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Sentiment Diffusion Patterns for Twitter Sentiment Analysis using Hybrid Deep Learning Approach

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ABSTRACT: Analysis of the sentiment has drawn interest from researchers. Earlier research in the field of artificial intelligence concentrate on understanding emotion rather than exploring the explanation why emotions are not recognized or misrecognized. The association between the emotions leads to the understanding of emotion loss. In this research system are trying to fill the gap between emotional recognition and emotional co-relation mining through social media reviews of natural language text. The association between emotions, represented as the emotional uncertainty and evolution, is mainly triggered by cognitive bias in the human emotion. Three different types of features and two deep neural-network models are provided to mine the emotion co-relation from emotion detection using text. The rule on conflict of emotions is derived on a symmetric basis. TF-IDF, NLP Features and Co-relation features has used for feature extraction as well as section and Hybrid deep learning algorithm for classification has used to demonstrates the entire research experiments. Finally system evaluates the performance with various existing system and show the effectiveness of proposed system.

KEYWORDS : TF-IDF, NLP Features and Co-relation features, Hybrid deep learning.

I.INTRODUCTION

Sentiment is dynamic, individualized, subjective and contextual sensitive. Sentiment drives decision making, trains the body to fight, and forms the behaviour. Intellectuals tend to believe empathy is a subjective. The answer to an objective world, meaning emotion, derives from the relationship between society and people. On the first hand, individual's feelings are complex due to individualized long-term social interactions, behavioural misunderstandings and the effect of external instant mood [1]. The public occasion is complex, with a collection of facets to it. Social event information is published online covering all sorts of subjects. Individualized sentiments prefer to take various things to heart. The readers' sentiments which be complex, making various facets of Public sentiment multiply and complex. There is also debate in the biomedical research field about the definition of emotions. One of the acknowledged categories is the division of human sentiment into six categories, that is, love, joy, rage, sadness, fear, and the same social gathering surprise. When the reader cares about more than one element, then words from the reviewers can bear upwards of one sort of sentiment [2].

The number of active online social network (OSN) users has grown considerably, and some studies indicate there will be 2.95 billion users by the end of 2020. This high number of users, on OSN, is mainly due to the increase of the number of mobile devices, such as smartphones and tablets, connected to the Internet. Currently, OSN have become a rich and universal means of opinion expression, feelings, and they reflect the bad habits or wellness practices of each user. In recent years, the analysis of the messages posted on OSN have been used by many applications, in the industry of health care informatics[1][10]. The sentiments and emotions, expressed on the messages posted on OSN, provide clues to different aspects of the behavior of users; for instance, sentences containing words with negative meaning may indicate sadness, stress, or dissatisfaction. Conversely, it can be inferred that if a person is in a positive mood state, this person can be more self-confident and emotionally stable. Users have different behaviors on OSN, if the sentiment intensity value of posted sentences remain at low levels, or if it frequently changes from high to low levels and vice versa, these facts can indicate some emotional disturbance, such as depression or stress events[9][8]. Hancock, Gee, Ciaccio et al. and Liu observed that users write short sentences when they are experiencing a period of depression. Also, these users use the first person pronoun in their sentences and suffer from chronic insomnia. Therefore, their behavior can be reflected in the sentences posted on OSN.

ILLITERATURE SURVEY

Xinzhi Wang et.al. [1] proposed sentiment analysis has been attracting researchers' attention. Most previous works in the artificial-intelligence field focus on recognizing sentiment rather than mining the reason why sentiments are not or wrongly recognized. The correlation among sentiments contributes to the failure of sentiment recognition. In this article, we try to fill the gap between sentiment recognition and sentiment correlation mining through natural language text from Web news. The correlation among emotions, expressed as the confusion and evolution of emotion, is primarily caused by human sentiment cognitive bias. To mine sentiment correlation from sentiment recognition through text, three kinds of features and two deep neural-network models are presented. The sentiment confusion law is extracted through an orthogonal basis. The sentiment evolution law is evaluated from three perspectives: one-step shift, limited-step shifts, and shortest path transfer. The method is validated using three datasets: 1) the titles; 2) the bodies; and 3) the comments of news articles, covering both objective and subjective texts in varying lengths (long and short). The experimental results show that in subjective comments, sentiments are easily mistaken as anger. Comments tend to arouse sentiment circulations of love–anger and sadness–anger. In objective news, it is easy to recognize text sentiment as love and cause fear–joy circulation. These findings could provide insights for applications regarding affective interaction, such as network public sentiment, social media communication, and human– computer interaction.

Renata L. Rosa et.al. [2] proposed online social networks (OSN) provide relevant information on users' opinion about different themes. Thus, applications, such as monitoring and recommendation systems (RS) can collect and analyze this data. This paper presents a Knowledge-Based Recommendation System (KBRS), which includes an emotional health monitoring system to detect users with potential psychological disturbances, specifically, depression and stress. Depending on the monitoring results, the KBRS, based on ontologies and sentiment analysis, is activated to send happy, calm, relaxing, or motivational messages to users with psychological disturbances. Also, the solution includes a mechanism to send warning messages to authorized persons, in case a depression disturbance is detected by the monitoring system. The detection of sentences with depressive and stressful content is performed through a Convolutional Neural Network (CNN) and a Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN); the proposed method reached an accuracy of 0.89 and 0.90 to detect depressed and stressed users, respectively. Experimental results show that the proposed KBRS reached a rating of 94% of very satisfied users, as opposed to 69% reached by a RS without the use of neither a sentiment metric nor ontologies. Additionally, subjective test results demonstrated that the proposed solution consumes low memory, processing, and energy from current mobile electronic devices.

Hong-HanShuai et.al. [3] proposed with the explosive growth in popularity of social networking and messaging apps, online social networks (OSNs) have become a part of many people's daily lives. Most research on social network mining focuses on discovering the knowledge behind the data for improving people's life. While OSNs seemingly expand their users' capability in increasing social contacts, they may decrease the face-to-face interpersonal interactions in the real world. Due to the epidemic scale of these phenomena, new terms such as Pubbing (Phone Snubbing) and Nomophobia (No Mobile Phone Phobia) have been created to describe those who cannot stop using mobile social networking apps.

Chih-Hua Tai et.al. [4] proposed the rise of social network websites such as Facebook and Twitter has significantly changed how people live. Currently, many people are accustomed to recording their daily life online, such as frequently share their thoughts, opinions, and ideas, and communicate and interact with friends online. Abundant data resulted provide great opportunities for understanding human behaviour and inspire many new applications for improving people's lives. Many studies in recent years have sought to understand how people feel by investigating online posts, messages, and diaries. They have considered the possibility of a relationship among linguistic expressions, emotion, and feelings. Several studies have even explored the characteristics of the emotional and linguistic expressions used by particular groups of people (such as those suffering from major depression and post traumatic stress disorder (PTSD)). Thus, new applications such as the service satisfaction survey and mental healthcare can be developed to benefit the society. Inspired by such thoughts, we observed that online posts/diaries not only represent the records of life and communication, but also reveal the satisfaction with life and relationships as well as potential mental illnesses.

Huijie Lin, Jia Jia [5] focus on Psychological stress is becoming a threat to people's health nowadays. With the rapid pace of life, more and more people are feeling stressed. According to a worldwide survey reported by New business in 2010, over

half of the population have experienced an appreciable rise in stress over the last two years. Though stress itself is non-clinical and common in our life, excessive and chronic stress can be rather harmful to people's physical and mental health. According to existing research works, long-term stress has been found to be related to many diseases, e.g., clinical depressions, insomnia etc. Moreover, according to Chinese Center for Disease Control and Prevention, suicide has become the top cause of death among Chinese youth, and excessive stress is considered to be a major factor of suicide. All these reveal that the rapid increase of stress has become a great challenge to human health and life quality.

Thus, there is significant importance to detect stress before it turns into severe problems. Traditional psychological stress detection is mainly based on face-to-face interviews, self-report questionnaires or wearable sensors. However, traditional methods are actually reactive, which are usually labor-consuming, time-costing and hysteretic. Are there any timely and proactive methods for stress detection? The rise of social media is changing people's life, as well as research in healthcare and wellness. With the development of social networks like Twitter and Sina Weibo², more and more people are willing to share their daily events and moods and interact with friends through the social networks. As these social media data timely reflect users' real-life states and sentiments in a timely manner, it offers new opportunities for representing, measuring, modelling, and mining users behaviour patterns through the large-scale social networks, and such social information can find its theoretical basis in psychology research. For example, found that stressed users are more likely to be socially less active, and more recently, there have been research efforts on harnessing social media data for developing mental and physical healthcare tools. For example, proposed to leverage Twitter data for real-time disease surveillance; while tried to bridge the vocabulary gaps between health seekers and providers using the community generated health data. There are also some research works, using user tweeting contents on social media platforms to detect users' psychological stress.

Yefeng Wang et. al. [6] demonstrates the incidence of mental disorders is higher in the US where 25% of adult Americans have been diagnosed with at least one mental disorder. Most of the mental disorders are typically treated with prescription drugs; for example, bipolar disorder is typically treated by lithium; however, these drugs are not always effective and may cause serious adverse reactions, which forces patients to resort to dietary supplements including melatonin, St. John's wort, kava, gingko biloba, and Ginseng. Approximately 65% of American adults use social media like Facebook and Twitter to get and share health-related information. Social networking sites allowing users to record and share their daily life with friends have been used to investigate the mental disorders. Previously, De Choudhury et al. explored the depression prediction potential of Twitter. The study also took antidepressant usage into account, but the effect of dietary supplement use was not considered. Coppersmith et al. looked into the difference of Twitter usage behavior between the users that have self-diagnosed mental disorders and control group users. While these studies put more emphasis on analyzing the language using patterns in the tweets, the influence of dietary supplement use among mental disorders group has been overlooked. Motivated by these facts, in this study, we investigated the association between mental disorders and dietary supplement in Twitter.

Md. Arafatur Rahman et. al. [7] proposed online social network (OSN) is a platform, where users are able to share information among them easily and instantly. Online Social Networks (OSN) is a medium where people are allowed to share personal backgrounds, interests, activities, and connections with OSNs users. The evolution of Internet technologies led to significant growth of the OSNs, e.g., Facebook, Twitter, LinkedIn, Google+ and so on. Among them Facebook is the largest online social network in the world which has over 1.86 billion active users. OSN allows registered users to create profiles, send messages, update status, upload photos and videos to connect with family members, friends and business associates. In a process of making a friend, OSNs users give an access to their personal information to other people, from old friends to strangers. The sociable and communal atmosphere of OSNs is very striking to users and it makes easy for the users to unveil information about themselves and their contacts with other users. Moreover, it is dangerous to share sensitive information in online, e.g., time-related information, personal characteristics and activities, and user's habit.

Madhuri Siddula et. al. [8] privacy in social networks is a large and growing concern in recent times. It refers to various issues in asocial network which include privacy of users, links, and their attributes. Each privacy component of a social network is vast and consists of various sub-problems. For example, user privacy includes multiple sub-problems like user location privacy, and user personal information privacy. This survey on privacy in social networks is intended to serve as an initial introduction and starting step to all further researchers. We present various privacy preserving models and methods

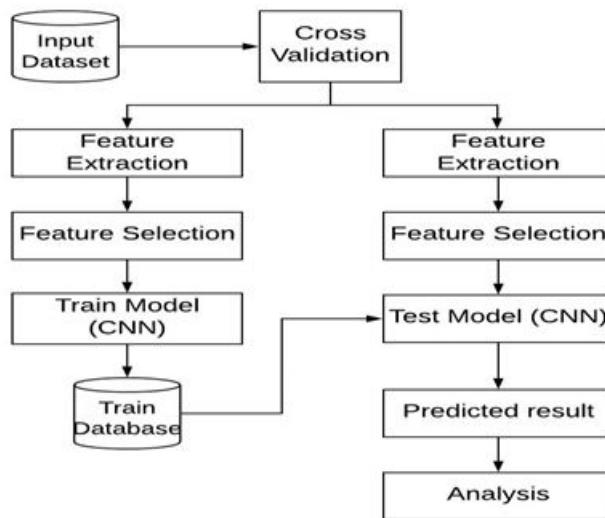
include naive anonymization, perturbation, or building a complete alternative network. We show the work done by multiple researchers in the past, where social networks are stated as network graphs with users and nodes.

Yefeng Wang et.al. [9] proposed the incidence of mental disorders is higher in the US where 25% of adult Americans have been diagnosed with at least one mental disorder. Most of the mental disorders are typically treated with prescription drugs; for example, bipolar disorder is typically treated by lithium; however, these drugs are not always effective and may cause serious adverse reactions, which forces patients to resort to dietary supplements including melatonin, St. John's wort, kava, gingko biloba, and Ginseng. Approximately 65% of American adults use social media like Facebook and Twitter to get and share health-related information. Social networking sites allowing users to record and share their daily life with friends have been used to investigate the mental disorders. Previously, De Choudhury et al. explored the depression prediction potential of Twitter. The study also took antidepressant usage into account, but the effect of dietary supplement use was not considered. Coppersmith et al. looked into the difference of Twitter usage behaviour between the users that have self-diagnosed mental disorders and control group users. While these studies put more emphasis on analysing the language using patterns in the tweets, the influence of dietary supplement use among mental disorders group has been overlooked. Motivated by these facts, in this study, we investigated the association between mental disorders and dietary supplement in Twitter.

Amir Hossein Yazdavar et. al. [10] demonstrates depression is a highly prevalent public health challenge and a major cause of disability worldwide. According to the World Mental Health Survey conducted in 17 countries, on average, about 5% of people reported having an episode of depression in 2011. It also affects 6.7% of Americans (that is, more than 16 million) each year. Untreated or under-treated clinical depression can be serious enough to lead to suicide and other risky behaviors such as drug or alcohol addiction. More than 90% of people who commit suicide have been diagnosed with depression. A global effort to curb clinical depression involves identifying it through survey-based methods via phone or online questionnaires. These approaches mainly suffer from underrepresentation as well as sampling biases (a small group of respondents). Besides, survey data also exhibit problems due to temporal gaps between the data collection and dissemination of findings, reflecting participant's responses over a short period of time. In contrast, with an unprecedented growth of social media, large number of people voluntarily share large amounts of data by expressing their moods, feelings, emotions, and daily struggles with mental health problems on social media platforms like Twitter. This offers opportunities for new understanding of these communities. For instance, the news headlines such as "Twitter Fail: Teen Sent 144 Tweets Before Committing Suicide & No One Helped" highlights the need for better tools for gleaning useful insights from user generated content on social media. Recent years have witnessed rapid growth in the analysis of social media for studying a wide range of health problems, from detecting influenza epidemic, and cardiac arrest to study mood and mental health conditions. Previous research efforts suggested that language style, sentiment, ego-network, and user engagement are discriminating features to predict the likelihood of depression in a post or in an individual, these studies often represent psychological status of online users via their language via psycholinguistic analysis, supervised and unsupervised language modelling, or studying individual's topic of interest. However, except few attempts [cite, cite, cite] investigations in the fields are seldom concerned with visual attributes of mental health reflects on various social media platforms. Interestingly, according to eMarketer, photos accounted for 75% of content posted by Facebook pages worldwide and they are the most engaging type of content on Facebook (87%). It has been argued that sharing them is the best way to get more attention from the followers. Indeed, an old saying of "a picture is worth a thousand words" recently changed to "photos are worth a million likes". Similar to Facebook, photos are more engaging for Twitter users. The tweets attached with image links get two times more engagement rate of those without, we recall that getting social support from peers has been highlighted as a primary motivation for sharing depressive indicative content in social media.

III.PROPOSED SYSTEM DESIGN

The proposed research work on text sentiment classification employs deep learning approach. This work basically illustrates various feature extraction as well as selection technique from text reviews and builds the train knowledge accordingly. Various feature selection methods have been used to extract the different parameters, Sometime text meta-data also used to identify the respective text sentiment. Normalize data set should be most impactful to achieve the better classification accuracy [2].

**Figure 1 : Proposed system design**

In the training phase, various features have been extracted from the training data set and a training model is built accordingly. A similar feature extraction strategy has been applied on the testing data set which extracts each text feature accordingly. The weight calculation process is identifying similarity between testing and training features. It is the sub process of similarity evaluation between two features sets [4]. The weight factor is evaluated with desire threshold values and defines sentiment labels accordingly. It is initial weight while threshold can be user defined. First we evaluate each text height and width accordingly and change as per the required size because few images contains some noise or specific input text already contains a different kind of noise. Using the noise filter we eliminate noise from images. The proposed deep learning module having ability to identify such features using text Net library. The DCNN classifier has used to detect the sentiment class of entire test dataset. System can works with flicker text dataset for sentiment classification with supervised learning approach, then we split the data into 5-fold, 10-fold and 15-fold cross validation respectively. The data has already pre-processed in trained module so system directly builds a train module for respective scaled images[17]. For testing dataset, performing evaluation has done with various test instances and calculates the confusion metrics.

Pre-processing: In the pre-processing, data have been validating according to given rule and policies written by us. Each attributes having lower and upper bound for specific values, whenever any attributes overflows or violate, system automatically eliminates such instances. The entire pre-processing covers data collection, data acquisition, data cleaning, data filtrations and normalizations etc.

Data Cleaning : Cleanliness and correction of (or deletion of) incorrect or misleading statements from records, tables, or databases is a method to identify and modify (or remove) missing, erroneous, inaccurate or meaningless data and then substitute, edit or delete dirty or delicate information. Data cleaning can be done interactively by scripting software or by transaction processing. The systematic sampling techniques have been used for data filtering; once filtration has done, we become balanced data that eliminate the misclassified instances from the normalized dataset.

Feature Extraction: The three different types of feature extraction techniques have been used these are mentioned in below. The features extracted include:

- Lemma based features
- Rule based features

- Hybrid collective features

Feature Selection : The appropriate set of features from the given document can be extracted such that it can improve the overall performance. In feature extraction, based on some counter measure the feature can be extracted.

Training of the classifier: After choosing proposed text classification algorithms including hybrid deep learning classification and feed the training corpus to the classifier to get a training model.

Testing classifier : After we get the training model, we can feed the testing data into it and get the prediction of classification. The testing stage includes preprocessing of testing text, factorization and classification of the testing text.

Algorithm Implementation

Ultimately, the task-specific interpretations generated by all of the declared multitasking assemblies are fed into numerous convolution layers that are also task-specific.

$$\hat{y}(m) = \text{softmax}_-(W(m) h(m) + b(m))$$

Here $\hat{y}(m)$ is extrapolation possibilities for task process m , $W(m)$ is the weight that essentials to be knowledgeable, and $b(m)$ is a bias term. Our comprehensive cost function is the linear arrangement of cost utility for all intersections.

$$\phi = \sum_{m=1}^M \lambda_m L(\hat{y}(m), y(m))$$

Now, λ_m is the respective weight for specific (m) task.

Algorithm of Hybrid CNN

Input: Training dataset TestDBLits [], Train dataset TrainDBLits[] and Threshold Th.

Output: Resultset <class_name, Similarity_Weight> all set which weight is greater than Th.

Step 1: For each testing records as given below equation, it works in convolutional layer for both training as well as testing

$$\text{testFeature}(k) = \sum_{m=1}^n (\text{featureSet}[A[i] \dots A[n]] \leftarrow \text{TestDBLits})$$

Step 2 : Create feature vector from testFeature(m) using below function.

$$\text{Extracted_FeatureSet_x}[t \dots n] = \sum_{x=1}^n (t) \leftarrow \text{testFeature}(k)$$

Extracted_FeatureSet_x[t] is the outcome of each pooling layer that is extracted from each convolutional layer and forward to net convolutional layer. This layer holds the extracted feature of each instance for testing dataset.

Step 3: For each train instances as using below function,

$$\text{trainFeature}(l) = \sum_{m=1}^n (\text{featureSet}[A[i] \dots A[n]] \leftarrow \text{TrainDBList})$$

Step 4 : Generate new feature vector from trainFeature(m) using below function

$$\text{Extracted_FeatureSet_Y}[t \dots n] = \sum_{x=1}^n (t) \leftarrow \text{TrainFeature}(l)$$

Extracted_FeatureSet_x[t] is the outcome of each pooling layer that is extracted from each convolutional layer and forward to net convolutional layer. This layer holds the extracted feature of each instance for training dataset.

Step 5 : Now evaluate each test records with entire training dataset, in dense layer

$$\text{weight} = \text{calcSim} (\text{FeatureSet}_x || \sum_{i=1}^n \text{FeatureSet}_y[y])$$

Step 6 : Return Weight

IV.RESULTS AND DISCUSSIONS

The below analysis is the system classification graph. The graphs display how system classify the overall inputs into classification various instances. The proposed system is implemented with deep learning combination, which gives all results with satisfactory level. The below Table 1 and Figure 2 demonstrates the classification accuracy of system with various algorithms.

Table 1 : Comparative analysis of various classification algorithms

No.	Method	Accuracy	Precision	Recall	F-1 score
1	SVM	0.89	0.86	0.82	0.85
2	RF	0.63	0.67	0.64	0.65
3	NB	0.83	0.83	0.81	0.82
4	Hybrid (Proposed)	0.90	0.89	0.90	0.90

The above Table 5.3 depicts the comparative analysis of various classification algorithms evaluation for proposed churn prediction module. The RF provides lowest accuracy thus proposed hybrid deep learning classification gives highest accuracy with 0.94% on various cross validation. The similar results have been demonstrated in below Figure 2.

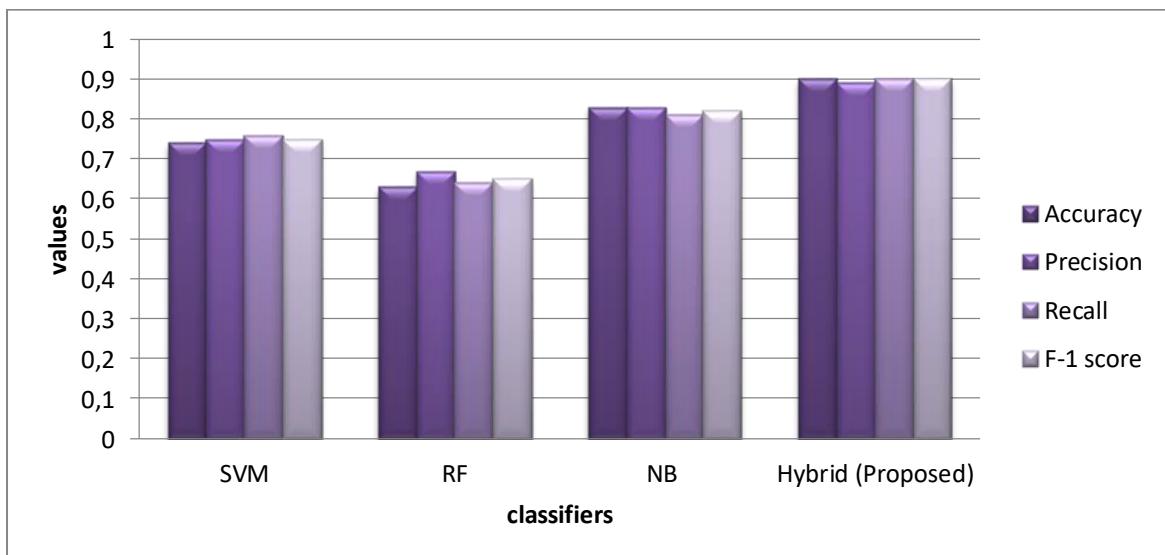
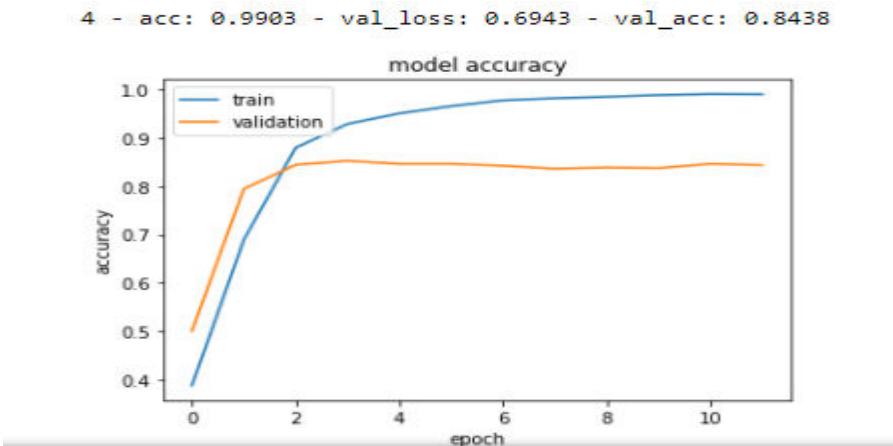
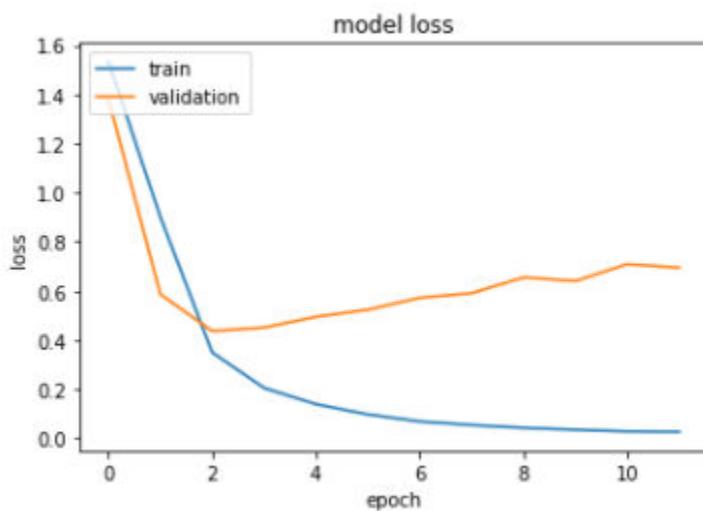


Figure 2 : Comparative analysis of various classification algorithms

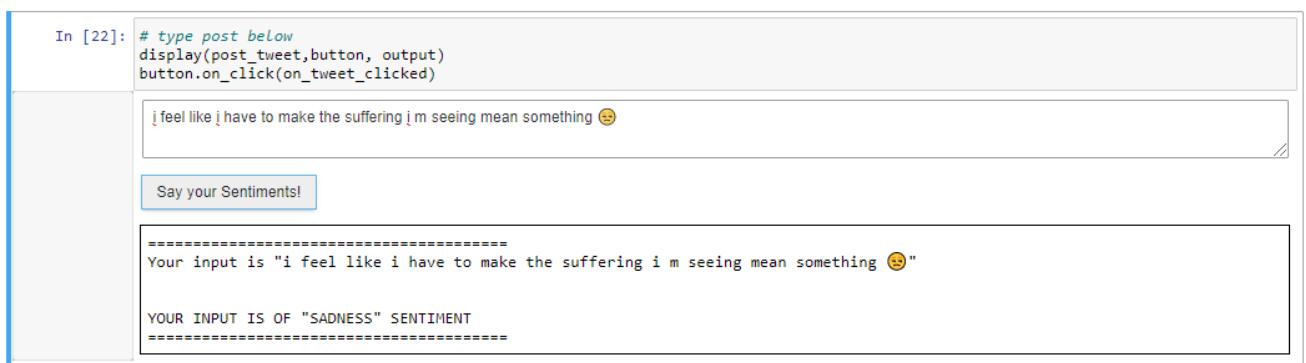
**Figure 3 : proposed hybrid model train and test accuracy with epoch size****Figure 4 : proposed hybrid model train and test loss with epoch size**

```
In [22]: # type post below
display(post_tweet_button, output)
button.on_click(on_tweet_clicked)

i do not feel reassured anxiety is on each side 😊

Say your Sentiments!
=====Your input is "i do not feel reassured anxiety is on each side 😊"
=====YOUR INPUT IS OF "JOY" SENTIMENT
=====
```

Figure 5 : Test data validation experiment-1 for proposed algorithm



```
In [22]: # type post below
display(post_tweet,button, output)
button.on_click(on_tweet_clicked)

I feel like i have to make the suffering i m seeing mean something 😢

Say your Sentiments!

=====
Your input is "i feel like i have to make the suffering i m seeing mean something 😢"
YOUR INPUT IS OF "SADNESS" SENTIMENT
=====
```

Figure 6 : Test data validation experiment -2 for proposed algorithm

This chapter describes the experimental data, results and their performance on the proposed model. It also provides details of the shainhautech dataset used as the input dataset for the system. The results show that the proposed model performs better than the existing methods. The results are more precise and accurate.

V.CONCLUSION

Our research shows that hybrid deep learning does provide promising results with a performance comparable to some methods using handcrafted features on emotion classification task, and also a few methods using deep learning for sentiment analysis. Sentiment classification in images has applications in automatic tagging of images with emotional categories, automatically categorizing video sequences into genres like thriller, comedy, romance, etc.

Our study reflects that hybrid Deep Learning does give promising results in both the classification of emotions as well as in performing sentiment analysis, even on the raw data collected directly from social media. The next step could be to run these experiments on bigger and cleaner datasets and see if they would improve the results. We believe they would. It would also be interesting to see what the salient regions in the images are, perhaps by using [6], and feed these preprocessed images to retrained networks. The idea behind this is that humans would decide the emotion detected by an image by looking at some salient regions in the image. By notifying the network of these beforehand might help in the training process.

VI.FUTURE WORK

To work unstructured data like image audio will be the interesting task in future work using hybrid deep learning algorithms.

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