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Psychological Analysis using Social Media Memes

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Abstract

Nowadays what social media stands for has completely changed. Earlier, people used it to post their vacation pictures and connect with their friends. But now people are more keen on posting about their opinions, what their thoughts and emotions are, and has become their daily sources of entertainment. Social media has also led to the emergence and distribution of memes in abundance. On close inspection, a correlation can be found between the memes being created and shared by an individual and their thought and behavioral patterns. The aim of this project is to detect and analyse such a correlation using big data analytics. Large volumes of memes can be collected and classified according to their underlying sentiments using supervised machine learning algorithms. It is expected that the outcome of this project will lead to a more detailed understanding of the mindsets of the individuals sharing them and the mental or social issues they might be facing.

Keywords: *Psychological Analysis, Memes, Social Media, classification, negative, positive, SVM, Random Forest, Logistic Regression.*

I. Introduction

Humans exhibit an infinite array of mental states and personal choices, which might reflect on the content they create and share online. The last five years have witnessed the exponential increase in the creation of a piece of media that serves mimicry and humorous purposes, commonly known as memes, that are distributed among the people via the Internet. Most of these memes are created and circulated to serve comic purposes, while others are created with malicious intent. They might incite hatred towards certain communities and even promote self harm. Such memes which present detrimental ideas in a

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humorous manner are called dark memes. Thus, harmless memes can be classified as positive and dark memes as negative. Using this system, one can delve into the pysche of the person creating the meme and determine whether he has a positive mindset or a negative one. For example, a person with a negative mindset would find memes on homicide humorous. One can also determine the views of the youth on certain subjects based on the memes being circulated. It can be deduced which topics are being taken seriously and which ones are being taken in a comical manner. Nowadays memes make up a dominant portion of social media data.A large number of people do not express their opinions and views publicly, but prefer to like and post memes and other posts that resonate with their view that they are connected to. Using this method we seek to identify the implicit emotions of social media users that are otherwise unlikely to be captured from their textual updates.

II. Literature Survey

Sharath Chandra Guntuku et al[1] have introduced a framework that studies the effects of using social media as a new tool for tracking individual and county stress levels. This closely examines the disparity between users who are depressed and users who are not, in the language of social media. This makes use of the study of correlation. It uses N-grams, LIWC, Tensist force and user engagement.

M. Trupthi et al[2] aims to provide an interactive predictive system that uses hadoop to predict social media reviews / tweets that can process the huge amount of information. It collects data from SNS services created using the Streaming API of twitter. This feature is accompanied by classification using Natural Language Processing(NLP), and machine learning techniques. The form used here is the grouping of naive bayes with uni-word.

Soujanya Poria et al[3] proposed a LSTM-based model that would allow contextual information to be captured by utterances from their surroundings in the same video and thus improve the classification process.The model takes the sequence of utterances in a video as an input and extracts unimodal and multimodal contextual features by modeling the dependencies between the input utterances.

Amir Karami et al[4] recommend a computational general assessment mining system to examine the thought of financial issues in web based life during a political race.This work incorporates two methods of text mining: sentiment analysis and topic modeling. The hypothetical philosophy was effectively applied to look at the financial worries of the individuals on a huge number of tweets during the 2012 U.S. presidential election.This paper proposes a general public mining approach dependent on financial matters with four segments: data collection, sentiment analysis, discovery of topics, and analysis.

Nitesh Sharma et al[5], developed a web-based application that allows current feelings associated with a keyword (hashtag, phrase or word) of Twitter messages to be visualized by plotting them on a map. In terms of geography, this allows users not only to measure the feeling, but also to map its intensity. Using the python text- blob module, they conduct tweet sentiment analysis. This library uses an advanced method to measure a text's feelings. Words in the text are assigned negative and positive polarity scores ranging from1 to 1. A polarity value of 0 indicates the text's feeling is negative.

Hanif Bhuyian et al[6] suggests a sentiment analysis approach based on Natural Language Processing (NLP) on user comments. Based on the search, this assessment assists with finding the most suitable and well known video on YouTube. The proposed framework works in four phases. To begin with, gathering comments and pre-preparing module gathers information (comments) from the particular YouTube video and pre-handling some language to be utilized. Second, the prepared content experiences NLP-based strategies to deliver datal collections. At that point apply the sentiment classifier on the data collections, to compute the energy and cynicism scores. Utilize the root mean square deviation at last to get the outcome run.

So as to derive connections among emotions and music, Lucia Martin Gomez et al[7] proposed a strategy for dissecting sentiments dependent on data mining. In general, different musical traits are extracted and categorized to examine the effect of certain music parameters on human emotions. Critical to the success of the proposal in this process were data mining algorithms such as Randomk-Label sets, Multi-Label k-Nearest Neighbors or Apriori. The study was performed using WEKA method. Once the data is fully analyzed, the classification process is performed. The aim is to identify the songs when listening according to their emotions.

Maria del Pilar Salas-Zarate et al[8] endeavors to give an angle level investigation approach dependent on ontologies in the diabetes space. The significance of the viewpoints is characterized by considering the terms acquired by Ngram techniques around the dimension (N-gram after, N-gram before, and N-grams around). On receipt of a corpus from Twitter to assess the effectiveness of our operation, which at aspect level was manually marked as positive, negative, or neutral.

Vasavi Gajarla and Aditi Gupta al[9] are exploring the possibility of using in-depth learning to predict an image's emotion. They aim to predict an image's emotional category from five categories-Love, Happiness, Violence, Fear, and Sadness. They do this by fine-tuning three different neural convolution networks for the tasks of predicting emotions and analyzing feelings.

Imani El Alaoui et al[10] propose a versatile way to deal with sentiment inspection that dissects posts via web-based networking media and concentrates on the opinion of the client continuously. In this paper they devise a three-stage approach consisting of, first building feeling terms, at that point characterizing and adjusting this arrangement of words before performing the algorithm of prediction.

V Subramaniyaswamy et al[11] propose a complete programming application which will fastidiously scratch data from Twitter and break down them utilizing the dictionary based investigation to search for potential dangers. They propose a procedure to acquire a quantitative outcome called criticality to evaluate the degree of threat for an open occasion. The outcomes can be utilized to comprehend individuals' sentiments and remarks with respect to explicit occasions.

F Poecze et al[12] present a paper that shows the results of examination of pointers for successful self-promoting procedures via web-based networking media. The members included YouTube gamers. They center around the substance of their correspondence on Facebook to distinguish noteworthy contrasts as far as their client created Facebook measurements and editorial sentiments. The results demonstrated the need to use NLP strategies to streamline brand correspondence via web-based networking media and highlighted the significance of considering the opinion of the majority for better comprehension of customer input.

S Ahmad et al[13] propose a terrorism related substance assessment structure with the accentuation on describing tweets into radical and non-radical classes. In light of web-based social networking posts on Twitter, they develop a tweet gathering system utilizing differential programming procedures.

I Cachola et al[14] study a huge scale, data driven experimental investigation of obscene words utilizing social media data. They dissect the socio-cultural and realistic parts of crudity utilizing tweets from clients with known socioeconomics. Further, they gather sentiment evaluations for obscene tweets to examine the connection between the utilization of indecent words and perceived opinion and show that expressly displaying foul words can support sentiment investigation performance.

D Azucar et al[15] direct a progression of meta-examinations to decide the prescient intensity of computerized impressions gathered from online life over Big 5 character attributes. Further, we explore the effect of various kinds of computerized impressions on expectation exactness.

III. Proposed Work

3.1. System Architecture:

This project aims to analyse the psychology of the person creating a meme. A set of social media memes is taken, from which the embedded text is extracted using Tesseract OCR. This step is performed twice, once for creating the train data and the other for creating the test data. Three instances of a model are built, one for each supervised ML algorithms namely Logistic Regression (LR), Random Forest and Support Vector Machine (SVM). The train data in each model is classified as follows: The value 0 is assigned to positive memes and the value 1 is assigned to negative memes. The test data is then fed into each of the models. Each model instance produces the output classifying the meme as positive or negative in a separate file. Finally, the accuracy score is calculated on the results of each model to determine the algorithm that gives the most accurate results.

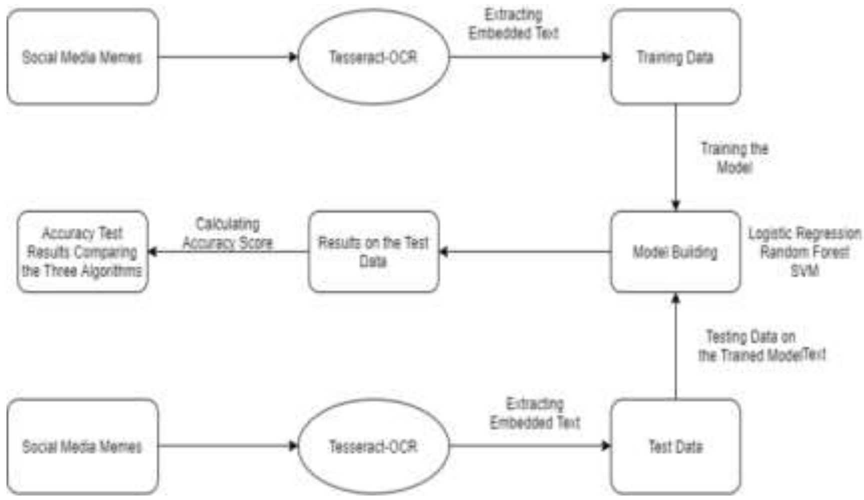

Figure 1. System Architecture

3.2. Data Preprocessing and Cleaning:

A number of memes is taken as a dataset for training and testing purposes. Unnecessary punctuation and characters are removed from the extracted text to improve precision. Tokenization is performed on the text. Long sentences are split up into smaller parts that retain the original meaning, Similarly, words are split down to their root. Then, text normalization is done. Normalization is the proces of converting data into a more uniform structure. These two processes ensure that the data is ready for the subsequent phases.

3.3. Data Vizualization and Wordclouds:

To undestand the concept of positive and negative memes two wordclouds are used. These wordclouds are used for visually understanding the text.Since the positive memes are labelled as 0 and the negative memes are labelled as 1, using these labels two worclouds for each type of meme having the most commomly occuring words in that category are created. Figure 2. shows the positive wordcloud and Figure 3. shows the negative wordcloud.

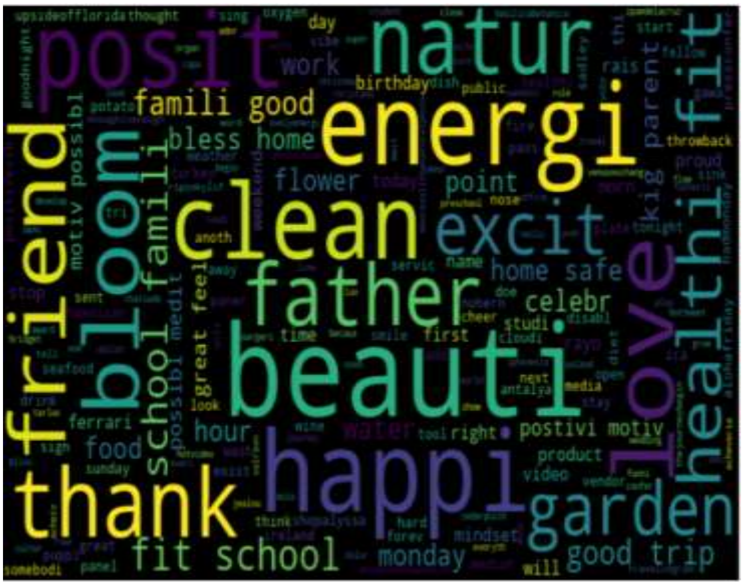

Figure 2. Positive Wordcloud

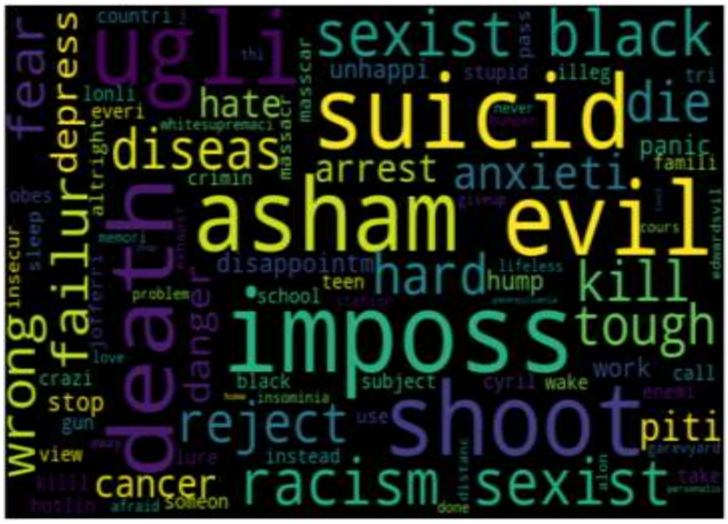

Figure 3. Negative Wordcloud

3.4. Classification Algorithms:

The three classification algorithms used are LR, Random Forest and SVM.

LR is a supervised classification algorithm.We use this menthod because it is the when the redicted variable is binary or categorical, this type of regression technique must be opted for.LR is utilized to portray information and to clarify the connection between one predicted binary variable and one or more independent variables.

Random forests are an supervised ML method for classification, regression and other tasks .During training a number of decision trees are created. Each tree gives it's own class as result.The class that gets the most number of votes is outputted as the result of the random forest classifier.

SVM is a supervised ML algorithm which is used also for classification. In this algorithm, an n-dimensional space,all the data points are charted.The objective is to find a hyperplane so that the distance between the hyperplane and support vectors are maximum.This hyperplane when found classifies the data into two different non-overlapping classes.

All three of these algorithms are used to build,train and test a model each. The Algorithm then splits the training data into a training set(70%) and validation set(30%) by setting the test size to 0.3. First the prediction is done on the validation set and then after fine tuning the model the prediction is carried out on the test data set. The result output from each of the model is stored in separate csv files.

3.5. Performance Comparison:

Accuracy score is the chosen metric to compare the results given by each of the three algorithms in our system. Accuracy is the fraction of predictions our model got right. Formally, accuracy has the following definition:

Accuracy = Number of correct predictions/Total number of predictions

Formally,

Accuracy = TP+TN/TP+FP+FN+TN

(1)

Where TP= True Positive, TN= True Negative, FP= False Positive, FN= False Negative.

IV. Implementation

The implementation of this project was done in a python environment. The "pandas", "numpy","string" and "nltk" libraries were imported for basic data manipulation and processing. The training dataset is created by using Tesseract-OCR to extract embedded text from memes which are in an image format. The training dataset is in a csv format. Similarly the test datset is also created. Data cleaning is done using a user defined function to remove unwanted patterns. String replace function is used to remove punctions, numbers and other special characters.

For classification the three algorithms, Logistic Regression, Random forest and SVM are imported from the "scikit-learn" library. Featured are extracted form the training dataset using Bag-0f-Words, for this the CountVectorizerare imported. This library is also used import train_test_split() function to split the training data. The accuracy_score is also imported from this very library.

The three output files obtained from the three models are in a csv format. The accuracy score for all the three models are calcluted and compared.

V. Results Discussion

The system implemented in this paper classifies the memes as positive and negative. Three algorithms give three output files. The accuracy scores of the three algorithms are caluclated. The Logistic Regression classifies the test dataset with 66.66% accuracy. The SVM classifies th test dataset with 73.33% accuracy and the Random Forest approach classifies the data with 83.33% accuracy. Thus the results given by Logistic Regression and SVM are less accurate compared to Random Forest which gives the best results.

VI. Conclusion

The research thus concludes with the creation of a system that classifies a given meme as positive or negative. This, in turn determines the mindset of the individual creating the meme. Despite of memes being such a huge part of social media, much thought has not be given to it. By analyzing these memes a lot can be learnt about its creators and the people who consume it. This reserach thus aims to explore a part pf this unchartered territory and gain valuable information.

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