*. Now, we have the url of all the multimedia content such as images or videos stored in the variable *media_files*.

5. **Downloading images -** Downloading files can be achieved in python using the wget library.

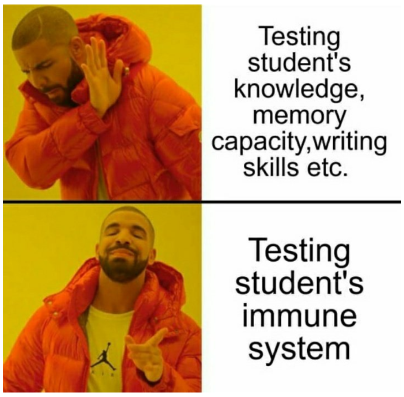
3.2 Dataset Annotation

After collecting 1,602 images across 10 different hashtags for our dataset, we manually annotated each image as a meme or a non meme.

We consider an image as a meme when the following conditions are met.

1. Image has an overlay text.
2. The text is mostly a message that is humorous, it can be a joke, irony or parody.

Figure 2 shows an examples of a meme and non-meme image.



(a) meme

(b) non-meme

Figure 2: Examples of meme and non-meme images.

Table 1 shows the distribution of the dataset.There are a total of 1602 images which consists of 776 meme and 826 non-meme images.

Table 1. Dataset Distribution

Hash Tags	Meme	Non-Meme	Total
#cancelboardexams2021	90	109	199
#NightCurfew	71	103	174
#WhereIsPM	85	93	178
#WeCantBreathe	93	74	167
#HarshVardhanShouldResign	43	44	87
#DelhiNeedsOxygen	32	97	129
#IPL2021	100	100	200
#StudentsLivesMatters	81	65	146
#FarmerProtests	49	56	105
#WestBengalElections	132	85	217
Total Images	**776**	**826**	**1602**

3.3 Convolutional Neural Network

3.3.1 Description

Convolutional Neural Network (CNN) is a type of Artificial Neural Network in which the connectivity pattern between its neurons is inspired by the organization of the visual cortex of animals. CNN is used in image recognition and classification. It basically has four layers – Convolutional layer, ReLU layer, pooling and fully connected layer. It takes meme and non-meme images as input and after training the model on this data the model predicts if the input image is of a meme or non-meme class.

The architecture of the CNN model is discussed as follows -

1. We have created a sequential model in which layers are connected in sequence to each other.
2. Input is passed to a series of convolution layers and ReLU activations. These layers help in removing certain features from the image. We used the ReLU layer to remove every negative value that we got from the output of the convolutional layer and replaced it with zeros.
3. Each convolution layer is followed by a max pooling layer that helps to reduce the dimension of input by calculating the maximum value.
4. Then we used the Flatten layer, this is the last layer where the real classification takes place. So here we take our filtered and shrink images and we put them in a one list.
5. Then we used Dropout for randomly discarding the neurons to avoid over fitting for regularization.
6. Finally, the output of the previous layer enters as an input into a dense layer with one neuron that finally classifies the input as 0 or 1.
7. Categorical cross-entropy as the loss function is used which is a logarithmic loss function.
8. Adam as an optimizer with learning rate set to 0.001 is used for reducing the loss.

Fig 3 and 4 presents the architecture of the CNN model.

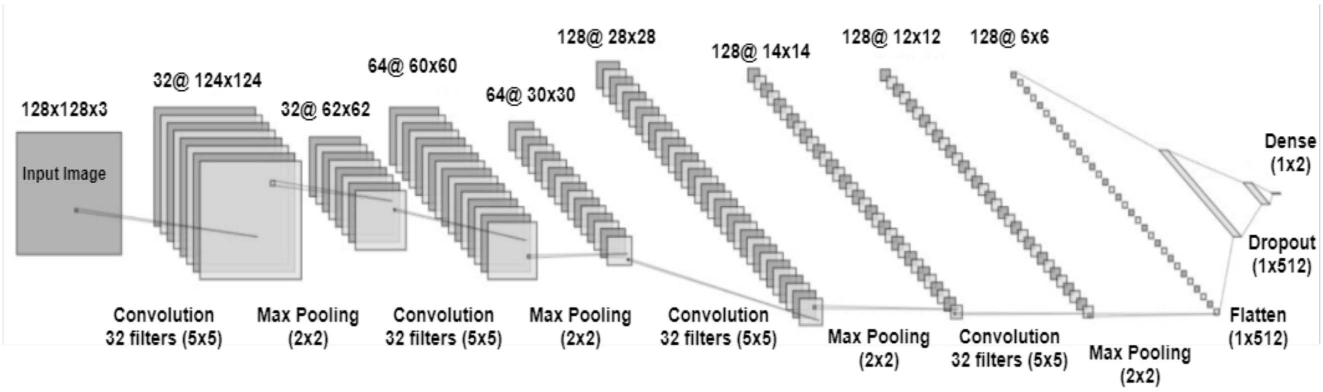


Figure 3: Architecture of CNN model diagrammatically.

Conv2d_10 (Conv2D)	input:	(None, 128, 128, 3)
	output:	(None, 124, 124, 32)
max_pooling2d_10 (MaxPooling)	input:	(None, 124, 124, 32)
	output:	(None, 62, 62, 32)
conv2d_11 (Conv2D)	input:	(None, 62, 62, 32)
	output:	(None, 60, 60, 64)
max_pooling2d_11 (MaxPooling	input:	(None, 60, 60, 64)
	output:	(None, 30, 30, 64)
conv2d_12 (Conv2D)	input:	(None, 30, 30, 64)
	output:	(None, 28, 28, 128)
max_pooling2d_12 (MaxPooling	input:	(None, 28, 28, 128)
	output:	(None, 14, 14, 128)
conv2d_13 (Conv2D)	input:	(None, 14, 14, 128)
	output:	(None, 12, 12, 128)
max_pooling2d_13 (MaxPooling)	input:	(None, 12, 12, 128)
	output:	(None, 6, 6, 128)
flatten_2 (Flatten)	input:	(None, 2, 2,128)
	output:	(None, 512)
dropout_2 (Dropout)	input:	(None, 512)
	output:	(None, 512)
dense_4	input:	(None, 512)
	output:	(None, 128)
dense_5	input:	(None, 128)
	output:	(None, 2)

Figure 4: Architecture of CNN model in tabular form.

Chapter 4: Experiment Design

We perform experiments in two ways, namely, combined-hashtag and one-vs-all hashtag settings.

4.1 Combined Hashtag Settings

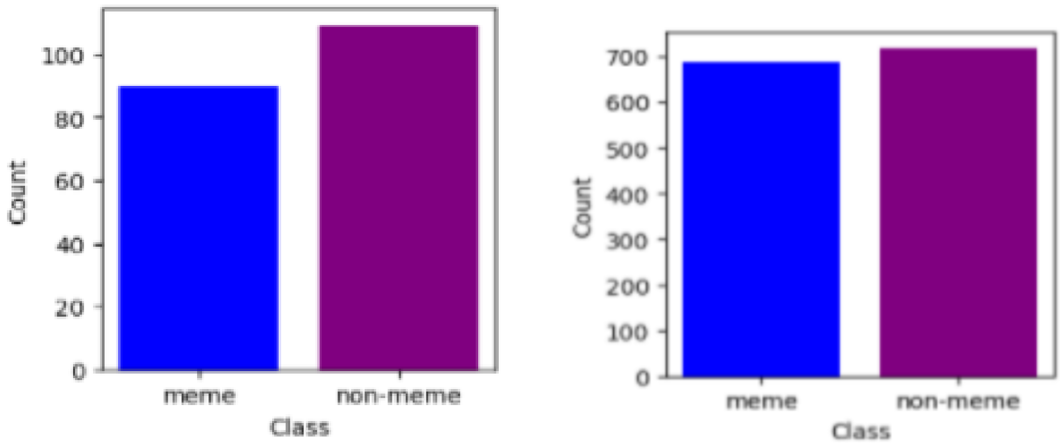
In combined hashtag settings, we combined all meme and non-meme images for all hashtags and divided the data set which consists of 1,602 images into training and test sets with 75:25 train-test split. The hyper parameters like number of epochs and batch size taken during this experiment are 50 and 12 respectively. Adam as an optimizer with learning rate set to 0.001 is used for reducing the loss.

4.2 One-vs-All Hashtag Settings

We perform experiments in a one-vs-all hashtag setting to check how good our model will perform when any one of the hashtags is used as testing data and all other hashtags are used for training the model.

Experiment-1 - In this experiment, we used 199 images of # **cancelboardexams2021** as testing data which consists of 90 meme and 109 non-meme images and used 1,403 images of all other nine hashtags as training data which consists of 686 meme and 717 non-meme images.

Figure 5 shows the distribution of train and test data when# cancelboardexams2021 is used as testing data.Training data consists of 686 meme and 717 non-meme images and testing data consists of 90 meme and 109 non-meme images.



(a) Distribution of Test data (b) Distribution of Train data

Figure 5: Distribution of data set used in experiment-1 of one-vs-all hashtag settings.

Experiment-2 - In this experiment, we used 174 images of # **NightCurfew** as testing data which consists of 71 meme and 103 non-meme images and used 1,428 images of all other nine hashtags as training data which consists of 705 meme and 723 non-meme images.

Experiment-3 - In this experiment, we used 178 images of # **WhereIsPM** as testing data which consists of 85 meme and 93 non-meme images and used 1,424 images of all other nine hashtags as training data which consists of 691 meme and 733 non-meme images.

Experiment-4 - In this experiment, we used 167 images of # **WeCantBreathe** as testing data which consists of 93 meme and 74 non-meme images and used 1,435 images of all other nine hashtags as training data which consists of 683 meme and 752 non-meme images.

Experiment-5 - In this experiment, we used 87 images of # **HarshVardhanShouldResign** as testing data which consists of 43 meme and 44 non-meme images and used 1,515 images as training data which consists of 733 meme and 782 non-meme images.

Experiment-6 - In this experiment, we used 129 images of # **DelhiNeedsOxygen** as testing data which consists of 32 meme and 97 non-meme images and used 1,473 images of all other nine hashtags as training data which consists of 744 meme and 729 non-meme images.

Experiment-7 - In this experiment, we used 200 images of # **IPL2021** as testing data which consists of 100 meme and 100 non-meme images and used 1,402 images of all other nine hashtags as training data which consists of 676 meme and 726 non-meme images.

Experiment-8 - In this experiment, we used 146 images of # **StudentsLivesMatters** as testing data which consists of 81 meme and 65 non-meme images and used 1,456 images of all other nine hashtags as training data which consists of 695 meme and 761 non-meme images.

Experiment-9 - In this experiment, we used 105 images of # **FarmerProtests** as testing data which consists of 49 meme and 56 non-meme images and used 1,497 images of all other nine hashtags as training data which consists of 727 meme and 770 non-meme images.

Experiment-10 - In this experiment, we used 217 images of # **WestBengalElections** as testing data which consists of 132 meme and 85 non-meme images and used 1,385 images of all other nine hashtags as training data which consists of 644 meme and 741 non-meme images.

Chapter 5: Results

In this chapter we have recorded the performance of the above mentioned experiments.

Table 2, shows the confusion matrix for combined hashtag experiment settings which consists of four different combinations of predicted and actual values for measuring the performance of CNN model. We observed, the value of True Negative is 160 i.e. our model predicted that an image is meme and it actually is, False Positive is 26 i.e. our model predicted that an image is meme and it actually is not, False Negative is 13 i.e. our model predicted that an image is non-meme and it actually is, True Positive is 200 i.e. our model predicted that an image is non- meme and it actually is not.

Table 2. Confusion Matrix for combined hashtag experiment settings.

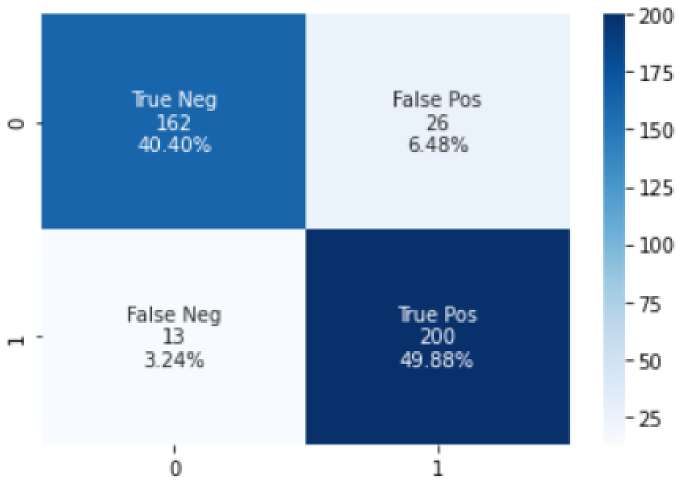


Table 3, displays the Training Accuracy, Testing Accuracy, Training Loss, Testing Loss, class wise Precision, Recall, F1-Score values observed in combined hashtag experiment settings. Precision = $\frac{\text{True Positive}}{TruePositive+FalsePositive}$ i.e. out of all the memes classes we have predicted, how many are actually memes. Recall = $\frac{\text{True Positive}}{TruePositive+FalseNegative}$ i.e. out of all the memes classes, how many we predicted as memes. F1- Score = $\frac{2*Recall*Precision}{Recall+Precision}$ i.e. the harmonic mean of recall and precision. Accuracy = $\frac{TruePositive+TrueNegative}{TruePositive+TrueNegative+FalsePositive+FalseNegative}$ i.e. out of all the classes, how many we predicted correctly. The results show that images were correctly classified with the training accuracy of 98% and testing accuracy of 90.22% . Meme class has high precision value and non-meme class has high recall value. We have got a F1-Score of 0.89 for meme class and 0.91 for non-meme class which is good as it's above 0.5.

Table 3. Results of combined hashtag experiment settings

Training Accuracy		0.9800
Testing Accuracy		0.9027
Training Loss		0.0621
Testing Loss		0.4088
Precision	meme	0.93
	non - meme	0.88
Recall	meme	0.86
	non - meme	0.94
F1 - Score	meme	0.89
	non - meme	0.91

Table 4, displays the Training Accuracy, Testing Accuracy, Training Loss, Testing Loss, class wise Precision, Recall, F1-Score values observed in one-vs-all hashtag setting. We observed, experiment 10 has achieved highest training accuracy and experiment 5 has achieved highest testing accuracy and the difference between the training and testing accuracies in experiment 6 is least which indicates very little overfitting. Experiment 10 has achieved the lowest training loss and experiment 6 has achieved lowest testing loss value.

Table 4. Results of one-vs-all hashtag setting

Experiment No.	**Training Accuracy**	**Testing Accuracy**	**Training Loss**	**Testing Loss**
1	0.9622	0.8342	0.1073	0.9625
2	0.9769	0.8915	0.0737	0.4973
3	0.9769	0.8915	0.0737	0.4973
4	0.9802	0.9080	0.0587	0.2831
5	0.9586	0.9200	0.1107	0.3577
6	0.9496	0.9195	0.1446	0.2825
7	0.9492	0.8973	0.1395	0.3204
8	0.9749	0.8443	0.0740	0.6438
9	0.9733	0.8295	0.0708	0.8531
10	0.9909	0.8483	0.0370	0.8581

Table 5, displays class wise Precision, Recall, F1-Score values observed in one-vs-all hashtag settings. The results show that the meme class has achieved highest precision value in experiment 7, highest recall value in experiment 4, highest f1-score value in experiment 5 and non-meme class has achieved highest precision value in experiment 5, highest recall value in experiment 9, highest f1-score value in experiment 2 and 6.

Table 5. Class wise Precision, Recall, F1-Score values in one-vs-all hashtag settings.

Experiment No.	Meme			Non-Meme		
	Precision	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**
1	0.76	0.92	0.83	0.92	0.76	0.83
2	0.82	0.72	0.77	0.91	0.95	0.93
3	0.88	0.73	0.80	0.80	0.91	0.85
4	0.87	0.95	0.91	0.95	0.86	0.90
5	0.88	0.98	0.92	0.98	0.86	0.91
6	0.88	0.93	0.90	0.95	0.91	0.93
7	0.95	0.86	0.90	0.85	0.94	0.89
8	0.88	0.84	0.86	0.81	0.85	0.83
9	0.99	0.73	0.84	0.70	0.99	0.82
10	0.79	0.93	0.85	0.92	0.77	0.84

In Figure 6, we show a plot between accuracies for different values of train - test split ratio where 0.1 means 90:10, 0.2 means 80:20, 0.3 means 70:30, 0.4 means 60:40, 0.5 means 50:50 train-test split. The best test-size is 0.1 where we get the maximum accuracy.

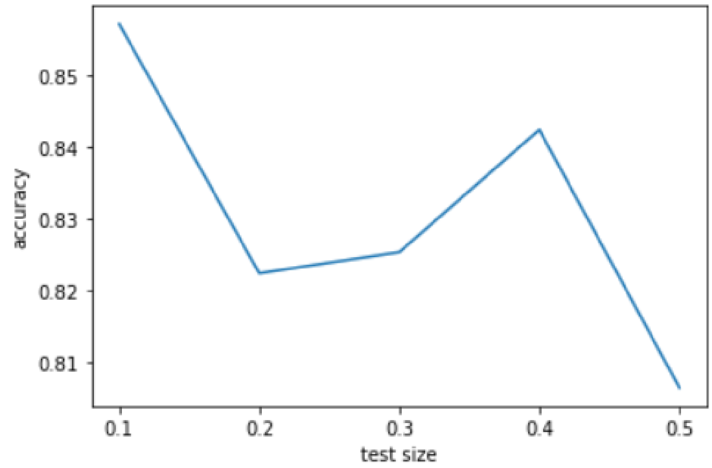


Figure 6: Graph between accuracy and different values of train-test split.

As the value of loss was decreasing in every epoch , so in figure 7 we made a plot between them where red dashed lines are representing training loss and blue are representing test loss. Our model is performing well on training as well as testing set and both curves are saturating around the same low value indicating a good fit.

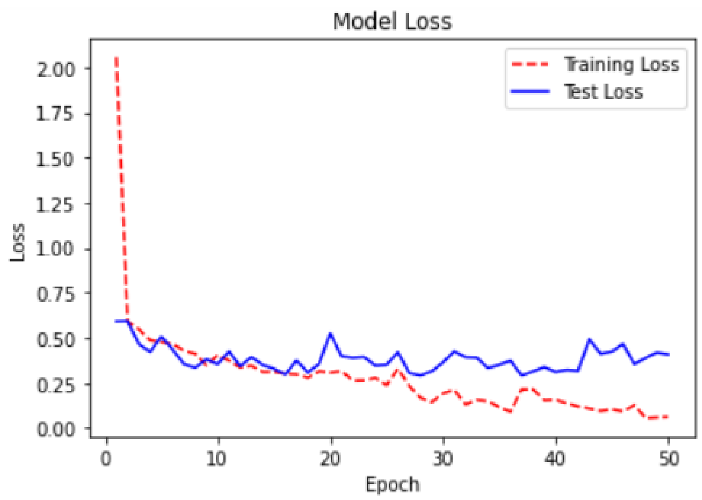


Figure 7: Graph between loss and epoch.

As the value of accuracy was increasing in every epoch. so, in figure 8 we made a plot between them where red dashed lines are representing training accuracy and blue are representing test accuracy. As the gap between training and testing accuracy curve is little and they are saturating around the same high value indicates very little over fitting.

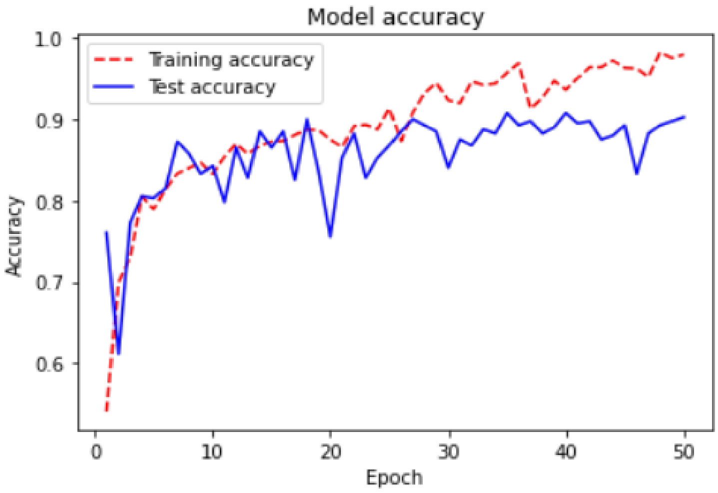


Figure 8: Graph between accuracy and epoch.

Chapter 6: Visualizations

Figure 9, highlights the most frequently occurring words in the dataset collected using # WeCantBreathe.

Figure 9: Word cloud for #WeCantBreathe

Figure 10 and 11, highlights the most frequently occurring words in the dataset collected using # DelhiNeedsOxygen and # IPL2021.

Figure 10: Word cloud for # DelhiNeedsOxygen

Figure 11: Word cloud for # IPL2021.

Figure 12 and 13, highlights the most frequently occurring words in the dataset collected using # NightCurfew and # WestBegalElections.

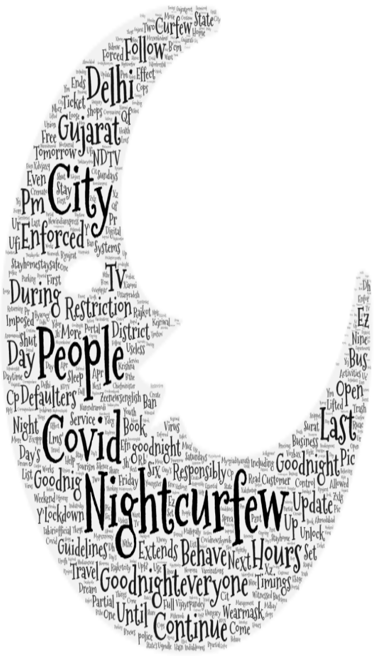


Figure 12: Word cloud for # NightCurfew

Figure 13: Word cloud for # WestBengal-Elections.

Figure 14, highlights the most frequently occurring words in the dataset collected using # cancelboardexams2021.

Figure 14: Word cloud for # cancelboardexams2021.

Figure 15, highlights the most frequently occurring words in the dataset collected using # FarmerProtests.

Figure 15: Word cloud for # FarmerProtests.

Figure 16, highlights the most frequently occurring words in the dataset collected using # HarshVardhanShouldResign.

Figure 16: Word cloud for # HarshVardhanShouldResign.

Figure 17, highlights the most frequently occurring words in the dataset collected using # StudentsLivesMatter.

Figure 17: Word cloud for # StudentsLivesMatter.

Figure 18, highlights the most frequently occurring words in the dataset collected using # WhereIsPM.

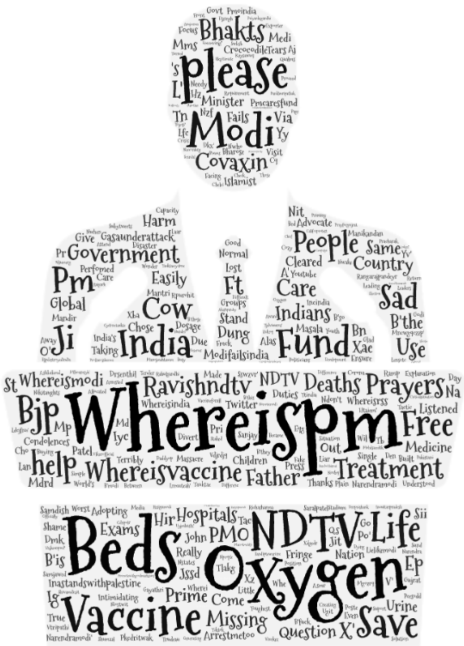


Figure 18: Word cloud for # WhereIsPM.

Chapter 7: Conclusions

To conclude, in combined hashtag settings, we have successfully classified the images and achieved an average training accuracy of 98 percent and average validation accuracy of 90.27 percent and in one-vs-all hashtag settings, we perform multiple experiments by using images of different hashtags as testing data one by one. We have observed that when we used # WestBengalElections as testing data we achieved an average training accuracy of 99.19 percent and when we used # HarshVardhanShould Resign as testing data we achieved an average validation accuracy of 92 percent and we have observed that the difference between the training and testing accuracies by using # DelhiNeedsOxygen as testing data is least which indicates very little overfitting. In our future work, we wish to analyze the sentiments of the people from these memes by automatically extracting text from memes and wish to analyze whether the meme describes confidence, hope, sadness, fear or anger as it is very important to understand public opinion in crisis situations. We wish to detect hateful memes and wish to determine the factors on which the popularity of the memes depends. We also wish to analyze tweet performance like whether the tweet is a part of a broader conversation or not by analyzing the count of retweets, follower count, shares and upvotes / downvotes of the tweet with the help of tweet id and analyze the tweet's location of the viral posts so that authorities can respond to real concerns raised by the public. .

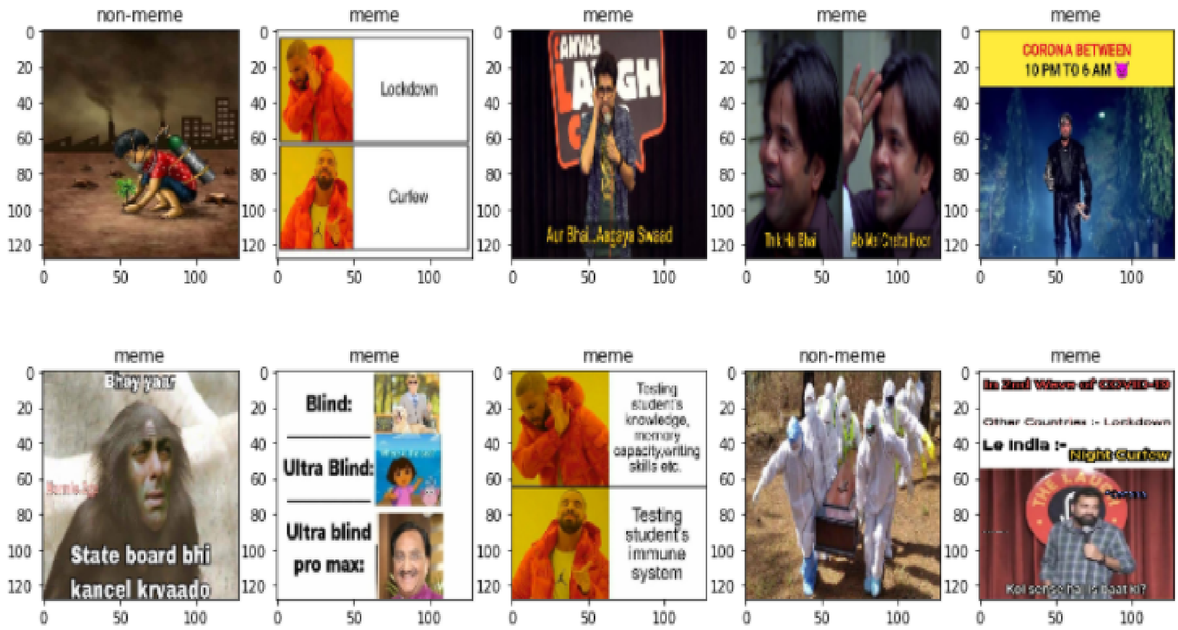


Figure 19: Classification of Images as a meme or a non-meme image.

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