A MAJOR PROJECT REPORT
ON
Mental Health Analyzer Using Image & Natural Language Processing

Submitted by

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MASTER OF COMPUTER APPLICATIONS
FROM

CENTRE OF COMPUTER EDUCATION

INSTITUTE OF PROFESSIONAL STUDIES
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MAY – 2020

CERTIFICATE

This is to certify that the Mini Project report titled “Mental Health Analyser Using Image And Natural Language Processing” submitted by Peeyush Sharma. The project report is approved for submission towards partial fulfillment of the requirement of “MASTER OF COMPUTER APPLICATIONS” from “CENTER OF COMPUTER EDUCATION” from “INSTITUTE OF PROFESSIONAL STUDIES, UNIVERSITY OF ALLAHABAD, PRAYAGRAJ (U.P.)”

Prof. R.R.Tewari

(Course Coordinator)

Centre of Computer Education

CERTIFICATE

This is to certify that the Mini Project report titled "Mental Health Analyser Using Image And Natural Language Processing" submitted by Peeyush Sharma. The project report is approved for submission towards partial fulfillment of the requirement of "MASTER OF COMPUTER APPLICATIONS" from "CENTER OF COMPUTER EDUCATION" from "INSTITUTE OF PROFESSIONAL STUDIES, UNIVERSITY OF ALLAHABAD, PRAYAGRAJ (U.P.)"

(Internal Examiner) (External Examiner)

Date: 30/05/2020 Date:30/05/2020

DECLARATION

I hereby declare that the project titled **“**Mental Health Analyser Using Image And Natural Language Processing**”** which is being submitted in partial fulfillment of the requirement for award of the Degree of “MASTER OF COMPUTER APPLICATIONS” from “CENTER OF COMPUTER EDUCATION” to “INSTITUTE OF PROFESSIONAL STUDIES, UNIVERSITY OF ALLAHABAD, PRAYAGRAJ (U.P.)**”** is an authentic record of my own work done under, CENTER OF COMPUTER EDUCATION, INSTITUTE OF PROFESSIONAL STUDIES, UNIVERSITY OF ALLAHABAD, PRAYAGRAJ(U.P.).

The matter reported in this Project has not been submitted earlier for the award of any other degree.

Dated: **30/05/2020** **Peeyush Sharma**

Place: PRAYAGRAJ

ACKNOWLEDGEMENTS

I take this opportunity to express deep sense of gratitude to “Prof. R.R. Tewari”, Course Coordinator of “Center of Computer Education” for his encouragement and kind approval. Also i thank him in providing the computer lab facility. I would like to express my sincere regards to him for advice and counseling from time to time.

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Dated: **30/05/2020** **Peeyush Sharma**

Place: PRAYAGRAJ

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INTRODUCTION

Everyone feels worried or anxious or down from time to time. But relatively few people develop a mental illness. What's the difference? A mental illness is a mental health condition that gets in the way of thinking, relating to others, and day-to-day function.

Dozens of mental illnesses have been identified and defined. They include depression, generalized anxiety disorder, bipolar disorder, obsessive-compulsive disorder, post-traumatic stress disorder, schizophrenia, and many more.

Mental illness is an equal opportunity issue. It affects young and old, male and female, and individuals of every race, ethnic background, education level, and income level. The good news is that it can often be treated.

Signs and symptoms of mental illness depend in part on the illness. Common symptoms include

- feeling down for a while
- extreme swings in mood
- withdrawing from family, friends, or activities
- low energy or problems sleeping
- often feeling angry, hostile, or violent
- feeling paranoid, hearing voices, or having hallucinations
- Often thinking about death or suicide.

In some people, symptoms of a mental illness first appear as physical problems such as stomach aches, back pain, or insomnia.

Individuals with a mental illness can often ease their symptoms and feel better by talking with a therapist and following a treatment plan that may or may not include medication.

Advantages

- To allow mental health practitioners and researchers to communicate more effectively with each other.
- There are some disease that a patient can’t find out
- “Patient has major depressive disorder”
  1.Conveys a greate deal of information in few words
  2.Mood is a central aspect of the presenting problem
  3.It is not the kind of “normal” mood fluctuation
  4.What is not to be found in this patient

Disadvantages

- Clinicians are accustomed to thinking in terms of diagnostic categories
- Data from large number of experiments may still be indecisive.
- Existing knowledge base about the presentation ,etiology ,epidemiology ,course ,prognosis,and treatement is based on these categories.
- Decision about the management of individual patients are easier to make if the patient is thought of as having a particular disorder.

OBJECTIVE FUNCTION AND SCOPE OF THE PROJECT

Objectives

We sought to use natural language processing to develop a suite of language models to capture key symptoms of mental illness from clinical text, to facilitate the secondary use of mental healthcare data in research.

Product Functions

- Image & Natural Language Processing
- Face & Emotion Detection
- Sentiment Analysis
- Daily Performance Graph & Reports
- Accurate and scalable.

Proposed Work

Objective here is to analyze user's facial expressions detection of face and sentimental analysis on voice of user. And trying to predict the current mood of user by recording video & audio of user through Webcam & Microphone.
After a certain time algorithm will analyze the input and store the results.
and at the end of day of when user wants the detailed reports and graphical data will be provided to user and % probability that defines chances of mental illness.

External Interface Requirements

User Interfaces

We will be using python command prompt or anaconda prompt.

Hardware Interfaces

System should have at least 4 GB of ram.

Operating Environment

Windows operating system with python 3.6 installed.

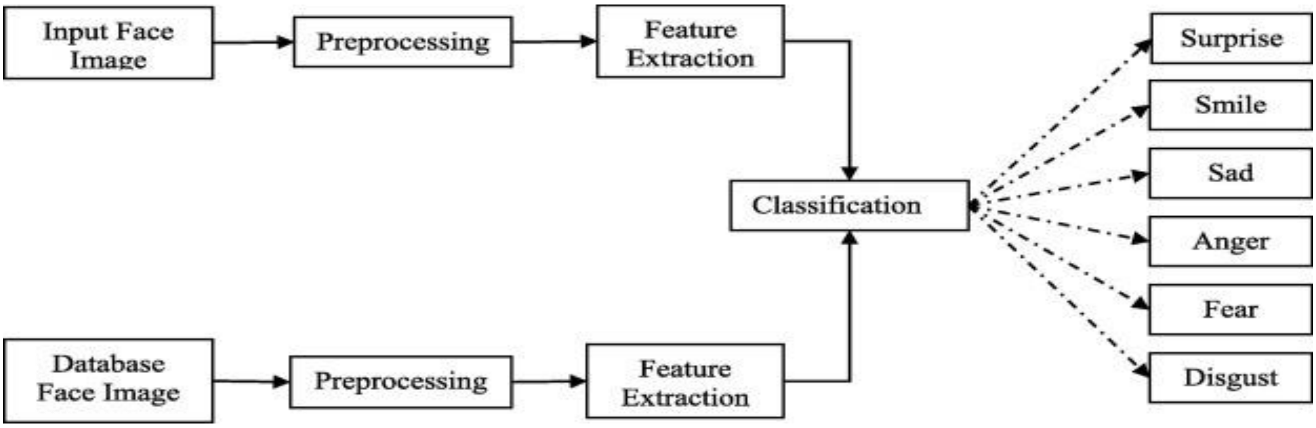
Design and Implementation Constraints

Python V3.6 Is Required.
Packages like –Pandas, Numpy, matplotlib, sklearn, Keras, Tensorflow should be installed.

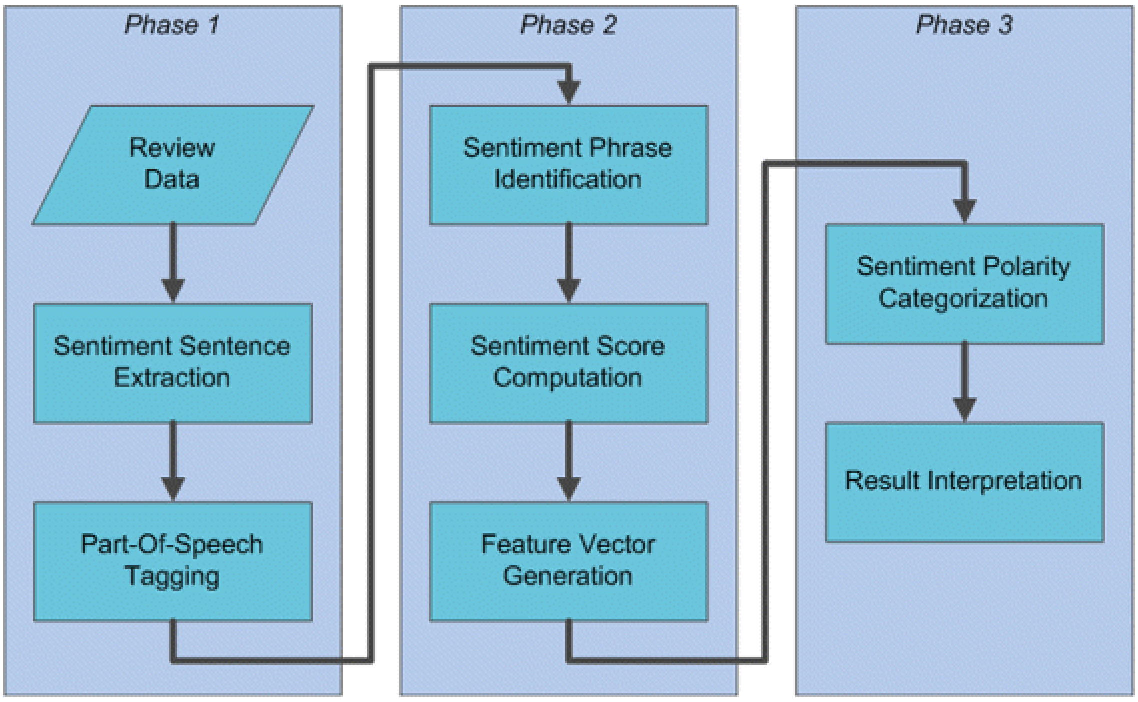
Assumptions and Dependencies

User provides Needed Permissions to Use His Webcam & Microphone.

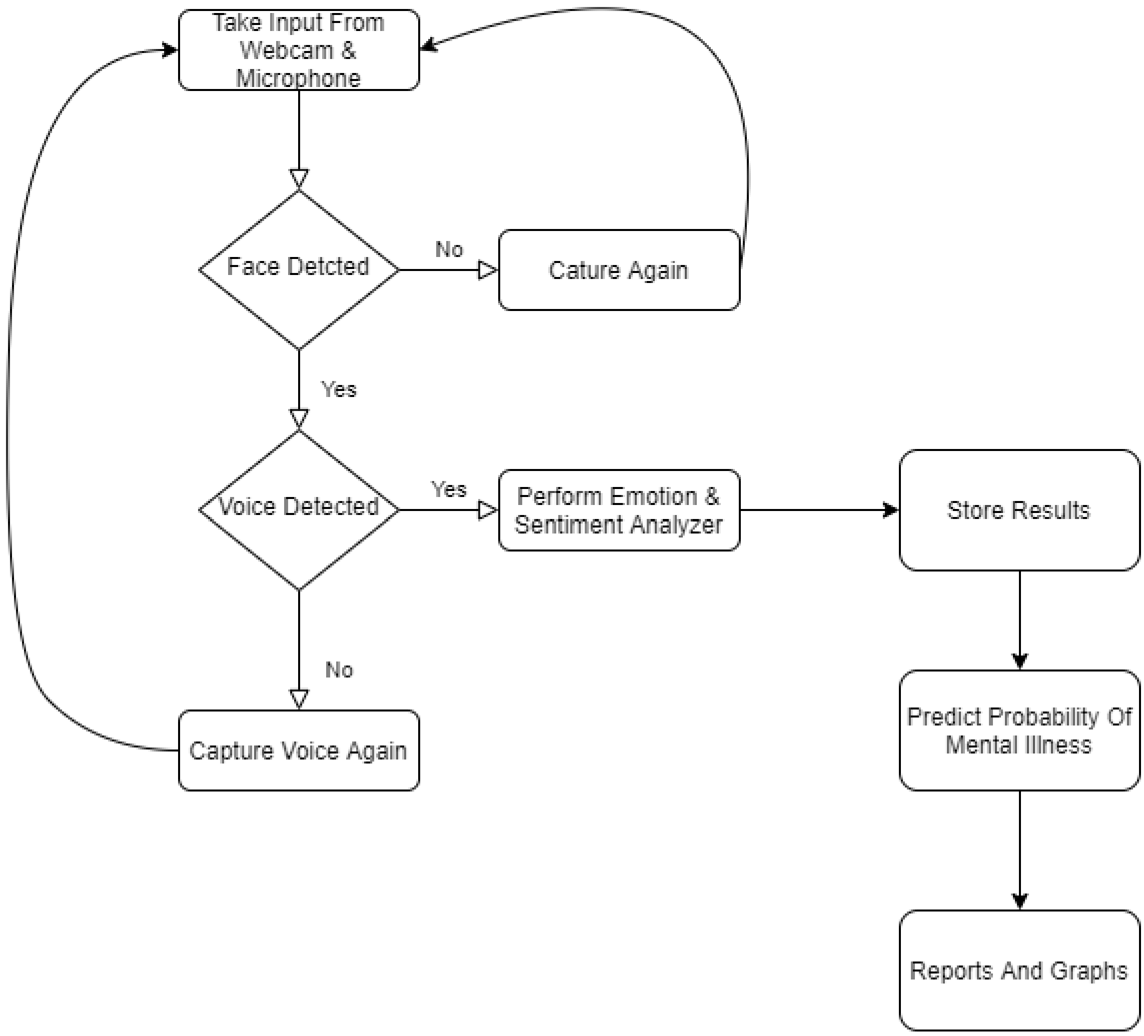
PROPOSED SYSTEM



Emotion Detection Steps



Sentiment Analysis Process Flow



Proposed System Process Flow

DEFINITION OF PROBLEM

Electronic health records (EHRs)

Electronic health records (EHRs) are recognised as a valuable source of data to support a wide range of secondary informatics use cases, such as decision support, observational research and business intelligence. With appropriate handling, EHRs may be able to overcome the cost barriers to generating sufficient data for addressing complex questions that would be out of reach for more conventional patient recruitment protocols.However, the use of EHRs in this way is known to create a range of new issues that need to be addressed before the data can be considered of sufficient quality suitable for research.

Symptomatology of severe mental illness

It is often argued that the symptoms expressed by a patient in the course of their illness represent a more useful description of the disorder and indications for intervention than the concept of a diagnosis.

While common conditions in mental health are represented in classification taxonomies such as the International Classification of Diseases (ICD) and Diagnostic and Statistical Manual(DSM) systems, generally speaking, it is the symptomatology of a condition that is used by clinicians to determine an appropriate treatment plan.

This is due to the broad symptomatic manifestations of mental disorders, in the sense that, at a given time, a patient assigned a diagnosis (such as schizophrenia) can present with all, many or very few of the symptoms associated with the condition.

The problems of diagnostic semantics are especially apparent in severe mental illness (schizophrenia, schizoaffective disorder and bipolar disorder). Here, the controversy is compounded by the high frequency of mental health comorbidities and shortcomings in our current understanding of the biological underpinnings of mental disorders, which in turn limit our ability to subclassify the conditions.

A common task in health research is to group patients with similar conditions into appropriate cohorts, which will almost inevitably require ascertaining common factors pertinent to their disorder.

Diagnoses form semantically convenient units, although the usefulness may be disputed and/or lacking in granularity. Symptomatology may offer more objective, relevant groupings but the data may be locked in unstructured free text, presenting unique data extraction problems.

Natural language processing and information extraction

Natural language processing (NLP) and its subdiscipline of Information Extraction (IE) are commonly employed within clinical records to process large quantities of unstructured (human authored) text and return structured information about its meaning.

Medical entities frequently targeted include medications, diagnoses, smoking status and other factors influencing risk, course or outcome for disorders of interest.A large number of tools and frameworks exist for general purpose information extraction from clinical dictionaries, such as TAKES,NOBLE and MedLee.

However, there has been little application of NLP techniques in mental healthcare data despite the volumes of text-based information contained here, and even less on ascertaining symptomatology.

Here, we introduce the project, which has the long-term objective of offering comprehensive NLP models for mental health constructs. The focus of the initial programme of work described here was to develop sentence classification models for a substantial range of SMI symptomatology, to allow automatic extraction for many of the most informative symptoms from the patient narrative. It is envisaged that the outcomes will support a range of future research and clinical applications.

Definitions of SMI symptoms

A keyword lexicon of SMI symptoms was defined by a team of psychiatrists, based on pragmatic criteria. First, the potential salience of symptoms for research applications was considered, particularly their incorporation in symptom scales in common clinical use, such as the Positive and Negative Symptoms Scale (PANSS) and Young Mania Rating Scale (YMRS) which were used as templates for guidance.

Second, the language used in routine clinical records was taken into consideration in choosing symptoms, focusing particularly on those which were likely to be recorded in the most consistent and tractable language, based on clinical experience.

Third, we sought a priori to extract sufficient numbers of symptom types to generate scales for further evaluation within the following five domains: (1) positive symptoms; (2) negative symptoms; (3) disorganisation symptoms; (4) manic symptoms and (5) catatonic symptoms.

Strengths and limitations of this study

- The number and diversity of symptomatology concepts that we successfully modelled indicates that this task is suitable for natural language processing.
- Our negative control group suggests a wide under-reporting of SMI symptoms in patients who have not received an SMI diagnosis, although our models were not validated in this group and such patients may have later received an SMI diagnosis after our analysis was concluded.
- We did not attempt to resolve temporal aspects of symptomatology in this study, which will be necessary for future predictive modelling approaches.

THEORETICAL BACKGROUND

Information extraction with TextHunter

TextHunter is an NLP information extraction suite developed jointly by SLaM and the Institute of Psychiatry, Psychology & Neuroscience at King's College London.Its principle purpose is to provide an interface to accomplish three tasks required to extract concepts from free text:

1. find instances of a concept in a database of documents using regular expression style matching of keywords;
2. provide an efficient interface to allow human annotators to label a portion of the sentences containing the concept instances in order to develop a gold standard and training corpora;
3. attempt to construct an appropriate support vector machine (SVM) language model of the concept, and validate it with the gold standard corpus.

Briefly, TextHunter is built around the ConText algorithm and the GATE framework Batch Learning plugin, a machine learning framework which in turn uses the LibSVM java library.

A SVM is a machine learning methodology that maps the features of human labelled input training data instances into vector space. Within this space, a learning algorithm is applied to construct a hyperplane, which attempts to accurately differentiate the different training instances based on their labels.

Once this hyperplane is ‘learnt’, the model can be applied to new, unseen instances to predict the label that should be assigned. TextHunter uses bag-of-words features such as keywords, surrounding word tokens and part-of-speech tags in conjunction with knowledge engineering features generated from ConText to build a sentence classifier.

Annotation of SMI symptom concepts

In order to produce annotation guidelines to ensure consistent, high-quality gold standard and training data, we developed annotation guidelines based around internal, iterative discussions.

Generally, we defined a relevant instance as a mention of a symptom observed in a patient, without a grammatical negation. Owing to the large numbers of concepts addressed by this work.

An independent set of gold standard data were also created for each symptom to assess the performance of each model. This was derived in the same manner as the training data.

For training and gold standard data, a relevant instance of a symptom was labelled as ‘positive’, (such as ‘the patient had poverty of speech’) whereas irrelevant or negated instances (such as ‘today I examined the patient for poverty of speech…’ or ‘the patient did not have poverty of speech’) were labelled as ‘negative’ to create a binary classification problem (for the special case of the ‘negative symptoms’ construct, this was annotated as positive when described as present (eg, ‘he experiences severe negative symptoms’) and negative when absent (eg, ‘there was no evidence of negative symptoms’)).

IMPLEMENTATION

Training Model :-

```
import pandas as pd
import numpy as np

from keras.datasets import mnist
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation, Flatten
from keras.layers.convolutional import Convolution2D, MaxPooling2D
from keras.utils import np_utils
from keras.regularizers import l2, activity_l2
from keras.optimizers import SGD, RMSprop

np.random.seed(2222)  # for reproducibility

#Load the scaled data, both pixels and labels
X_train = np.load('./data/Scaled.bin.npy')
Y_tr_labels = np.load('./data/labels.bin.npy')

#reshape the given pixels into 48 X 48 images
shapex , shapey = 48, 48
X_train = X_train.reshape(X_train.shape[0] ,  shapex , shapey,1)

#convert labels to one-hot-encoding
Y_tr_labels = np_utils.to_categorical(Y_tr_labels)

#define the model 32 filters in first convolution layer followed by a max
pooling and dense layer with dropout (50%)
model = Sequential()
model.add(Convolution2D(32, 3, 3, border_mode='valid',
input_shape=(48,48,1)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(128,init='lecun_uniform'))
model.add(Dropout(0.4))
model.add(Activation('relu'))
model.add(Dense(7))
```

```
model.add(Activation('softmax'))

#training the model with cross sgd and nesterov momentum

sgd = SGD(lr=0.055, decay=1e-6, momentum=0.9, nesterov=True)
#optm = RMSprop(lr=0.004, rho=0.9, epsilon=1e-08, decay=0.0)
model.compile(loss='categorical_crossentropy', optimizer=sgd)

model.fit(X_train,Y_tr_labels , batch_size=128 , nb_epoch=15)

#save the model weights
import h5py
json_string = model.to_json()
model.save_weights('./models/Face_model_weights.h5')
open('./models/Face_model_architecture.json', 'w').write(json_string)
model.save_weights('./models/Face_model_weights.h5')
```

Detect Emotion:-

```
from keras.models import model_from_json
from keras.optimizers import SGD
import numpy as np
from time import sleep
model =
model_from_json(open('./models/Face_model_architecture.json').read())
#model.load_weights('_model_weights.h5')
model.load_weights('./models/Face_model_weights.h5')
sgd = SGD(lr=0.1, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='categorical_crossentropy', optimizer=sgd)
def extract_face_features(gray, detected_face, offset_coefficients):
    (x, y, w, h) = detected_face
    #print x , y, w ,h
    horizontal_offset = np.int(np.floor(offset_coefficients[0] * w))
    vertical_offset = np.int(np.floor(offset_coefficients[1] * h))


    extracted_face = gray[y+vertical_offset:y+h,
                x+horizontal_offset:x-horizontal_offset+w]
    #print extracted_face.shape
    new_extracted_face = zoom(extracted_face, (48. / extracted_face.shape[0],
                                48. / extracted_face.shape[1]))
```

```
        new_extracted_face = new_extracted_face.astype(np.float32)
        new_extracted_face /= float(new_extracted_face.max())
        return new_extracted_face
from scipy.ndimage import zoom
def detect_face(frame):
        cascPath = "./models/haarcascade_frontalface_default.xml"
        faceCascade = cv2.CascadeClassifier(cascPath)
        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
        detected_faces = faceCascade.detectMultiScale(
                gray,
                scaleFactor=1.1,
                minNeighbors=6,
                minSize=(48, 48),
                flags=cv2.cv.CV_HAAR_FEATURE_MAX
            )
        return gray, detected_faces

import cv2
cascPath = "haarcascade_frontalface_default.xml"
faceCascade = cv2.CascadeClassifier(cascPath)

video_capture = cv2.VideoCapture(0)

while True:
    # Capture frame-by-frame
#    sleep(0.8)
    ret, frame = video_capture.read()

    # detect faces
    gray, detected_faces = detect_face(frame)

    face_index = 0

    # predict output
    for face in detected_faces:
        (x, y, w, h) = face
        if w > 100:
            # draw rectangle around face
            cv2.rectangle(frame, (x, y), (x+w, y+h), (0, 255, 0), 2)

            # extract features
```

```
            extracted_face = extract_face_features(gray, face, (0.075, 0.05))
#(0.075, 0.05)

            # predict smile
            prediction_result =
model.predict_classes(extracted_face.reshape(1,48,48,1))

            # draw extracted face in the top right corner
            frame[face_index * 48: (face_index + 1) * 48, -49:-1, :] =
cv2.cvtColor(extracted_face * 255, cv2.COLOR_GRAY2RGB)

            # annotate main image with a label
            if prediction_result == 3:
                cv2.putText(frame, "Happy!!",(x,y), cv2.FONT_ITALIC, 2, 155, 10)
            elif prediction_result == 0:
                cv2.putText(frame, "Angry",(x,y),
cv2.FONT_HERSHEY_SIMPLEX, 2, 155, 10)
              elif prediction_result == 1:
                cv2.putText(frame, "Disgust",(x,y),
cv2.FONT_HERSHEY_SIMPLEX, 2, 155, 10)
              elif prediction_result == 2:
                cv2.putText(frame, "Fear",(x,y), cv2.FONT_HERSHEY_SIMPLEX,
2, 155, 10)
              elif prediction_result == 4:
                cv2.putText(frame, "Sad",(x,y), cv2.FONT_HERSHEY_SIMPLEX,
2, 155, 10)
              elif prediction_result == 5:
                cv2.putText(frame, "Surprise",(x,y),
cv2.FONT_HERSHEY_SIMPLEX, 2, 155, 10)
              else :
                cv2.putText(frame, "Neutral",(x,y),
cv2.FONT_HERSHEY_SIMPLEX, 2, 155, 10)

            # increment counter
            face_index += 1
# Display the resulting frame
    cv2.imshow('Video', frame)

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

# When everything is done, release the capture
```

```
video_capture.release()
cv2.destroyAllWindows()
```

The Data:

The data consists of a 48 X 48 pixel images which contains different emotions: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral.
The data is from kaggle competition and an open source data.

The Model:

We have trained a convolution neural network model on the given data, the layers of the conv nets are:

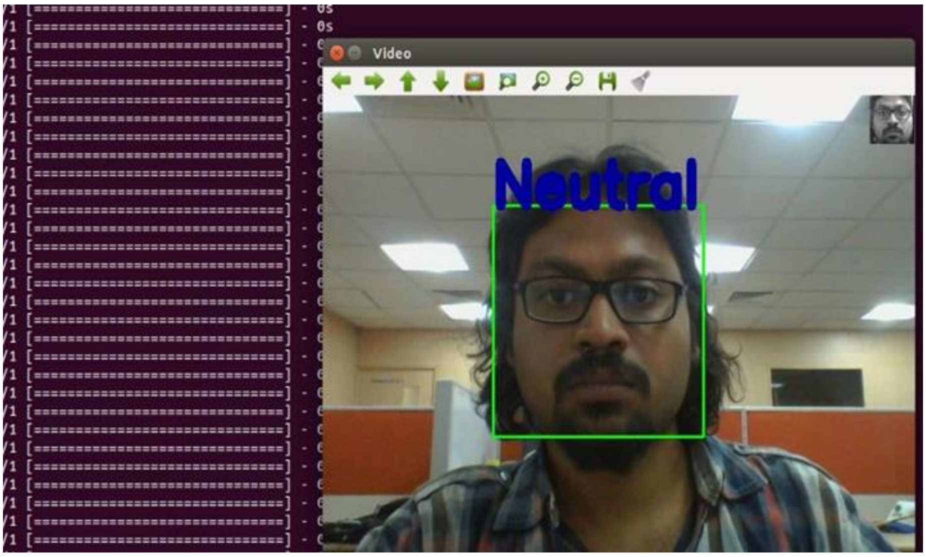
a) Convolution 2D, which takes a 48 X 48 input and maps it into 16 feature maps with 3 X 3 filters/kernels
b) The layer is followed by a non-linear relu layer
c) Followed by a max pooling layer on 2 X 2 feature matrix
d) Again followed by a relu layer
e) The next layer is a fully connected layer with 128 neurons
f) The last layer is a softmax layer with 7 neurons

The network is trained using SGD and nestelrov momentum, on a batch size of 128 and 10 epochs

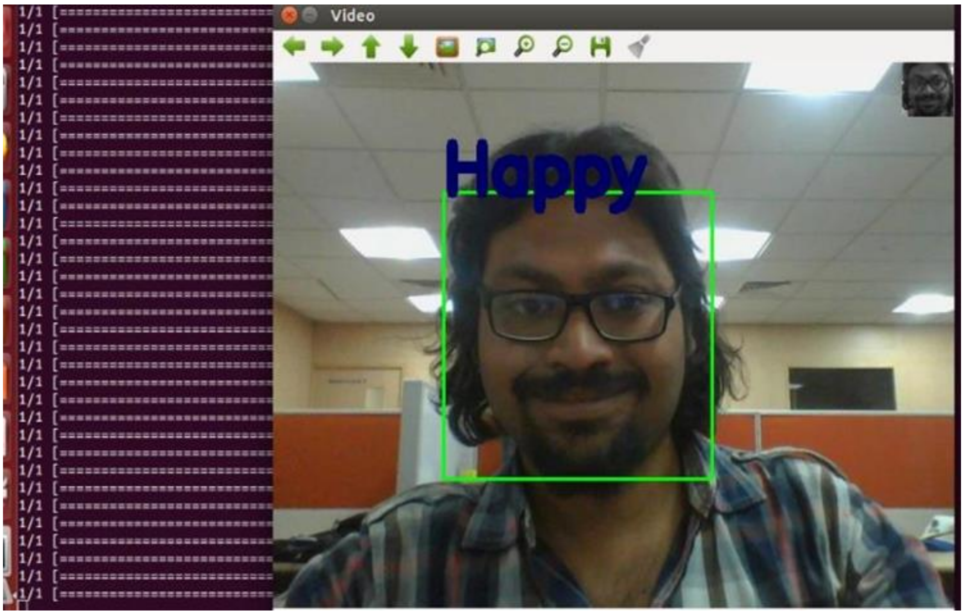
The Application:

The application is a simple one, where we use open-cv tool kit to capture a 48 X 48 image from the webcam, feed it to the trained conv net classifier and predict the emotion.

SCREENSHOTS



Prediction: Neutral



Prediction: Happy

Conclusion

The primary purpose of the developments described was to improve the depth of information available on patients with these disorders represented on healthcare datasets, as these information resources frequently contain little information beyond a diagnosis.

The case for identifying symptoms of SMI as a source of data for mental health analysis is driven by widely recognised deficiencies of diagnostic categories alone for capturing mental disorders or providing adequate classes with which to cluster groups of patients for research or intervention.

This is compounded by the lack of an instrument to capture symptomatology, as most research instruments would be considered overly cumbersome for routine clinical application outside specialist services. Furthermore, even if a fully structured instrument was identified as acceptable for use in initial assessment, obtaining real-time repeated measurements would present even more substantial challenges.

The situation currently in mental health EHRs is that symptom profiles have been 'invisible' when it comes to deriving data for research, service development or clinical audit.

Given that they are key determinants of interventions received and outcomes experienced, this has been a major deficiency.

We therefore hope that the outputs of this project will offer the tools/techniques to use the large amounts of SMI symptomatology data contained within EHR systems, and provide new insight into the value of using SMI symptoms as predictors of a range of outcome measures.

Although we did not seek to extend our analyses beyond simple descriptions of distributions, these strongly indicate that symptoms cross diagnostic groupings—for example, indicating that affective symptoms were not restricted to bipolar disorder.

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FUTURE ENHANCEMENTS

This project was developed to fulfil user requirement; however therearelots of scope to improve the performance of the Mental Health Analyser in the area of medical.
So there are many things for future enhancement of this project. The future enhancements that are possible in the project are as follows-

- Provide more online tips and help.
- Suggesting precautions and informing nearest psychologist and relatives.