



Depression Detection By Analyzing Social Media Post Of User: Research Paper

¹Nishad Jangam, ²Kartik Jaiswal, ³Kapil Jaiswal, ⁴Pritish Pawar

^{1,2,3,4}Student, ^{1,2,3,4}Computer Engineering,

^{1,2,3,4}Sandip Institute of Engineering and Management, Nashik, Maharashtra, India.

Abstract: Moment, the problem of the early discovery of depression is one of the most important in psychology. Mental health problems are frequently among the most important health stressors in the world, with over 300 million people presently affected by depression alone. As large quantities of manly or womanish signups are generated on social media platforms, experimenters are adding the use of substantiation- gathering bias to determine if this content material can be used to uncover internal health issues in druggies. Depression is a complaint that poses a major problem in our society and is a continuing concern, according to experimenters around the world. With ubiquitous computing bias like smartphones, prognosticating depressive moods remains an open question. Social media testing is frequently enforced to address this issue. In this composition, a depression standing and suicidal creativity discovery system were proposed to prognosticate suicidal acts supporting the magnitude of depression. To do this, expert and well-established classifiers were used to distinguish whether someone is depressed or not, using capabilities from their sporting exertion within positions. analogous tool algorithms are used to train it and classify it into different situations of depression on a scale of 0- 100. In depression or not, the use of Art Machine Learning algorithms is a prophetic system for the early discovery of depression or unusual internal ails. The main donation of this test is the discourse of a faculty network and its counteraccusations for recognizing the degree of depression. This system aims to gain an in-depth understanding of the model used to classify druggies with depression by understanding some cases where manly or womanish undergraduate markers are examined to uncover postgraduate markers. By combining all of the post-label order possibilities, you can produce temporary post-biographies that are also used to classify guests with depression. This paper shows that there are fluid performances in the posting patterns between depressed and non-depressed guests, as represented by the combined odds of the posting label order. Natural Language Processing (NLP), distributed the use of the BERT set of regulations to find out depression presumably in a lesser on-hand and inexperienced way.

Index Terms - Machine Learning, NLP, BERT Algorithm, Depression, Classification, Social Media Post.

I. INTRODUCTION

Currently, the hassle of early depression discovery is one of the maximum critical withinside the area of psychology. Depression is also a mean intellectual problem. In the moment's world, the stresses of living sports in one's life ought to develop the possibility of depression. Over 350 million people encyclopedically are bothered by depression, which is set 5 of the whole population. near people die because of self-murder every 12 months and its long hauls are statistically the alternate bone essential purpose for loss of life amongst people 15 – 29 times old. At the equal time, the number one form of self-murder is related to depression. Recent inquiries display that depression is likewise the primary purpose of incapability and violent physical conditions. The proliferation of the net and advertisement technologies, especially online social networks have rejuvenated how people have interacted and talked with every unique electronically. The packages which encompass Facebook, Twitter, Instagram, and likewise now no longer nice host the written and multimedia content

material still likewise give their guests precise passions, feelings, and sentiments roughly a subject, hassle, or a problem online. On one hand, that's atrocious for guests of social networking websites to overtly and freely contribute and reply to any hassle matter online; on the indispensable hand, it creates possibilities for people of America of a person who replied to a subject in a particular manner. To offer such a notion, device studying strategies ought to presumably give many precise chops that could help in examining the precise styles hidden in online advertisement and way them to reveal the intellectual us also, there can be a developing frame of literature addressing the specific of social networks withinside the shape of social connections which incorporates breaking up connections, intellectual illness(' depression ', ' anxiety ', ' bipolar 'etc.), smoking, and eating relapse, sexual importunity and for self-murder creativity. youngish grown-ups, ethnical/ ethnical nonages, pivotal staff, and overdue character caregivers supported having intimate disproportionately worse character issues, raised substance use, and bettered unstable celebration. Youth is outlined as age fifteen to twenty- 4 times, consisting of center and history due to nonage. It's characterized through the way of the approach of present-day variations in physical, cerebral, and social confines. For healthy increase and development, youthful grown-ups need to have a nice manner of happiness, love, action, and independence and to have a reason in life. Throughout this natural way stage, numerous forms of conduct blockish degree evolved that my purpose every normality or character sickness. Anyhow of what you nearly surely did presently on your mobile phone or PC, it's egregious that social media changed duly into a concern. Did you capture up with musketeers on Facebook, put up shots of your cat, or videotape your totter tromping for 1st time on Instagram? presumably, a Twitter hyperlink introduced you then. These days elders tend to particular their feelings, review abettor situations reveal their ordinary lives thru the growth of social media systems like Twitter, Facebook, and In. Instagram. These expressions are blockish degrees generally thru shots, vids, and trendy posts. In this study, we intend to probe Social Media posts to come across any rudiments that could image the depression of applicable Social Media guests. colorful gear for studying strategies is hired for similar purposes. Considering the pivotal element purpose of this study, the posterior coming studies bear situations addressed withinside the paper. We'll be fitted to tend to intend to make use of gear-studying strategies and algorithms for depression discovery on social media posts of guests.

NLP (NATURAL LANGUAGE PROCESSING):

The oils defined in this paper belong to the vicinity of Natural Language Processing (NLP) and the textual content's splendor is specific. The origins of textual content splendor liabilities may be determined in early studies to mechanically classify lines primarily grounded completely on a statistical evaluation of specific indication expressions in 1961. latterly, similar studies ask to affect in rule- primarily grounded surely textual content splendor structures like CONSTRUE in 1990, and eventually, the vicinity started to shift decreasingly tool studying algorithms in a many unidentified time withinside the fortune of the 3 hundred and sixty- 5 days of 2000. In addition to textual content categorization, tool assessment will come likewise the operation of strain in outstanding textual content- primarily grounded completely on liabilities like sentiment evaluation, which is concentrated on rooting reviews and sentiment from textual content lines. It'll come first to be finished in total with the tool studying to find out high-quality or horrible reviews in film reviews and end up also dragged to outstanding evaluation disciplines, in addition to specific regions like social media shadowing and preferred evaluation of purchaser stations. More lately, a deep assessment has been finished for textual content splendor in addition to its further not unusual position vicinity application withinside the print graph splendor. State- of- the- artwork issues in multitudinous textual content- primarily grounded liabilities that could, for illustration, be finished through switch studying strategies like Universal Language Model Fine-tuning(ULM Fit) and the Google studies task Bidirectional Encoder Representations from Mills(BERT) for the education of language representations, which incorporates ULM Fit and multitudinous outstanding The law of BERT and multitudinous-expert models.

II. LITERATURE REVIEW

Instrumental opportunities of studying the conduct of customers in social networks are actively developing. In particular, strategies of computational linguistics are efficiently utilized in studying the posts from social media.

1) A records-analytic-primarily based totally version to hit upon melancholy of any individual is proposed withinside the paper. The records are gathered from the customers' posts on famous social media websites: Twitter and Facebook. In this research, device studying is used to manner the scrapped records gathered from SNS (Social Networking Sites) customers. Natural Language Processing (NLP), labeled the usage of Support Vector Machine (SVM) and Naïve Bayes set of rules to hit upon melancholy probably in an extra handy and greenway. [1]

2) The research employs Natural Language Processing (NLP) strategies to increase a melancholy detection set of rules for the Thai language on Facebook in which human beings use it as a device for sharing opinions, feelings, and existence events. [2]

3) The fitness tweets are analyzed for Depression, Anxiety from the blended tweets via way of means of the usage of Multinomial Naive Bayes and Support Vector Regression (SVR) Algorithm as a classifier in paper [3].

4) In the paper, researchers gift a way to discover the melancholy degree of someone via way of means of looking at and extracting feelings from the text, the usage of emotion theories, device studying strategies, and herbal language processing strategies on unique social media platforms. [4]

5) The paper, pursuits to use herbal language processing on Twitter feeds for engaging in emotion evaluation specializing in melancholy. Individual tweets are labeled as impartial or negative, primarily based totally on a curated phrase listing to hit upon melancholy tendencies. In the manner of sophistication prediction, a guide vector device and Naive-Bayes classifier had been used. The consequences had been offered the usage of the number one category metrics inclusive of F1-score, accuracy, and confusion matrix. [5]

6) The paper, proposes a melancholy evaluation and suicidal ideation detection system, for predicting suicidal acts primarily based totally on the extent of melancholy. Real-time records changed into gathered withinside the shape of Tweets and Questionnaires. Then, category device algorithms are used to teach and classify it in 5 degrees of melancholy relying on severity. [6]

7) Yates et al. used a neural community version to show the dangers of self-damage and melancholy primarily based totally on posts from Reddit and Twitter and confirmed the excessive accuracy of this diagnostic approach. The authors suggest that proposed strategies may be used for large-scale research of intellectual fitness in addition to for scientific treatment. [8]

8) O'Dea et al. tested that Twitter is gradually researched as a way for spotting mental well-being status, inclusive of melancholy and suicidality withinside the population. Their research found out that it's miles workable to understand the extent of fear amongst suicide-associated tweets, using each human coder and a programmed device classifier.[10]

There is a severe and developing variety of methodologies and strategies for detection of the melancholy degree from the posts on Social Media networks. In our study, we consolidate a technical description of strategies implemented for melancholy identity the usage of the Natural Language Processing approach labeled the usage of the BERT set of rules to hit upon melancholy. The framework is created from Data pre-processing step, the Feature extraction step following the Machine Learning classifiers, the Feature evaluation of the records, and the Experimental Results.

III. PROBLEM STATEMENT

Depression has been vindicated to have an impact on the language of individualities. To expand a software to probe and come across despair of social media posts of guests via tool studying ways. This challenge aims to use natural language processing, tool studying ways, and neural network infrastructures to make, tune and have a look at models that classify social media Post of druggies as "depressed" or "non-depressed"

IV. OBJECTIVE

The targets are as follows:

1. The system will constantly hold on to tracking the posts and exchanges of druggies. And if it detects the bad notion kind of conduct also the device will mechanically put up the high-quality put up on his/ her wall primarily grounded completely on the extent of depression.
2. Help the individual to pop out of depression.

V. METHODOLOGY

Machine Learning Classification Techniques used for the mode

1. BERT Algorithm:

“BERT stands for Bidirectional Encoder Representations from Mills. It's designed to re-educate deep bidirectional representations from the unlabeled textual content with the salutary aid of the operation of cooperative exertion on each left and proper terrain. As a result, the there-expert BERT interpretation may be fine-tuned with in reality one farther affair caste to produce slice-edge fashions for a large kind of NLP tasks.” We advanced a Bidirectional Encoder Representations from Mills(BERT)- primarily predicated virtual interpretation, it's a brand-new language illustration interpretation as defined in. As the choice suggests, it changed into designed-to-educate deep bidirectional representations that may be fine-tuned with a further

affair sub-caste. For this design, this labor caste- a pooled affair- changed into used for the double shape of the commentary. From the various- expert fashions available, we determined the English- language uncased(all lowercase before tokenization) interpretation of BERT, as case records are not particularly critical to the adventure of social media commentary type.

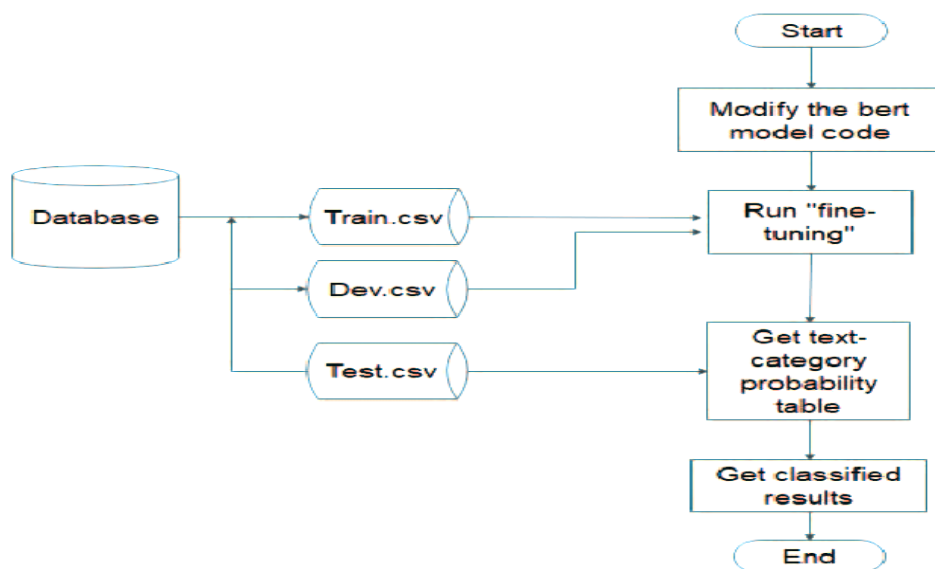


Fig.1 BERT Algorithm

2. Relevant Mathematics Associated with The Project:

System Description:

S= I, O, F, DD, NDD, Failure, Success

Where,
S=System
I= Input
O=Output
F=Failure
S=Success

I is Input of system
 Input I = set of Inputs

Where,
 I= {Users Social media posts}
 F is Function of system
F = set of Function

Where,
 F1= {Input Dataset}
 F2= {Json to CSV Conversion}
 F3={Pre-processing}
 F4={Cleaning}
 F5= {Train test split}
 F6= {Sentiment Dictionary}
 F7= {Classifier (BERT Algorithm)}
 F8={Tokenization}

O is Output of system

Output O1= {Depression detection}

- **Success Conditions:** Product working Smoothly. depression detection successfully.
- **Failure Conditions:** if internet connection Unavailable.

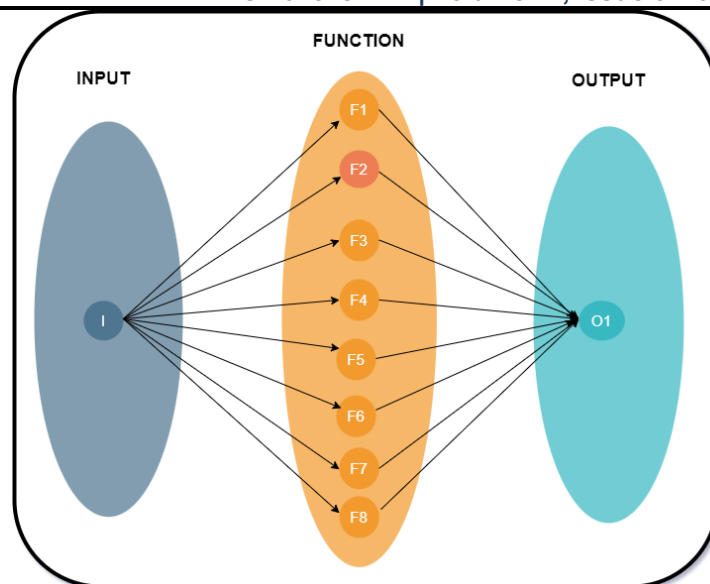


Fig.2 Venn Diagram

Where ,

$I = \{ \text{Users Social media posts} \}$
 $F1 = \{ \text{Input Dataset} \}$
 $F2 = \{ \text{Json to CSV Conversion} \}$
 $F3 = \{ \text{Pre-processing} \}$
 $F4 = \{ \text{Cleaning} \}$
 $F5 = \{ \text{Train test split} \}$
 $F6 = \{ \text{Sentiment Dictionary} \}$
 $F7 = \{ \text{Classifier (BERT Algorithm)} \}$
 $F8 = \{ \text{Tokenization} \}$
 Output $O1 = \{ \text{Depression detection} \}$

VI. SYSTEM ARCHITECTURE

Depression is a severe challenge in private and public health. One of the important results of this hassle is an in-intensity have a take examine an existent's behavioral attributes. These attributes are available on numerous social networking websites collectively as Facebook, Twitter, Instagram, etc. Social networking platform is a high-quality way to understand a character's gesture, questioning style, mood, egoistic networks, evaluations, etc. The use of social networking websites is developing, specifically among the ultimate of the several further immature generations. mortal beings on social media specifically their heartstrings, regular sports exertion, evaluations of numerous motifs, etc. So social networking websites are used as netting contraptions to assume depression ranges. These social networking structures offer a character's exploits, evaluations, socialization, and personality. The superior system of evaluation of the affected character is not so applicable but the use of consumer-generated content material fabric material cloth on social media posts lets one to are looking for the intellectual health ranges and depression of a particular existent. Our challenge purpose is to prize data from social media posts and thru a manner of the system of getting clean moxie of a character's behavioural attributes and tried questionnaires, depression ranges of the consumer are predicted. A quantitative appearance is achieved to educate and check numerous contraptions studying classifiers to determine whether or not or now no longer or now no longer or no longer a social media position of the consumer is depressed, from posts initiated thru the manner of the system of the consumer or his/her sports exertion on social media. The following strength of mind illustrates depression discovery by using the hobby and content material fabric material cloth capabilities kind model. First, all tweets for depressed and non-depressed haves owed, similar to data of consumer capitalist-possessed and sports exertion collectively with the kind of followers, the amount of following, time of posts, the kind of mentions, and the number of reposts, are reacquired. Next, all posts of an account are assembled in an unattached document. Text pre-processing is achieved on all documents. First, a corpus is created and posts in each document are tokenized. BERT Bracket Algorithm can be used.

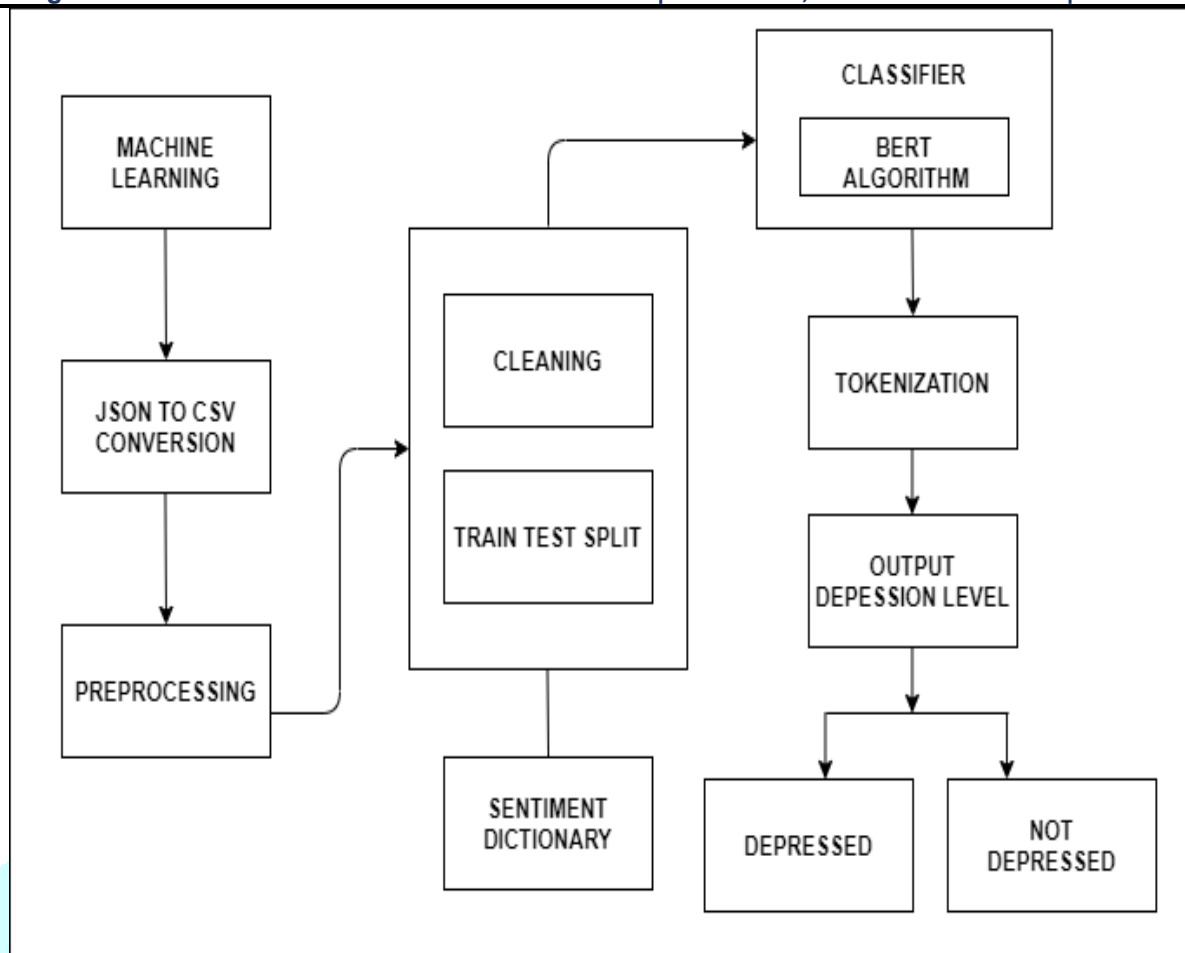


Fig.3 System Architecture

- **EXITING SYSTEM**

The formerly-gift tool provides a long-haul easy flowing way to determine the depression position of guests using the Naïve Bayes algorithm. The birth of textual statistics is completed via the birth beauty from Facebook with the help of the Facebook Graph API. After birth, the statistics are pre-processed. The missing or repetitious attributes are taken care of in pre-processing. ways like tokenization, lowercase conversion, word stemming, and terms junking are used for Preprocessing of statistics. In the proposed tool, regular guests' Facebook put-up model can find out whether or not or now no longer he is depressed or now no longer. But the utmost effective studying posts won't supply accurate consequences so we also observe the commentary via the customer and his musketeers and his exchanges are also anatomized due to the fact the customer will truly change his depression inclusively alongside together on with his friend. On the base of these analyses, the guests can be distributed as pressured and non-pressured.

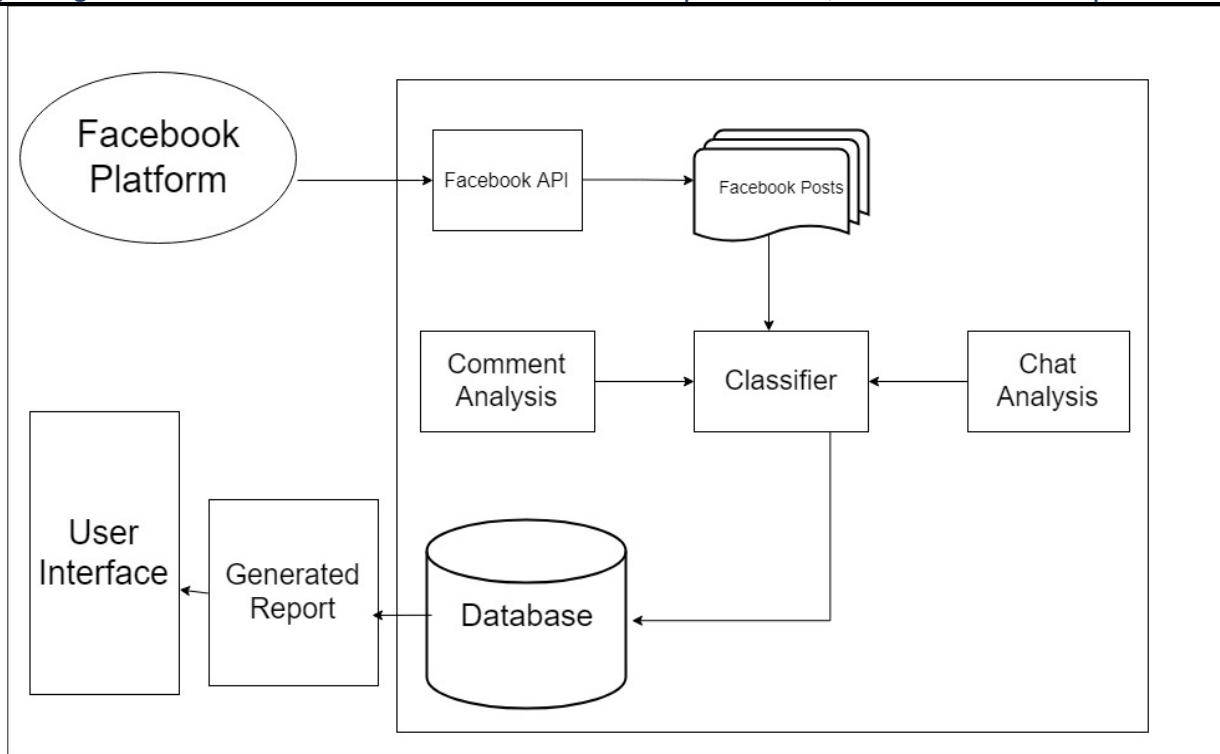
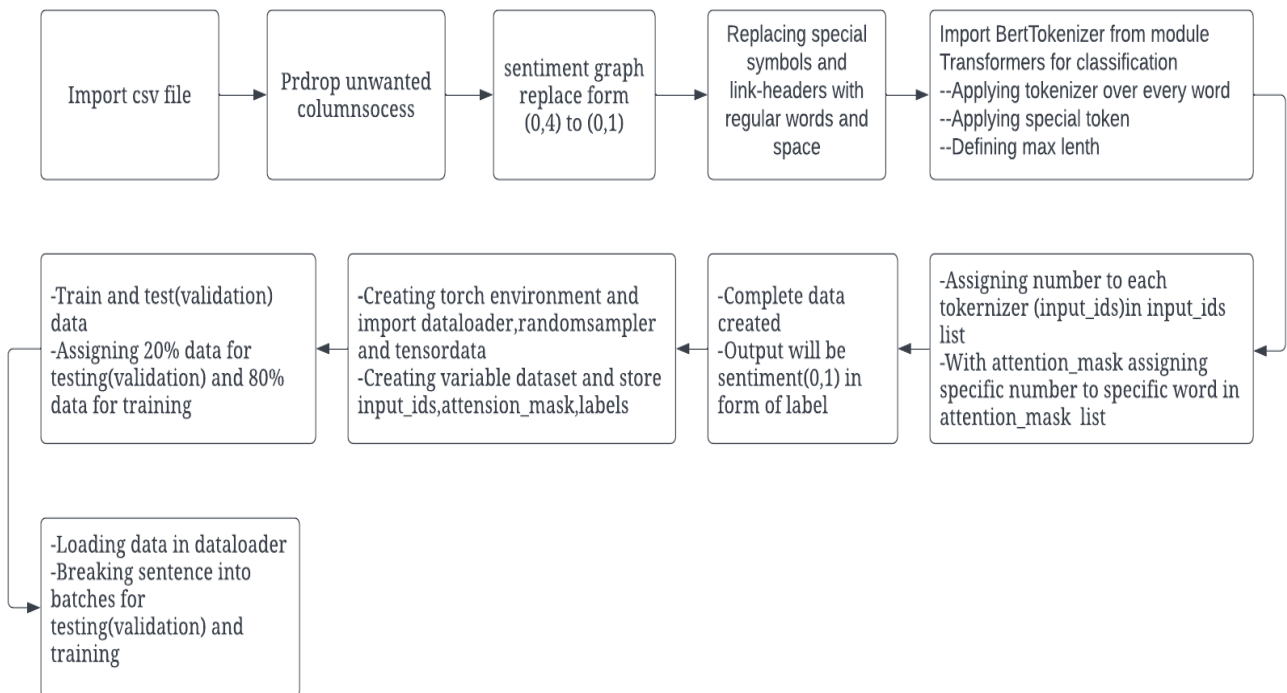


Fig.4 Existing System Architecture

VII. IMPLEMENTATION

• **Module Split-Up:**

- a) Data Processing (Module-I)
- b) Data Training, Testing (Module-II)
- c) Creating Frontend (Module-III)



a) Data Processing (Module-I):

Fig.VII-a-1 Data Processing (Module-I)

- Screen-View Result:

```
df = pd.read_csv('C:/Users/karan/OneDrive/Desktop/Depression/Dataset/depression.csv', encoding='latin-1', header = None)
df.columns=['Sentiment', 'id', 'Date', 'Query', 'User', 'Tweet']
df = df.drop(columns=['id', 'Date', 'Query', 'User'], axis=1)
✓ 13.2s
```

```
df.head()
✓ 0.3s
```

	Sentiment	Tweet
0	0	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	is upset that he can't update his Facebook by ...
2	0	@Kenichan I dived many times for the ball. Man...
3	0	my whole body feels itchy and like its on fire
4	0	@nationwideclass no, it's not behaving at all...

Fig. VII-a-2 Module-I

```
hashtags = re.compile(r"^#\S+|\s#\S+")
mentions = re.compile(r"^@\S+|\s@\S+")
urls = re.compile(r"https?://\S+")

def process_text(text):
    text = re.sub(r'http\S+', '', text)
    text = hashtags.sub(' hashtag', text)
    text = mentions.sub(' entity', text)
    return text.strip().lower()
✓ 0.1s
```

```
df['Tweet'] = df.Tweet.apply(process_text)
✓ 41.2s
```

```
df.head()
✓ 0.3s
```

	Sentiment	Tweet
0	0	entity - awww, that's a bummer. you shoulda ...
1	0	is upset that he can't update his facebook by ...
2	0	entity i dived many times for the ball. manage...
3	0	my whole body feels itchy and like its on fire
4	0	entity no, it's not behaving at all. i'm mad. ...

Fig. VII-a-3 Module-I

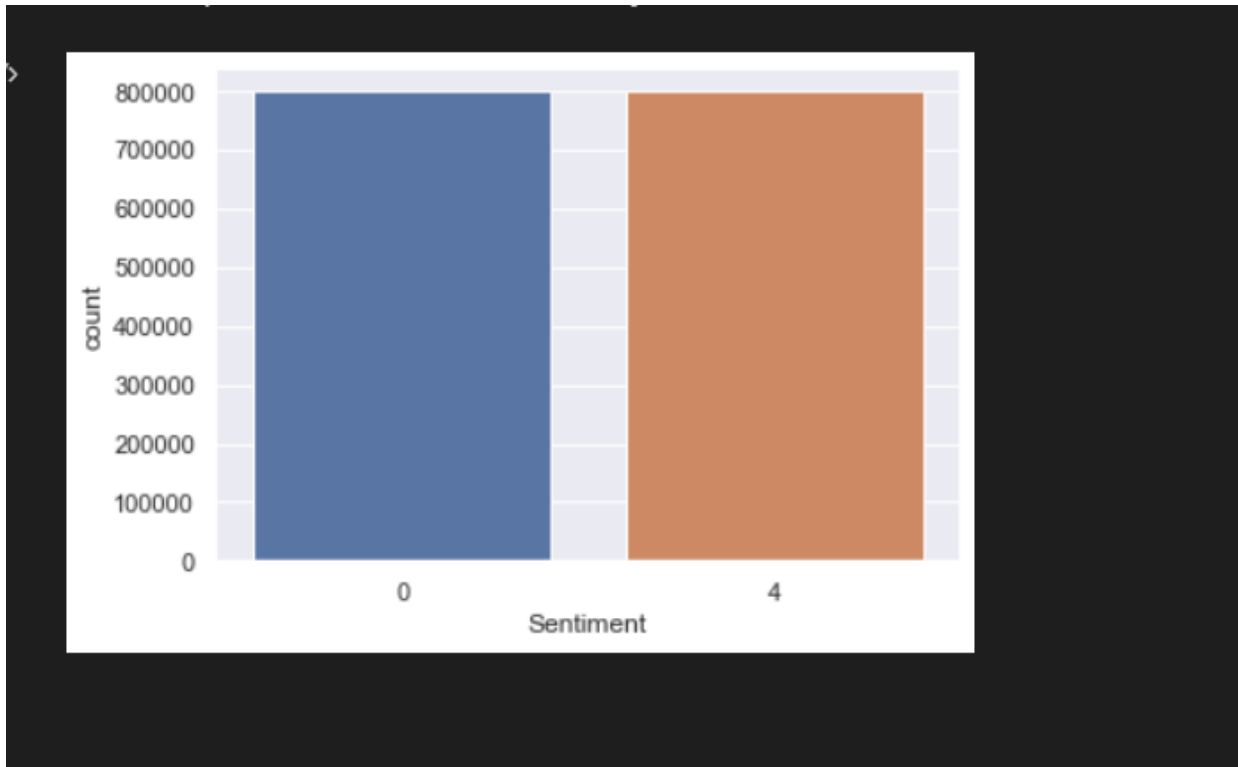


Fig. VII-a-4 Module-I



Fig. VII-a-5 Module-I

```
train_size = int(0.8*len(dataset))
val_size = len(dataset) - train_size

train_dataset,val_dataset = random_split(dataset,[train_size,val_size])

print('Training Size - ',train_size)
print('Validation Size - ',val_size)

Training Size - 1280000
Validation Size - 320000

train_dl = DataLoader(train_dataset,sampler = RandomSampler(train_dataset),
                      batch_size = 32)
val_dl = DataLoader(val_dataset,sampler = SequentialSampler(val_dataset),
                   batch_size = 32)

len(train_dl),len(val_dl)

(40000, 10000)
```

Fig. VII-a-6 Module-I

b) Data Training, Testing (Module-II):

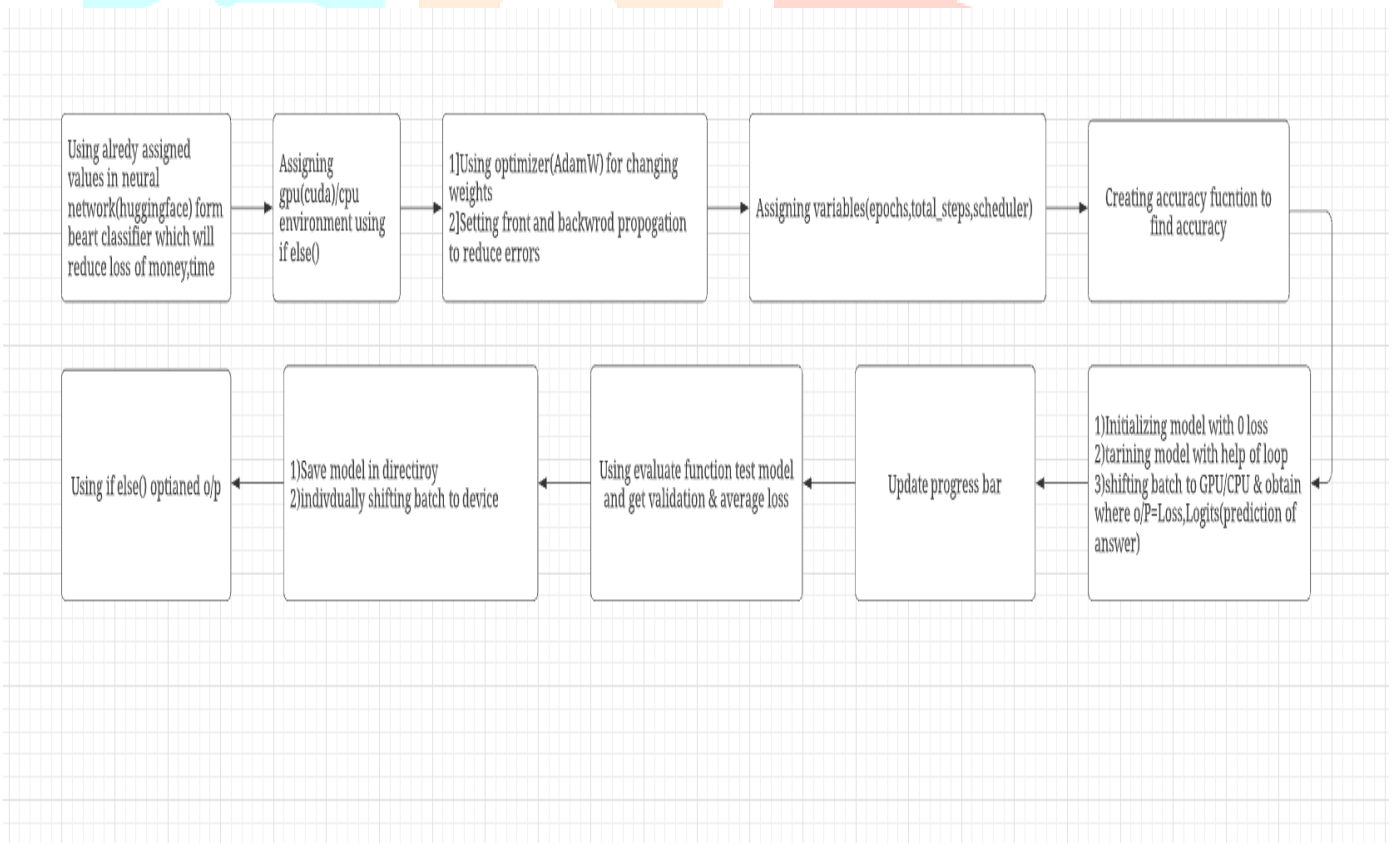


Fig. VII-b-1 Module-II

- Screen-View Result:



Module II

```

model = BertForSequenceClassification.from_pretrained(
    'bert-base-uncased',
    num_labels = 2,
    output_attentions = False,
    output_hidden_states = False)

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu') # GPU/CPU env set for cpu device = torch.device('cpu')
model.to(device)

print(device)

```

cuda

Some weights of the model checkpoint at bert-base-uncased were not used when initializing BertForSequenceClassification: ['cls.predictions.bias', 'cls.predictions.transform.dense.weight', 'cls.predictions.transform.dense.bias', 'cls.predictions.decoder.weight', 'cls.seq_relationship.weight', 'cls.seq_relationship.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.predictions.transform.LayerNorm.bias']

- This IS expected if you are initializing BertForSequenceClassification from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertForSequenceClassification from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are newly initialized: ['classifier.weight', 'classifier.bias']

You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

Fig. VII-b-2- Module-II

Defining Accuracy and Evaluate Function

```

def accuracy(preds,labels):
    pred_flat = np.argmax(preds,axis=1).flatten()
    label_flat = labels.flatten()
    return np.sum(pred_flat==label_flat)/len(label_flat)

```

Python

```

def evaluate(dataloader_test):
    model.eval() # eval mode
    loss_val_total = 0
    predictions,true_vals = [],[]
    for batch in dataloader_test:
        batch = tuple(b.to(device) for b in batch)
        inputs = {
            'input_ids':batch[0],
            'attention_mask': batch[1],
            'labels': batch[2]
        }
        with torch.no_grad(): # No gradient descent
            outputs = model(**inputs)
        loss = outputs[0] #1. Loss
        logits = outputs[1] #2. Logits
        loss_val_total += loss.item() # Validation Loss

```

Fig. VII-b-3- Module-II

Training Model

```

from tqdm.notebook import tqdm
torch.cuda.empty_cache()
for epoch in tqdm(range(1, epochs+1)):

    model.train()#Training mode

    loss_train_total = 0 #initialize with zero loss

    progress_bar = tqdm(train_dl, desc='Epoch {:1d}'.format(epoch), leave=False)
    for batch in progress_bar:

        model.zero_grad() #Start with zero as gradient descent

        batch = tuple(b.to(device) for b in batch)#shifting my batch to device

        inputs = {'input_ids': batch[0],
                  'attention_mask': batch[1],
                  'labels': batch[2],
                  }

        outputs = model(**inputs)# 3 inputs
        # outputs -> Loss , Logits (prediction of answer)
        loss = outputs[0]
        loss_train_total += loss.item()# Sum up the loss
        loss.backward() # Backward Propagation

        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

        optimizer.step() # change weights for neuron using optimizer in d
        scheduler.step()

        progress_bar.set_postfix({'training_loss': '{:.3f}'.format(loss_train_total/len(train_dl))}) #update progress bar

    tqdm.write(f'\nEpoch {epoch}')

    loss_train_avg = loss_train_total/len(train_dl)
    tqdm.write(f'Training loss: {loss_train_avg}')

    val_loss, predictions, true_vals = evaluate(val_dl)
    val_acc = accuracy(predictions, true_vals)
    tqdm.write(f'Validation loss: {val_loss}')
    tqdm.write(f'Accuracy: {val_acc}')
    
```

Epoch 1
 Training loss: 0.32305857977699487
 Validation loss: 0.2975687838617712
 Accuracy: 0.87379375

Fig. VII-b-4- Module-II

```

output_dir = 'Model/'
model_to_save = model.module if hasattr(model, 'module') else model
model_to_save.save_pretrained(output_dir)
tokenizer.save_pretrained(output_dir)

('./tokenizer_config.json',
 './special_tokens_map.json',
 './vocab.txt',
 './added_tokens.json')

model_loaded = model_loaded.to(device)
#previously i was shifting whole batch into device
input_id = input_id.to(device) #individually shifting to device
attention_mask = attention_mask.to(device)#individually shifting to device

with torch.no_grad():
    outputs = model_loaded(input_id, token_type_ids=None, attention_mask=attention_mask)

logits = outputs[0]
answer = logits.argmax()
return answer

ans = Sentiment('i am happy')

Truncation was not explicitly activated but 'max_length' is provided a specific value, please use 'truncation=True' to explicitly truncate examples to max length. Defaulting to 'longest_first' truncation strategy. If you encode pairs of sequences (Q&A-style) with the tokenizer you can select this strategy more precisely by providing a specific strategy to 'truncation'.
C:\Users\karan\anaconda3\lib\site-packages\transformers\tokenization_utils_base.py:2271: FutureWarning: The 'pad to max length' argument is deprecated and will be removed in a future version, use 'padding=True' or 'padding='longest'' to pad to the longest sequence in the batch, or use 'padding='max_length'' to pad to a max length. In this case, you can give a specific length with 'max_length' (e.g. 'max_length=45') or leave max_length to None to pad to the maximal input size of the model (e.g. 512 for Bert).
warnings.warn(

if ans == 1:
    print("Happy")
else:
    print("Depressed")
    
```

Loading BERT tokenizer...
 Loading BERT tokenizer...
 Depressed

Fig. VII-b-5- Module-II

c) Creating Frontend (Module-III):

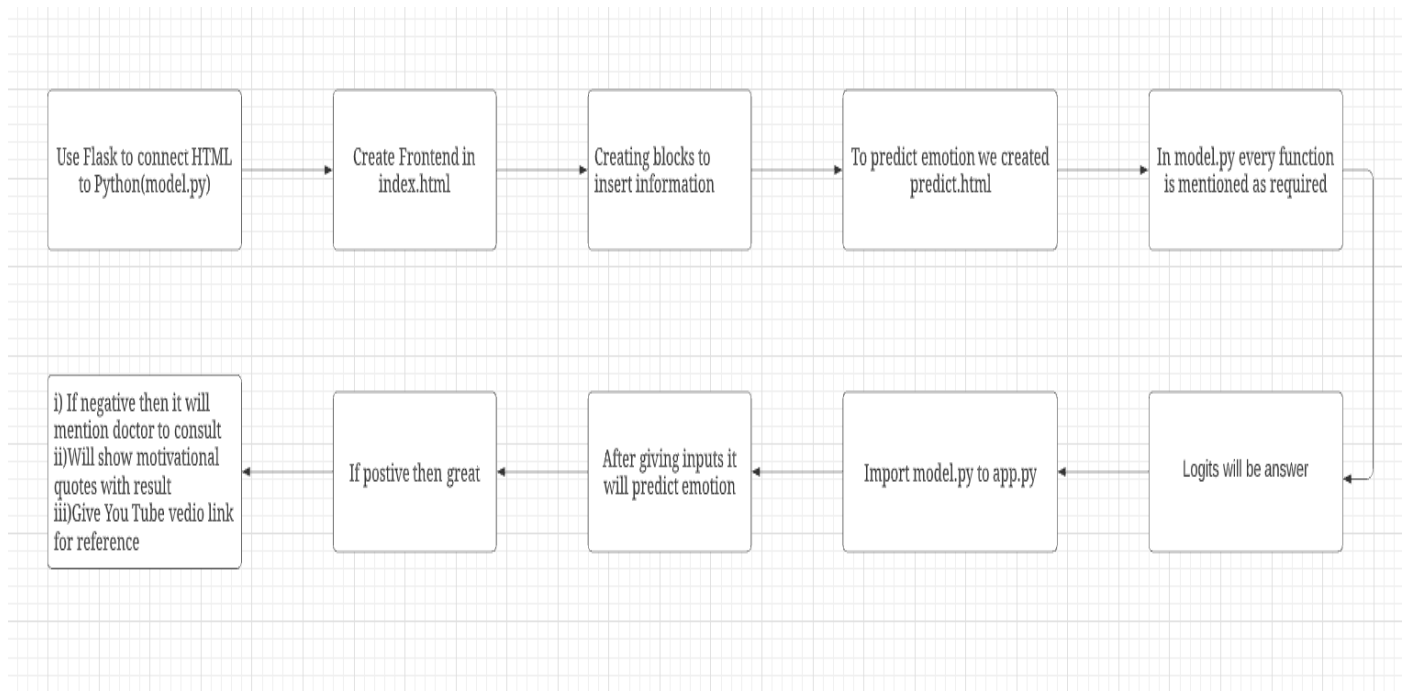


Fig. VII-c-1- Module-III

• Screen-View Result:

```
Anaconda Prompt (anaconda3) - python app.py
(base) C:\Users\karan>cd C:\Users\karan\OneDrive\Desktop\Depression_final\Bert-Sentiment
(base) C:\Users\karan\OneDrive\Desktop\Depression_final\Bert-Sentiment>python app.py
* Serving Flask app "app" (lazy loading)
* Environment: production
  WARNING: This is a development server. Do not use it in a production deployment.
  Use a production WSGI server instead.
* Debug mode: on
* Restarting with watchdog (windowsapi)
* Debugger is active!
* Debugger PIN: 534-379-669
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

Fig. VII-c-2- Module-III

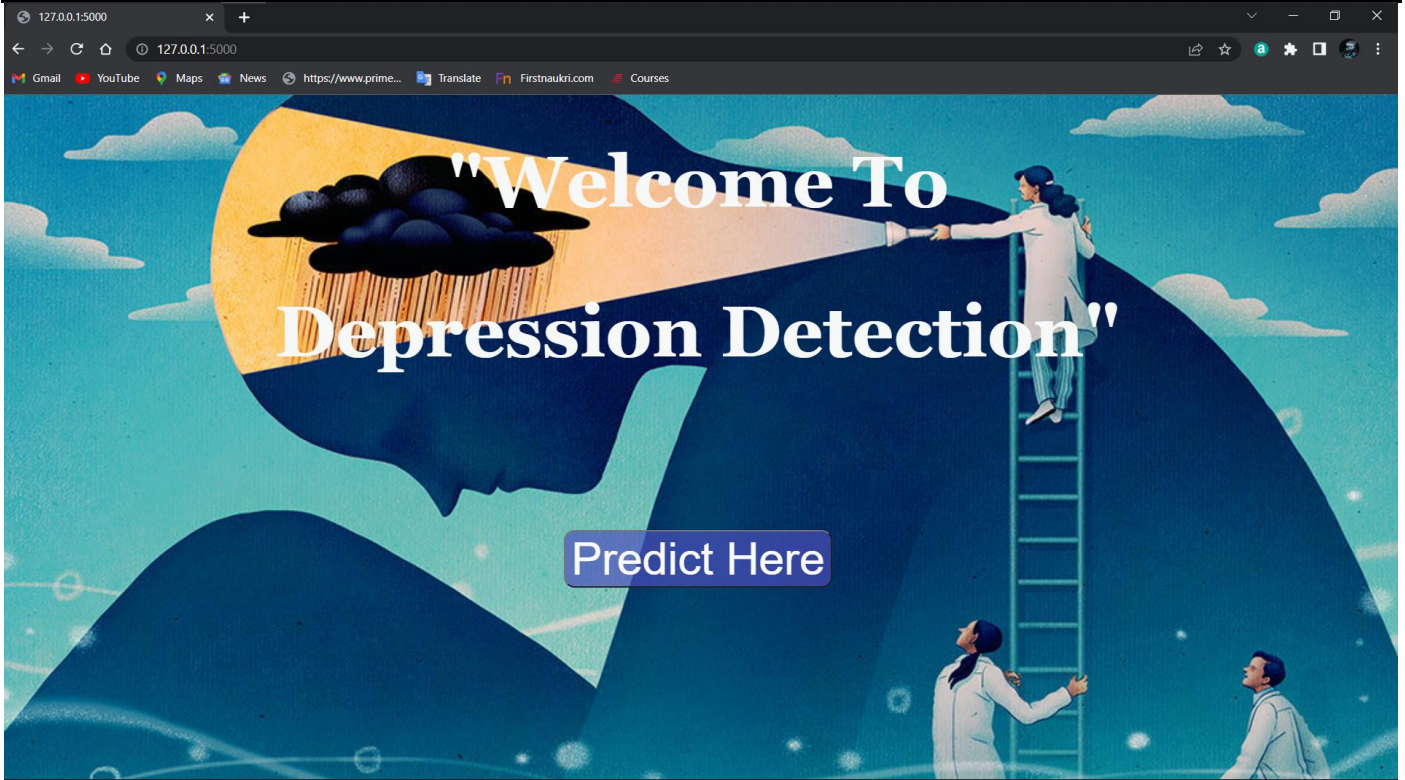


Fig. VII-c-3- Module-III

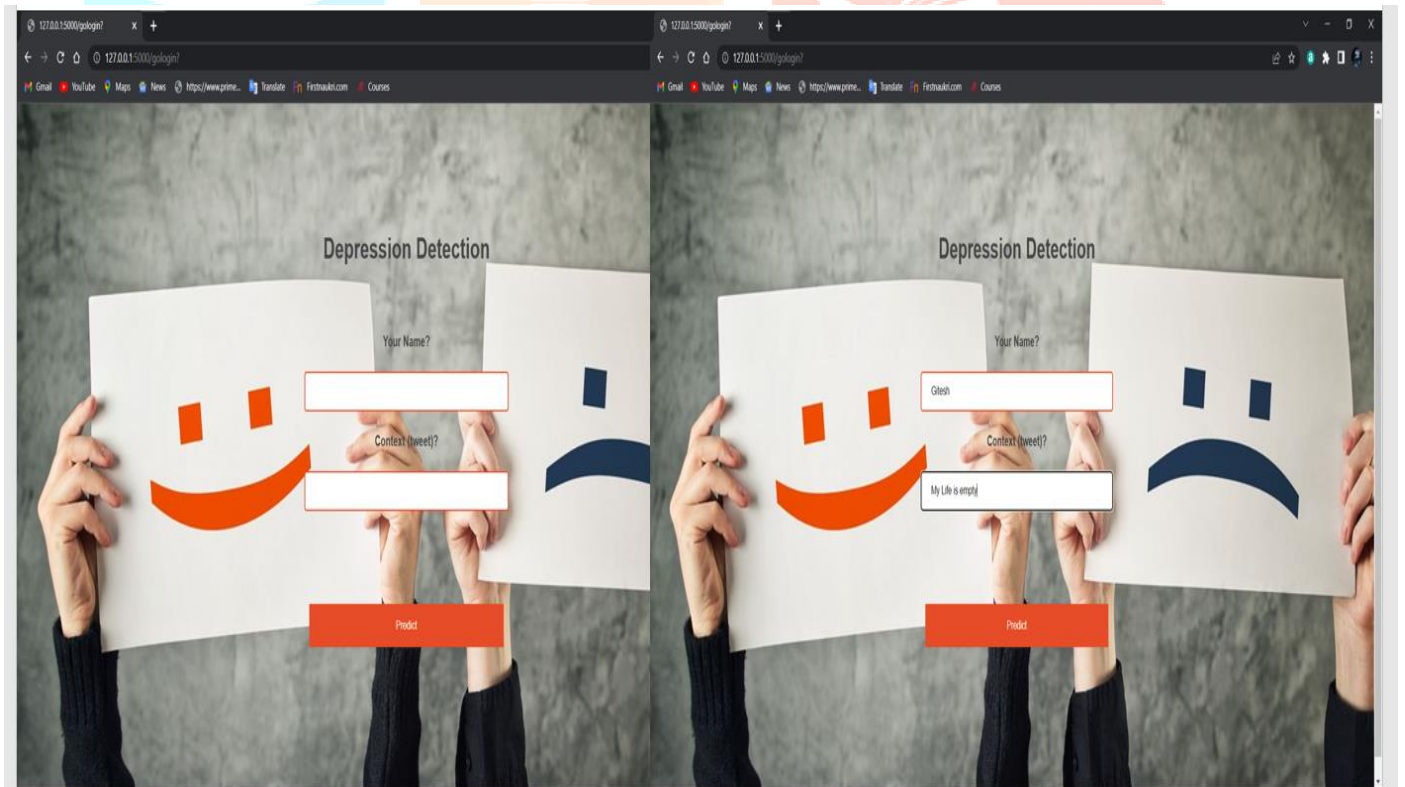
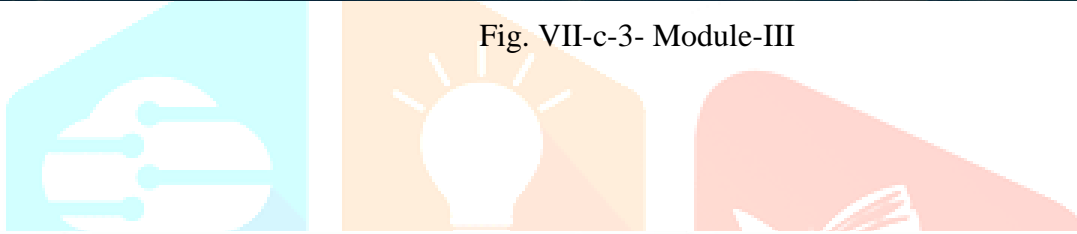


Fig. VII-c-4- Module-III

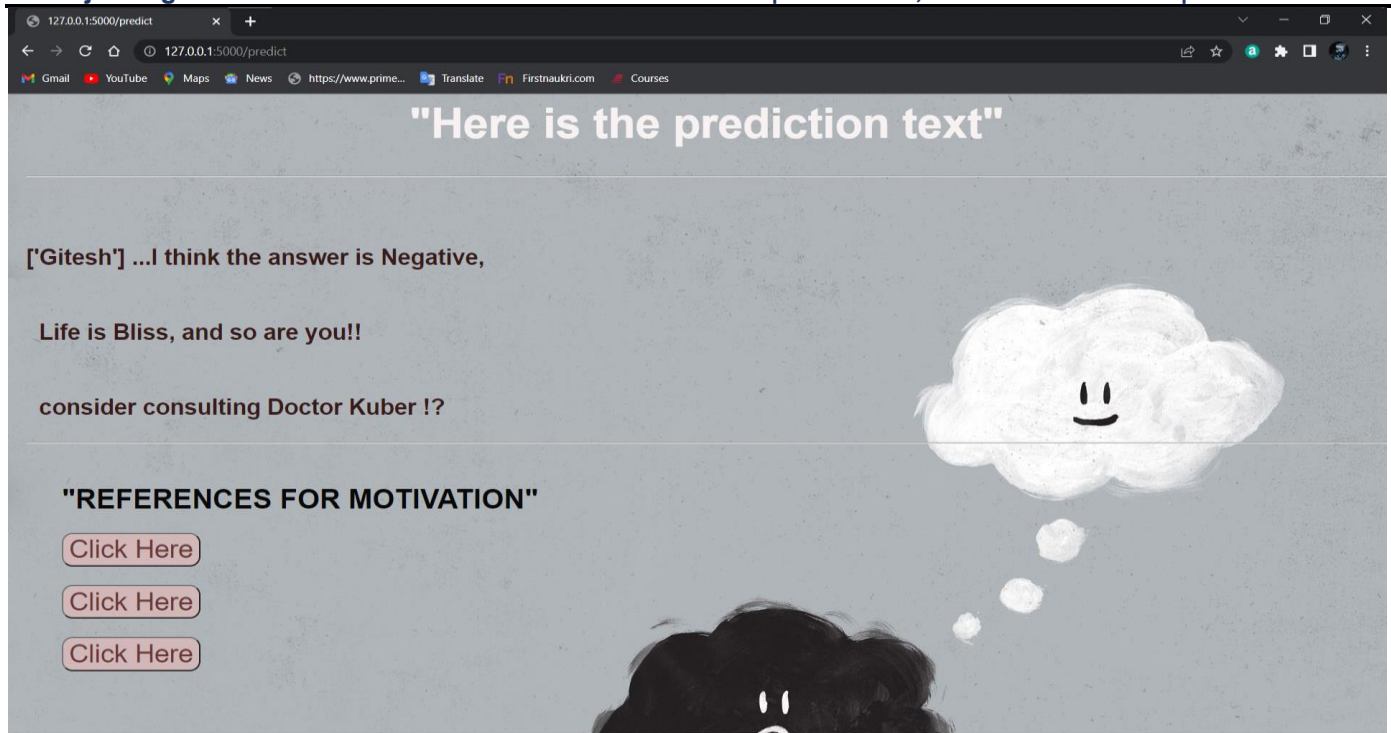


Fig. VII-c-5- Module-III

VIII. CONCLUSION

The proposed device can also help the suspected patron to keep his/ her life, thru manner of the approach of know- style in advance whether or not or now no longer or now not or now not the client is depressed or conceivably the device will deliver some motivational posts to the client grounded substantially on the volume of his depression. We give up the device that is presumably veritably useful in moment's world wherein utmost humans don't have time to satisfy our musketeers, percent their studies and passions as we achieved in aged days due to busy schedules. So, our device plays a critical point proper right then to avoid any unwanted mortal loss. The device will inform their veritably-public circle of cousins' members or consorts and youths regarding the state of affairs of a depressed man or woman. So that each own circle of cousins or confidante circle will help the man or woman to come out of depression.

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