

# Behavior Analysis For Mentally Affected People Through Face Emotion Detection

**Mrs. Vennamaneni Reshma**

*Asst. Professor*

*Dept. of. CSE*

*St. Peter's Engineering*

*College Hyderabad, TS, India*

*reshmarao218@gmail.com*

**Buddila Anitha Joy**

*IV B.Tech*

*Dept. of. CSE*

*St. Peter's Engineering*

*College*

*Hyderabad, TS, India*

*anithaanu9572@gmail.com*

**Chatla Deekshitha**

*IV B.Tech*

*Dept. of. CSE*

*St. Peter's Engineering*

*College Hyderabad, TS, India*

*deekshithachatla@gmail.com*

**Kanukuntla Chakravarthy**

*IV B.Tech*

*Dept. of. CSE*

*St. Peter's Engineering*

*College*

*Hyderabad, TS, India*

*chakravarthy9899@gmail.co*

*m*

**Gangarapu Keerthi**

*IV B.Tech*

*Dept. of. CSE*

*St. Peter's Engineering*

*College*

*Hyderabad, TS, India*

*gangarapu.keerthi06@gmail.*

*com*

**Abstract—** A person's emotional, psychological, and social well-being could all be reflected in their mental health. It determines one's thoughts, emotions, and reactions to situations. Working successfully and reaching one's full potential requires good mental state. psychological health is important at every age, from childhood through adulthood. A number of factors, including stress, social anxiety, depression, obsessive compulsive disorder, substance abuse, and personality disorders, affect one's mental state. It's more important than ever to recognise the signs of a mental condition to maintain a healthy sense of balance in your life. Additionally, machine learning algorithms and artificial intelligence (AI) are prone to fully utilising their capabilities to predict the onset of mental states. The Mean Opinion Score was frequently used in real-time deployments to validate the labels that were acquired as a result of clustering. The classifiers created using these cluster labels may be able to predict a person's mental state. Target demographics were established for the population, including high school students, college students, and dealing professionals. The study assesses how the

aforementioned machine learning algorithms have affected the target demographics and offers suggestions for additional investigation.

**Key Words-** Behavior Analysis, psychological state, Surveillance tool, Machine learning algorithms, computer science.

## I.Introduction

The previous ten years have seen a closer relationship between technology and human action. As we can see, more individuals are quickly embracing today's technology, which is why using technology in some capacity for healthcare is becoming more and more acceptable. Underserved minority groups are more likely to acquire smartphones than non-Hispanic whites, who own them at a rate of 42% compared to 47% of black non-Hispanics and 49% of Hispanics. For instance, a recent community-based assessment of over 1,500 individuals with severe mental illnesses discovered that more than 80% of patients with manic depression (BD) owned and frequently used mobile phones for calling, messaging, and consequently the internet. From the standpoint of providing care for people with mental illnesses, mobile technology seems to be a

practical delivery method (Ben Zeev, Davis, Kaiser, Krzsos, & Drake, 2013).

- Using Facial Landmarks we are detecting emotions, more robust and powerful than the sooner used fisherface classifier, but also requiring some more code and modules. Nothing insurmountable though.

we want to try to some things:

1. Get images from a webcam
2. Detect Facial Landmarks
3. Train a machine learning algorithm
4. Predict emotions

## II. RELATED WORK

The connection between a person's mental health and general well-being has long been researched in many nations. It is crucial to customise decision support and prediction systems since, in many regions, social and cultural elements are intricately tied to mental health. Bijl et al. looked into the frequency of mental illnesses in the Dutch population. The early detection of psychological state aberrations is directly related to the mental health of a personality. The WHO releases regional evaluations on the situation of various barriers to diagnosing psychological state diseases. The study promotes the use of knowledge and technology in all nations to address problems with psychological well-being. It was necessary for those exhibiting strange conduct to first get in touch with a psychologist in order to be classified with the type of mental state they were going through. It was common practise to first diagnose a person before setting up therapy appointments. Thanks to technology development, there are now many methods for predicting psychological state. Even while mental health issues might manifest as behavioural issues, if they are not promptly addressed, they can trigger a cascade of disorders. Stress may be a psychological and physiological imbalance brought on by an imbalance between a person's capacity and drive to meet situational demands and their personality. a demanding or difficult situation-related state of strain or stress on the mind or the heart. Depression and anxiety therefore a manifest conducted a thorough investigation into

a range of mental disorders, their causes, and effects due to the modalities employed for diagnosis and control. One way to assess mental state is via survey questions, wearable sensors, and bio signals. Our study's focus is on how machine learning algorithms can be used to measure different aspects of psychological condition. Jeremy D. Schaefer Many academics have thoroughly studied the social and behavioural elements of various groups of people. For a variety of reasons, different populations are affected by psychological state problems. There are a variety of factors that vary with cohort and contribute to psychopathy Exam stress, peer and family pressure regarding academics, and employment opportunities are a few of the elements that have an impact on schoolchildren's mental health. Working professionals are impacted by work deadlines, promotion anxiety, job ennui, financial position, family duties, and other concerns. The Internet of Things can analyse how device usage patterns change as people's mental states change (IoT) enables us to more correctly analyse people and identify behavioural changes. The task teaches us how to deal with such a circumstance more skillfully. It's becoming more and more important to keep tabs on people who are suffering from severe mental diseases. Such persons must be closely watched, and critical signals must reach medical professionals so that they can act swiftly when necessary. Chinaveh et al. investigated the benefits of problem-solving for Iranian college students in terms of enhancing their capacity for successful coping and psychological adjustment. Hajiyakhchaliyeh et al. showed the benefits of problem-solving on realistic coping mechanisms and psychological adjustment among Iranian college students. Aghaei et al. used questionnaires to try and predict things like age, general health (GH), characteristics of life orientation, quality of life (QoL), and life satisfaction. Descriptive and multivariable multivariate analyses were used to analyse the data. For the analysis of mental state clinical forms, Strausset and colleagues investigated the application of machine learning techniques such cluster analysis, K-nearest neighbours (KNN), decision trees, and support vector machines

(SVM). Bio sensors were employed to produce stress, normal, and relaxed bio indices that were then categorised using SVM and symbolic logic. According to Xiang et al., a multi-label prediction model for categorising anatomical medicinal substances should be created utilising an ontology method. The effectiveness of ontology-based and conventional classifiers is also compared and contrasted in this study. Smart health homes with a variety of sensors were taken into consideration for this. Physiological indicators such as the electrocardiogram (ECG), galvanic skin response (GSR), respiration, temperature, etc. can be used to identify mental stress. Smets et al. examine six machine learning techniques that are also used for diagnosing mental illnesses. Additionally, it claimed that SVM and Bayesian networks offered sufficient accuracy. MOS (mean opinion score) is a statistic that can be used to evaluate the calibre of an experience (QoE). In general, QoE is used to determine whether customers are satisfied with the calibre of service received. The relationship between MOS and QoE was studied by Xue and colleagues. The more satisfied and experienced the user is, the higher the MOS. In this study, QoE is used to determine whether the identified labels are accurate. In the dataset, Junget al. claim that K-Means is utilised to hunt for clusters where the class labels are unclear.

### III. Methodology

#### A. Data Preprocessing

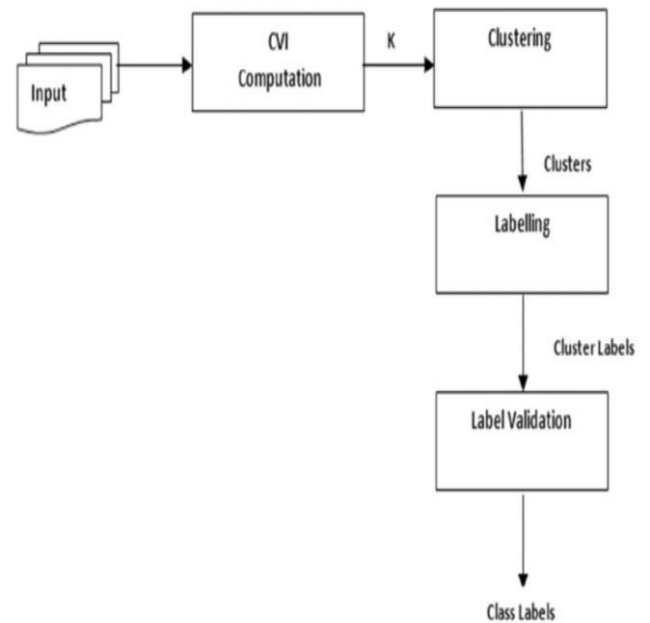


Fig.1 Steps of Data Pre-processing

#### B. Clustering and Label Validation-

To find probable groups within the two target populations under consideration, clustering is performed. The study evaluates the impact of the aforementioned machine learning algorithms on the target demographics and makes recommendations for further research. Through the use of an iterative heuristic technique called K-means clustering, the number of clusters  $K$  is ascertained. Information points, also known as the quantity of samples and subsequently the number of clusters  $K$ , are needed as input. The studies were repeated while altering the levels of  $K$ . In order to determine the number of clusters  $K$  within the two populations, the results of the runs were recorded for later processing. The hierarchical clustering agglomerative approach was used. It uses a bottom-up approach to find commonalities between data points by first considering each one as a cluster. The Euclidean distance method was used to do hierarchical clustering on the information samples from populations 1 and 2. In the agglomerative technique, the data samples and, consequently, the separation between clusters, serve as the input for hierarchical clustering. The partitioning around medoids (PAM), also known as K-medoids clustering, uses the  $K$ -cluster

heuristic and is applied to the information samples from populations 1 and 2. In order to determine the distance between nearby data points, the method iteratively calculates the number of clusters  $K$  that were provided as input for that iteration, using the centroid as the real datum. We selected the appropriate number of clusters and their associated labels. Utilizing the labels and features identified during clustering, the next step is to construct a classifier model. We naturally decided to join target populations 1 and 2 using samples since they both generated the same amount of clusters.

### C. Classification-

K-nearest Neighbors, Naive Bayes, Support Vector Machines, Decision Trees, and Logistic Regression are some of the classification techniques we use in this situation. In addition to the existing models, we have created tree ensemble models using random forest and ensemble bagging techniques. The training set is given to several classifiers, and models are also created. The test set is used to assess each classifier's performance. F-1, precision, recall, accuracy, and accuracy measurements were used to gauge performance. Ensemble approaches were utilised to increase the classification's accuracy. Decision trees, support vector machines, logistic regression, and K-nearest neighbours were used to implement bagging.

The random forest classifier was also used to create a tree ensemble. Classifiers' decision-making abilities are evaluated using their performance metrics. The F-score, recall, accuracy, and precision are examples of typical performance indicators. The accuracy score was used to assess the performance of the classifier. In order to select the best classifier model, the precision, recall, and F-score of the category labels are compared between classifiers. The reliability of the classifier was examined using the LIME. According to LIME, a subset of features is the optimal choice when utilising classifiers for trust computation.

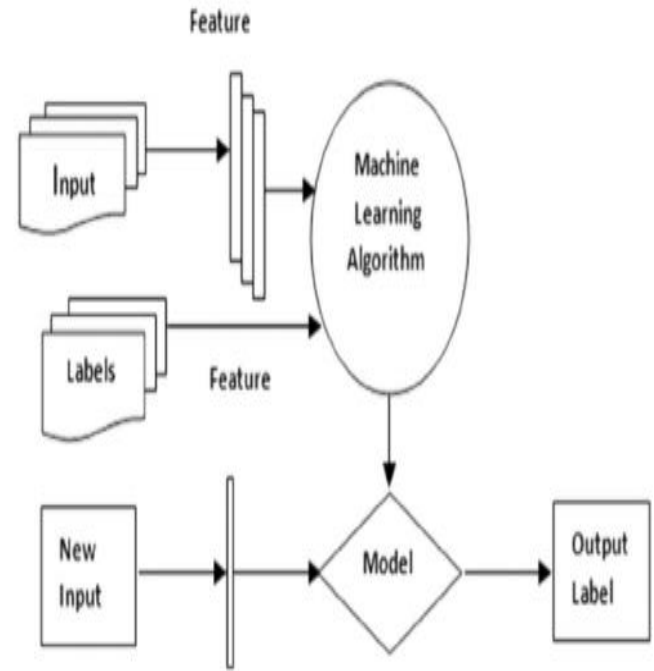


Fig2 Architecture of a Classifier

We assessed the PRIMSA literature review standards to organise the search for and selection of pertinent publications for our study.

#### 1. Record Identification:

We looked for intriguing publications in the most comprehensive electronic bibliographic database for computing and HCI research, the Association for Computing Machinery (ACM) Guide to the Computing Literature. ACM, IEEE, Springer, Elsevier, John Wiley & Sons, and Kluwer are just a few of the prestigious publishers that have full text papers in it. It also includes abstracts from conference proceedings, journals, magazines, and books. On November 15, 2019, a search that yielded the corpus shown here was carried out. "Mental health" and "ML" produced 122 documents in the search

#### 2. Record Selection:



1) The 122 records were evaluated by two researchers independently to see whether they were appropriate for addressing an application of "ML" in the context of "mental health." Papers were taken into account for inclusion. If they included examples of how machine learning was applied to advance understanding of affective mental health disorders or conditions, such as stress, depression, and anxiety, psycho-social functioning, such as general mental health or well-being [188], or general mental health practises (e.g., mental health care providers). Schizophrenia is one of the most common psychological disorders, along with problems with mood, anxiety, eating, personality, and substance abuse. The literature

on mental health and further systematic reviews on emotional mental health provide support for this selection criterion. database privacy encryption methods, and reviews or summaries of articles that did not directly address using machine learning (ML) for mental health. Seven records were missing and were never found. We identified 38 records that were qualified, 42 that were disqualified, and 42 that had classification concerns that required full-text screening based on the title and abstract. 26 articles were eliminated following full-text screening, leaving a corpus of 54 papers for the systematic review.

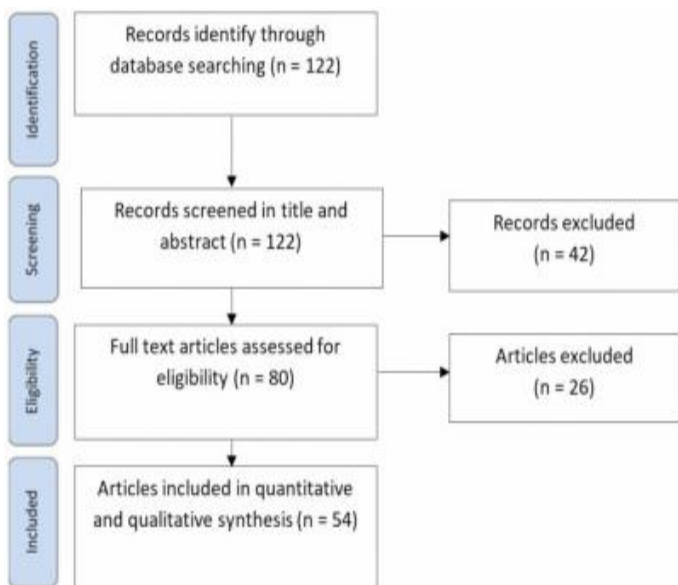


Fig. 3. Procedural flowchart following the guidelines provided by PRISMA.

### 3.Data Extraction:

We developed a data extraction to make it easier to extract systematic data from the articles. The intended audience, the primary data source, the type of machine learning application, and the rationale for the application are all specified separately. It also has columns for the authors' connections, the year of publication, the abstract, and the title. In addition to the machine learning methods used and Finally, we took into account issues like actual use, challenges with research or design, and possible ethical issues. Ten articles that randomly met the criteria for inclusion served as the pilot test subjects for the extraction sheet. new columns were introduced to aid with article synthesis. We took into account the primary publication type (Figure 4), the target mental illness or behaviour (Figure 5, left), and the type of machine learning approach used. The findings include a narrative, a numerical analysis of the corpus, and examples of individual, pertinent articles. This approach was chosen to highlight the complexity and diversity of the trends and problems that have been researched as well as any gaps in the body of information already in existence.

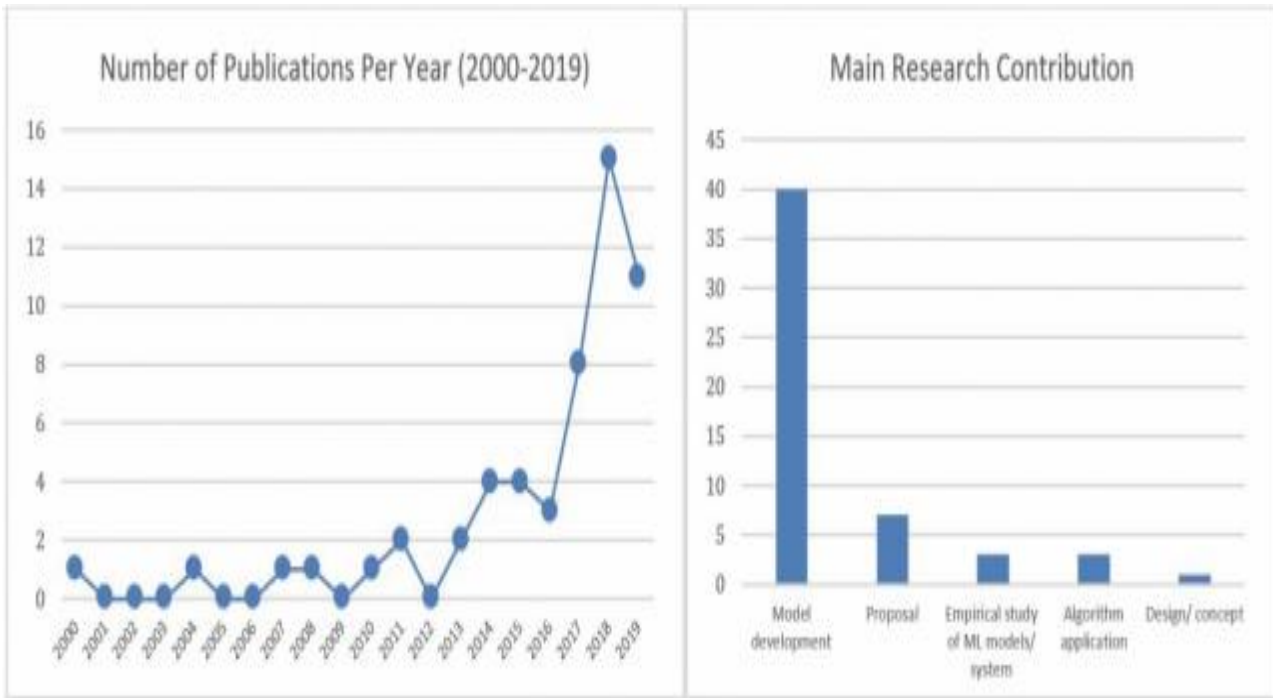


Fig. 4. Graph showing the growing trend in ML articles about mental health over time. Right: The frequency distribution of the various research contribution types in the review corpus publications.

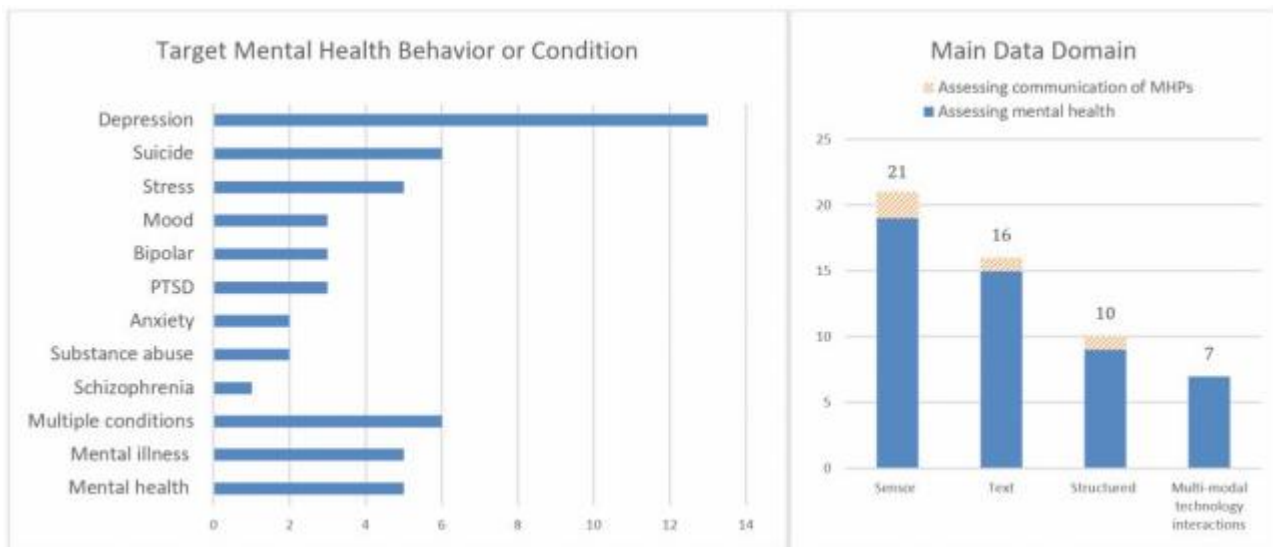


Fig. 5. Distribution of the various mental health conditions or practises that were backed by all review studies. Right: The frequency distributions of the principal data fields as they were applied in the related research to draw insights for mental health.

#### IV.EXPERIMENT DETAILS

##### I.Datasets:

Deep networks in particular require a large amount of training data from neural networks. Additionally, a sizable portion of the final model's performance is determined by the choice of images utilised during training. It

makes reference to the need for a complete set of top-notch quantitative data. For study on emotion recognition, there are several datasets available, ranging from a few hundred high-resolution photos to tens of thousands of smaller images. We'll concentrate on two topics: the Face Expression Recognition Challenge (FERC-2013) and the Japanese Female Face (JAFFE). They both include seven different emotions, including anger, surprise, happiness, sadness, disgust, fear, and neutrality.

- 1).Webcam connection: using this module application are connected to measure webcam.
- 2).Load & Preprocess Dataset: using this module application read all dataset images from numpy array and so normalize and extract features from images.
- 3).Train CNN Algorithm: Extracted features are going to be accustomed train CNN algorithm

4).Capture Person: using this module we are going to capture person image and so detect face from that image

5) Detect Emotion: This module will take detected face as input then by using CNN algorithm will predict person mental behaviour as SAD, HAPPY, NEUTRAL, ANGRY etc.

## V. RESULTS AND DISCUSSIONS

This can be accomplished by having users directly enter the data into the system or by having them read it from a written or printed document while gazing at the computer. The goals of input design include reducing the amount of input necessary, controlling errors, reducing delays, eliminating additional processes, and streamlining the procedure.

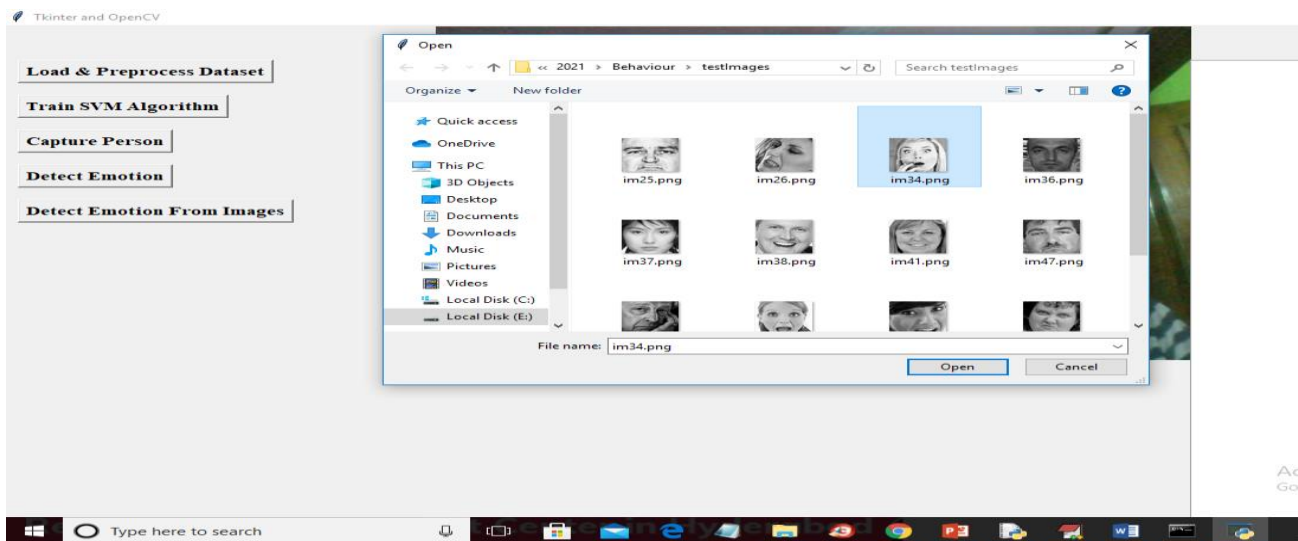


Fig. 6. Detecting the emotion of a captured image

The method of output design determines how the data will be produced for both immediate use and hard copy output. For the user, it is the most significant and immediate source of

information. The output design is more intelligent and efficient, which improves the user's interaction with the system.

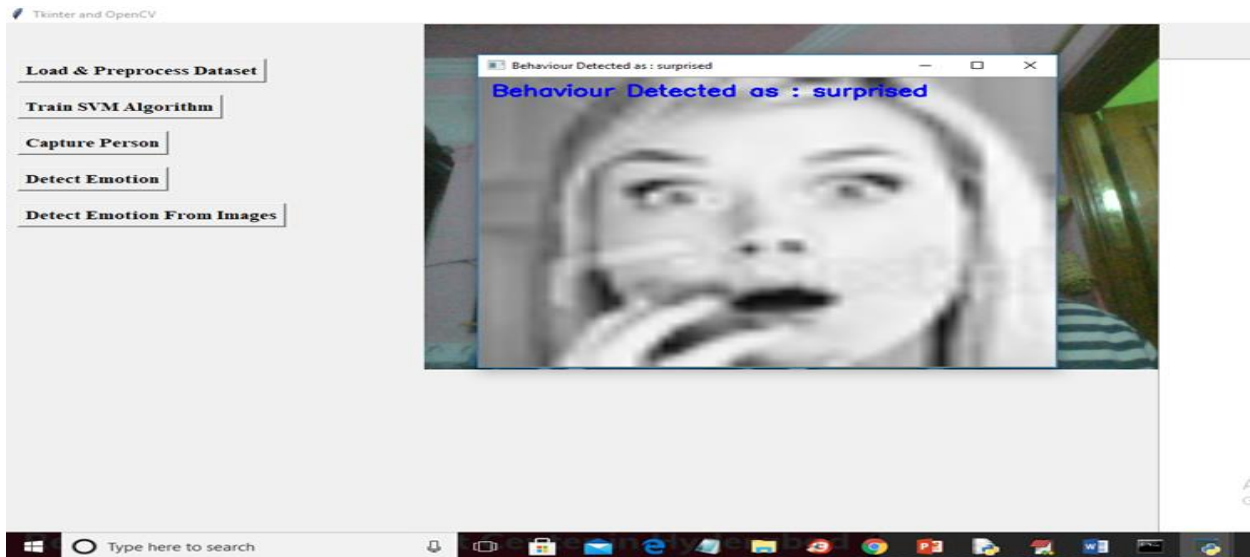


Fig. 7. Emotion detected as Surprised

\*The computed recognition accuracy of emotions by using the ML Algorithm (SVM) is 99%.

## CONCLUSION

Prior research has demonstrated that many college students face mental health and behavioural issues, which can negatively affect their welfare and increase the rate at which they drop out. By measuring baseline rates of mental health and behavioural issues, as well as aid seeking, among a representative sample of students starting university in Northern Ireland, the current study expands on prior findings. These results make it possible to identify those who need help before they become too far gone and to tell them of their options. Higher retention rates, academic success, and the maintenance or enhancement of psychological health and wellbeing after graduation may all be influenced by this. The results of the data analysis showed how crucial it is to inform students about their options and available resources, as well as to train university staff members on how to help students who are experiencing mental health problems. Staff workers must be prepared to suggest children and knowledgeable about the options at their

disposal. Additionally crucial are improved disease detection and early diagnosis. Enhancing grades and retention rates, managing behavioural and mental health concerns before they worsen, and treating mental health disorders are all possible with early intervention and encouraging help-seeking

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