Chrome extension for detecting mental health on social media

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Abstract — People use social media to stay in touch with their friends and share their moods, emotions, and other information. This enables businesses to analyse emotional data from social networks to better understand how people feel and act when communicating via these online platforms. People do not seek professional aid due to a lack of willingness. Also, because of the Covid 19 pandemic, many were confined to their homes and chose to express themselves through social media. To address this problem, we plan to build and develop a Chrome extension that will give an instant evaluation of the user's tweet. Our technology would use a machine learning model to analyse their posts and then ask them questions. Depending on the user's response to the questions, the system will determine if the person requires professional assistance.

Keywords — Deep Learning, Logistic Regression, Machine Learning, Natural Language Processing, Sentiment Analysis, Social Media

I. INTRODUCTION

Our psychological, intellectual, and social well-being are all part of our mental health. It has an impact on how we think, feel, and act. It also aids us in making decisions, dealing with stress, and interacting with people. Mental health is important at all ages, from childhood to adulthood [4].

Mental illness applies to a variety of mental illnesses that affect thoughts, mood, and behaviour. The COVID-19 widespread and subsequent credit crunch has adversely affected the mental health of many and created new hurdles for those already undergoing mental illness and alcohol abuse disorders [1]. Many adults have certain adverse outcomes on mental health and welfare, including somnipathy about 36%, anorexia (32%), increased alcohol and drug use around 12%, and deteriorating chronic illness of about 12%. As the pandemic progresses, the obligatory general public health measures in progress bring into the open many circumstances associated with badly off mental sanity, such as quarantine and unemployment [10].

WHO has also expressed concern about the psychological and psycho-social impacts of the pandemic. It postulates that new course of action such as self-harm and quarantine may interfere with the normal activities, daily lives of people and increase loneliness, anxiety, depression, insomnia and the use of harmful alcohol and drugs, self harm or suicidal behavior or thoughts [9]. There are several online resources that help to manage the stress caused by a pandemic. Assisting others manage their stress strengthens the community. Still, the massive challenge in alleviating the psychological impact of the COVID-19 widespread is the lack of mental illness doctors, professionals, counsellors, and also healthcare providers seeking such assistance will be a real task for a country like India with 0.07 psychologists, 0.07 psychologists, 0.29 psychiatrists, and 0.36 other paid mental illness staff per 100,000 population [5].

The Natural Language processing regime method is commonly used to assist in this source in the modern world. Recent developments in the field have demonstrated convincingness in tackling many complex natural language analysis tasks such as sentimental analysis and machine translation etc. However, enormous changes in lexicon among other social platform users pose significant challenges to the language model used for specific tasks to function effectively. We devised a chrome extension that would provide assessment instantly as it is essential to cater their needs at that moment.The system would analyse their post and ask them if they need any assistance. If the user agrees then, they would go through a WHO questionnaire. After examination of the questions depending on the user's response the system would compute if the person requires professional guidance [1].

II. RELATED WORK

The approach that was examined by Yadav S helped to understand the gradual increase in social media usage. This is because it has become a valuable tool for the end-users to interact with their peers and exchange their knowledge and

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give and take opinions, videos, photos, thoughts. All of these posts represent a person‘s mood, emotions, and mental health. The main goal of the project is to learn more about a person’s mental health as if they were suffering from a mental disorder (depression). Our social, mental, emotional well-being are all part of our mental health. It affects our thoughts, feelings, and actions. It also affects how the person interacts with others, copes with stress, and makes important decisions [2].

The key objective observed by Pedro M through the proposed methodology was the difference learned between the LSTM + CNN model and the SVM model. The model receives input, processes a single numeric output based on the likelihood that the tweet indicates depression, and makes comparisons using various indicators such as accuracy, accuracy, f1-score, and model loss. As a result, it is found that deep learning models (CNNs, RNNs) can process and create predictions more efficiently than machine learning algorithms (Naive Bayes, SVM, Decision Trees) [11].

Mental health has become an essential part just like any physical pain, mental pains also need to be treated at every phase of life, from infancy to teens to adulthood. Mental health refers to a variety of illnesses that affect behaviour, mood, thoughts.Various examples of mental illness include eating disorders, anxiety disorders, schizophrenia, depression and addiction [2]. WHO estimates that 788,000 people passed away from suicide in 2015, that was the second largest (major) cause of death for many people between the ages of 15 and 29 in the world. Depression in inclusion to this is a major reason for various physical illnesses such as cardiovascular and tuberculosis disease [7]. As an outcome of examining the above facts, it was certified that the evaluation of depression is very important for ensuring the psychological well-being of today‘s society. Mental disease is a major cause of isolation and social withdrawal [3].

This paper shows an early analysis of mental health through end users data procurement from the social networking sites, as it is a proven and constructive mechanism. Methods from the NLP regime are largely deployed to support the basis in the new fashioned world. Current progress in the field have proven successful in addressing many complex natural language analysis tasks such as sentiment analysis, machine translation etc.It talks about how web scraping can be used to extract live data from popular social media platforms such as Twitter and Facebook can perform sentiment analysis on the posts or tweets of a person [5][6]. It has used different kinds of models like naive bayes, logistic Regression, Sentiment Intensity Analyzer with support of libraries like nltk, WordNet Lemmatizer, stop words. Naive bayes gave an accuracy of 0.76 logistic-regression gave an accuracy of 0.74, Sentiment Intensity Analyzer is a method in which the compares each word and gives points if it comes under negative or positive the word sentence is scored accordingly [13].

III. Detailed Architecture

The architecture in Fig. 1. is primarily composed of a chrome extension, Twitter user login, and the Sentiment analysis using machine learning model. The user posts tweets and the machine model detects whether the tweet is negative or positive and generates results and the extension then provides further professional assistance[1].

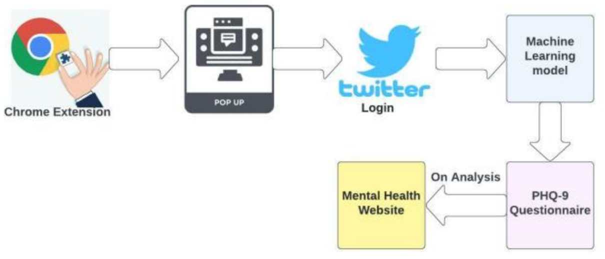

Fig. 1. System Architecture.

Although Google Chrome extensions are written in JavaScript and hosted on extension sites, they have access to Application Programming Interface that web pages do not. Pages that are extensions run in the context of the extension process, as opposed to the browser processes, as well as the capacity to access and enhance them. Extension pages can register to list the special content in the browser User Interface such as window shutting, tab switching and other browser actions [14].

Chrome extensions are useful not only for recognising individuals who are suffering from mental illness, but also for text analysis in order to locate persons on social media platforms. These extensions can use permissions to interact with your Chrome browser’s tabs, identify URL matches, inject code (HTML, JavaScript, and CSS, for example), and make API calls [14].

We will build an extension on chrome using logic files, background scripts, user interface elements and content scripts that will allow users to login into their social media accounts for example like twitter and the extension will extract tweets and the same will be passed on to machine model for sentiment analysis. Post the analysis of the tweet a WHO based questionnaire will be provided in the extension to determine the severity of mental disorder. The questionnaire is based on self-reporting by patients so all replies should be validated by the doctor hence the extension would then redirect the user to a professional help [14].

IV. Methodology

Other than NLP, depression detection among people has a wide range of real-time applications. The problem of depression detection can be structured as follows: Given a set of Twitter users (Tweets by users), identify users at risk of depression and assess CNN and RNN-based models, as well as the Support Vector Machine as a comparative

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analysis. The scope of this study is to design deep learning and machine learning-based algorithms for predicting depression on social media. Although the use of social network data to assess depression has made waves around the worldwide, there are still a few dimensions that are yet to be discovered. The objective of this research is to conduct depression analysis using Twitter information gleaned from a public web source [1].

Fig. 1. depicts the overall layout of our strategy. We propose a method that uses social media posts to pinpoint individuals who are at risk of depression.The developer's twitter account will be used to scrape data that will be sent to analyse the emotion to the trained machine model. We will conduct a comparative analysis of CNN, Decision Tree, SVM, RNN, and Multinomial NB models, observing all models for the prediction on the basis of the f1-score, recall, and precision, and then picking which model to choose to achieve the highest accuracy [13].

A. Flowchart

As a preliminary step, users will be posting tweets on twitter, the tweets will be extracted then will be sent to a machine model for prediction of the result and if it is positive then another step to be verified will be the PHQ-9 questionnaire. The combined result will corroborate the traits of depression and users will be provided expert assistance for the same.

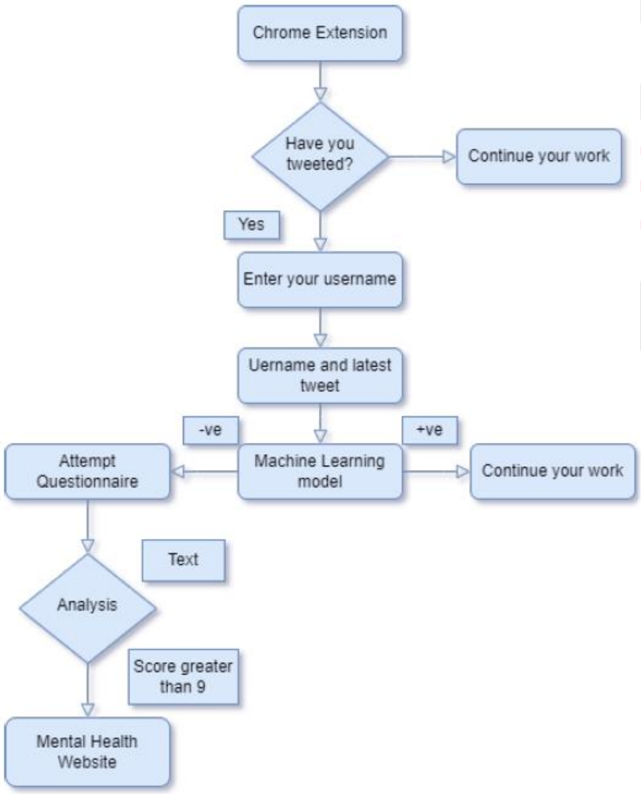

Fig. 2. System Flowchart.

The procedure in Fig. 2. System Flowchart is performed in the following order:

1) Chrome extension is activated.
2) Tweets will be posted on twitter.
3) Developer account will scrape the tweets posted on twitter.
4) The tweets will be passed onto a machine model for sentiment analysis.
5) If analysis is negative the user will be asked to answer the PHQ-9 questionnaire.
6) If analysis is depressive the user will be provided mental health professional assistance.

B. Data Scraping

Data scraping is a way to enable professionals who use a variety of tools, such as data extraction, analysis, and integration, to work with data. Data scraping can be tedious and often effective for humans by leveraging the ability to efficiently extract data from multiple websites or extract data from legacy systems when APIs are not available. It is an efficient way to replace missing programs and tasks [12].

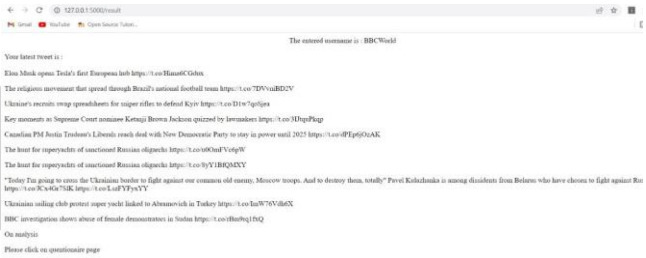

Fig. 3. Data Scraping.

Fig. 3. depicts the program has extracted the user's latest tweets.

1) Twitter Developer Account:

For scraping the tweets the team had applied for Twitter's developer account. The proposal was accepted by the Twitter team. Twitter's developer account opened possibilities to extract up to 2M tweets per month with 3 app environments on data endpoints.

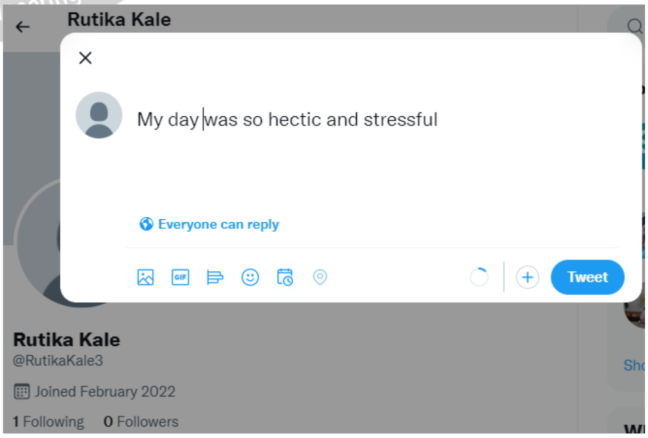

Fig. 4. Twitter Developer Account.

Fig. 4. depicts a tweet posted by the developer on the Twitter developer account.

2) Chrome extension

The Chrome extension has a small UI, mostly HTML pages,

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made interactive using JavaScript and jQuery. The Chrome extension has three main parts: manifest.json, JavaScript file, HTML file. The Chrome extension is developed using HTML, CSS, and JavaScript. Firstly, we created a Chrome extension for Twitter and Facebook to display HTML content in popups. Then click the Chrome extension icon to see the URL of the currently displayed page. Get the selected text from the currently searched page and perform some actions. Modify the current DOM element for which the Chrome extension is being clicked [14].

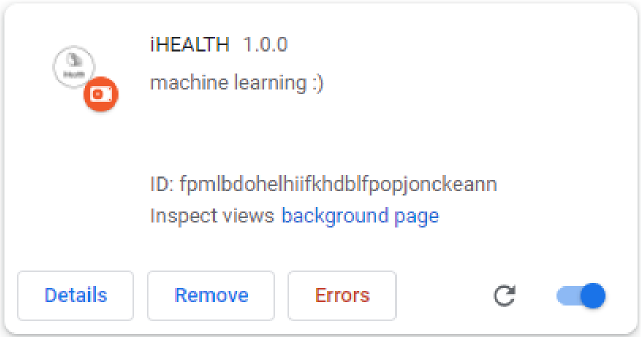

Fig. 5. Chrome extension.

Fig. 5. is an instance of iHealth chrome extension.

Every Chrome app has a JSON file called manifest.json. This file contains information about your app in JSON format. It basically contains metadata such as description, icon ,name used in the app, icon size, HTML page used, permissions, browser actions, version and so on. The Privileges for creating a chrome extension the team used a third party library i.e the chrome API. Authentication data is required to include this in the project. We mentioned permissions in manifest.json [14].

Extended Manifest: The extension identifies the resources and required features in the extended manifest file. When a user tries to install an extension, Google Chrome reads the extension manifest and displays a specific warning [14].

Cross-Browser Deployment: Allows the same extension source to be served in multiple browsers using several code generators implemented by the Fine compiler (including the new JavaScript backend) [14].

C. PHQ-9 Questionnaire

The questionnaire as shown in Fig. 6. is based on patient self-report, and all replies should be confirmed by a clinician [16]. A definite diagnosis is determined based on clinical grounds, taking into account how well the patient comprehended the questionnaire as well as other relevant information from the patient.

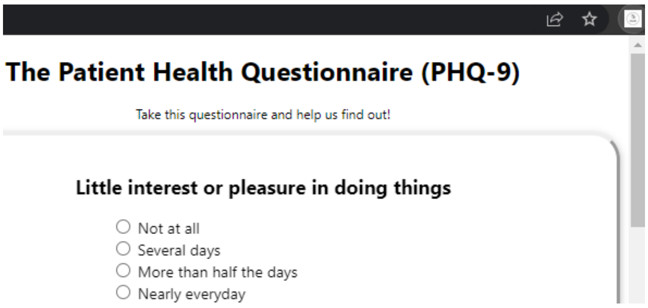

Fig. 6. PHQ-9 questionnaire.

In order to be diagnosed with Major Depressive Disorder or Other Depressive Disorder, users must have impairments in their social, cognitive, and emotional functioning.

After ruling out typical bereavement, occupational, or other critical areas of functioning (Question 10), and a history of manic episodes (Bipolar Ailment) and a physical disorder, medication, or other chemical as the cause of the manic episode. Depressive symptoms have a biological cause. The PHQ-9 can be used as a screening tool, diagnostic assistance, and symptom tracking tool to measure a patient's overall depression severity as well as the improvement of individual symptoms as treatment progresses. There are 9 WHO based questions that would be asked to the user which will help the ML model to understand if the person needs professional guidance [16].

Total Score	Depression Severity
1-4	Minimal depression
5-9	Mild depression
10-14	Moderate depression
15-19	Moderately severe depression
20-27	Severe depression

Fig. 7. PHQ-9 questionnaire result calculation.

The severity of depression is determined by assigning scores of 0, 1, 2, and 3 to the response categories of "not at all," "many days," "more than half of the days," and "almost every day," respectively, using the WHO-based PHQ-9 questionnaire as depicted above in Fig. 7. The total score for the nine items on the PHQ-9 scale runs from 0 to 27 [16].

D. Methodological Overview

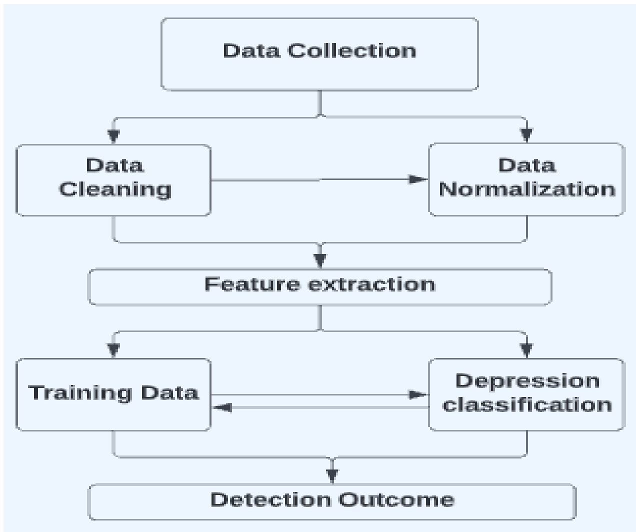

Fig. 8. Methodological overview.

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Fig. 8. depicts the methodological process of depression detection.

Creating a data set:

LIWC Software was used to collect and analyse raw Twitter data. LIWC, which can process text line by line, is at the heart of the text analysis technique. This section explains how we used ground truth label data to generate our data set (on whether the comments are depression indicative). The user comments on Twitter were divided into two groups: (a) the positive (YES) class (depression suggesting comments) and (b) the negative (NO) class (non-depression indicating comments) (non-depression indicative comments) [8].

As shown in Fig. 9, the team developed a dataset of 1200 different words that were not present in the previous dataset. It returns about 70 components with greater degrees of psycholinguistic function, including emotional, social, cognitive, perceptual, biological, drives, temporal orientation, theory of relativity, and personal concerns, as well as all psychological processes [7].

```
'victimized': 'cheated',
'agonized': 'sad',
'alarmed': 'fearful',
'amused': 'happy',
'angry': 'angry',
'anguished': 'sad',
'animated': 'happy',
'annoyed': 'angry',
'accused': 'cheated',
'acquitted': 'singled out'
'adorable': 'loved',
'adored': 'loved',
'affected': 'attracted',
'afflicted': 'sad',
'aghast': 'fearful',
'agog': 'attracted',
'agonized': 'sad',
'alarmed': 'fearful',
'agog': 'attracted',
'apprehensive': 'fearful',
'approved of': 'loved',
'ardent': 'lustful',
'aroused': 'lustful',
'attached': 'attached',
'attracted': 'attracted',
'autonomous': 'independent
```

Fig. 9. Training Dataset.

E. Training Machine Model

Using pipeline classes, the procedure of Vectorizer-Transformer-Classifier was simplified. Grid search was used to alter hyper parameters including N-gram range, IDF usage, TFIDF normalisation type, and Naive Bayes Alpha. In a test set that was not used in the model training stage, the performance of the selected hyper parameters was evaluated. Multinomial NB, SVM, CNN+RNN, and Decision Tree were all compared [13]. Linear kernel support Vector machines are a quick solution, although they aren't always effective. When compared to support vector machines with non-linear kernels, it has the highest classification accuracy. A non-linear kernel is used in the support vector machine training process.In comparison to the other classifiers studied, Decision Tree class accuracy was the lowest (min in trigram: 24.10 percent, max in uni/bi/tri-gram: 34.58 percent). The average classification accuracy values for naive bayes, random forests, and support vector machines are comparable (minimum 33-34 percent for tri-grams, maximum 43-45 percent for uni / buy / trigrams), and naive bayes 1 – The average classification accuracy is 2% higher than Random Forest and Support Vector Machines, but the difference is not statistically significant [15].

```
LogisticRegression
              precision    recall  f1-score   support

           0       0.96      0.99      0.98      2011
           1       0.99      0.96      0.97      2011

    accuracy                           0.97      4022
   macro avg       0.98      0.97      0.97      4022
weighted avg       0.98      0.97      0.97      4022

 MultinomialNB
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      2011
           1       0.95      0.95      0.95      2011

    accuracy                           0.95      4022
   macro avg       0.95      0.95      0.95      4022
weighted avg       0.95      0.95      0.95      4022


Enter Your Message: sad life
```

Fig. 10. Trained Machine model.

The average classification accuracy values as shown in Fig. 10. for naive bayes, random forests, and support vector machines are similar (minimum 33-34 percent for trigrams, maximum 43-45 percent for uni / buy / trigrams), and naive bayes 1 – 3 are similar (minimum 33-34 percent for trigrams, maximum 43-45 percent for uni / The average classification accuracy is 2% higher than Random Forest and Support Vector Machines, although the difference is not statistically significant. The performance of the investigated classification methods is more steady, with the exception of logistic regression, and the mean classification accuracy values are less scattered [18].

Logistic regression is a classification model, not a regression model, despite its name. In the literature, logistic regression is also known as logit regression, maximum-entropy classification (MaxEnt), or the log-linear classifier. In this model, a logistic function is used to predict the probability of the likely outcomes of a single experiment [4]. It works in a similar way to Linear Regression, which tries to fit a linear function to a set of data. Despite its name, Logistic

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Regression is a classification approach that outputs a probability that can be used to categorise the data, whereas Linear Regression creates continuous data and is used for regression [15].

V. Result and Analysis

The machine model is trained with the logistic regression approach using numerous data sets that demonstrate the maximum accuracy in terms of f1-score, support, precision, and recall.It has been determined that synset, an unique type of simple interface included in NLTK, is used to seek up terms in WordNet. Synset instances are a collection of synonyms that communicate the same meaning. Synsets() contains an optional pos argument that allows to confine the word's part of speech [17]. Each synset has one or more lemmas, which express a particular meaning of a word. WordNet only defines relationships over lemmas. synset1.path similarity(synset2): Return a score indicating how similar two word senses are, based on the is-a (hypernym/hyponym) taxonomy's shortest path connecting the senses. The score ranges from 0 to 1 [17]. By default, verbs now include a fake root node, which should deliver a value in circumstances where a path could not be found earlier and None was returned. Simulate root can be changed to False to restore the previous behaviour. A score of 1 indicates identity, i.e. comparing a sensation to itself will result in a score of 1 [13].

Fig. 11. Depressive graph.

Fig. 11. displays the graph, the positive or negative attitude is represented by a label on the X-axis, while the count is shown by the Y-axis.

The user login is displayed in Fig. 12. It is a hosted website login page that prompts users to login to their Twitter accounts and showcases the user's most recent tweet, which is scraped using the Twitter API that was accessed by the twitter developer account using access key and token key.

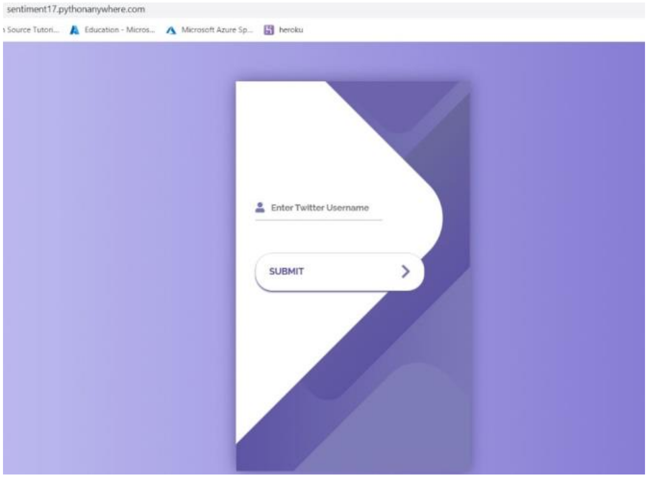

Fig. 12. User Login.

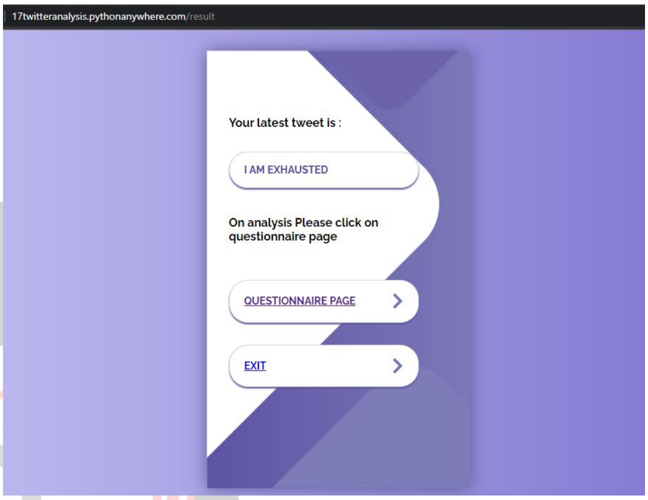

Fig. 13. User's latest tweets.

Fig. 13. depicts the user's most recent tweet and the subsequent analysis phase of redirecting the user to the questionnaire page. If the tweet is positive, the user can quit the page and resume work.

VI. Conclusion

The system was proposed for the sentimental analysis of Twitter tweets using the iHealth chrome extension [6]. The World Health Organisation-based PHQ-9 questionnaire comprises 9 questions that do the initial clinical assessment of the user. Analysis of algorithms in comparison to choosing the best accurate technique for additional machine analysis of the tweet, Logistic Regression, CNN, SVM, and Multinomial NB was assessed. It also has NLP and LIWC libraries for improving the performance of the model.A chrome extension and website were created to assist depressed social media users in seeking professional help [10].

Acknowledgment

It gives us great pleasure in presenting the preliminary report on "Chrome extension for detecting mental health on social media".

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