**Amigo: Your Second Self**

Srishti Singh

*Computer Science and Engineering*

*Sharda University*

Greater Noida, India

[2018013720.srishti@ug.sharda.ac.in](mailto:2018013720.srishti@ug.sharda.ac.in)

Harsh Gupta

*Computer Science and Engineering*

*Sharda University*

Greater Noida, India

[2018014931.harsh@ug.sharda.ac.in](mailto:2018014931.harsh@ug.sharda.ac.in)

Prashant Singh

*Computer Science and Engineering*

*Sharda University*

Greater Noida, India [2018013967.prashant@ug.sharda.ac.in](mailto:20180137967.prashant@ug.sharda.ac.in)

Prof. (Dr.) Arun Prakash Agrawal

*Computer Science and Engineering*

*Sharda University*

Greater Noida, India

arun.agrawal@sharda.ac.in

***Abstract—*Amigo, a web app that is meant to help people who are dealing with stress, anxiety, or depression. Whether you are looking to better understand your feelings, or you are experiencing anxiety, depression, or elevated levels of stress, Amigo is designed to help you feel better. Here is the gist of how it works: There is a questionnaire that will help you determine the severity of the symptoms of depression, anxiety and stress using machine learning model. The questionnaire will contain two psychometric tests and other technical information about the user for checking the validity of responses leading to better assessment. We also propose to make an anonymous chat section, where people from around the world could talk about their feelings without the fear of being judged.**

***Keywords—Depression, Loneliness, Health, Anxiety, Machine Learning, Web Applications***

# I. INTRODUCTION

Depression is classified as a mood disorder. It can be defined as sadness, loss, or anger that interferes with a person's daily activities [1]. People experience depression in unusual ways. It could affect your daily routine, resulting in misbehave not being punctual and less energetic, and lower productivity. It has the potential to affect relationships as well as some chronic health conditions [2]. The foremost common cause of Misery is Forlornness.

Loneliness leads to poorer physical and mental health. Loneliness has been defined in diverse ways. "Depression is not continuously around being alone," says another definition. Having a bad feeling and ugly” and “a subjective, terrible feeling related to the poor social family members” “a feeling of disconnectedness or isolation.” [3] and so on., are the alternative approaches to define loneliness. It is reported to be more dangerous than smoking; a high degree of loneliness precipitates suicidal ideation and para-suicide, Alzheimer's disease, and other dementia and adversely affects the immune and cardiovascular system. It is widely believed that loneliness causes a decrease in well-being and harms physical health due to immunologic or neuroendocrine alterations. Loneliness is thus, many of the latent reasons for hospitalization and of placement in nursing homes. Loneliness, which leads to distress and dysfunction, may be assessed in many ways and is, thus, can be diagnosed as a disease entity [4]. A lonely character often feels low, helpless, separated, or discriminated; unearths issues during interactions; feels deserted and on my own.

To address the problems stated above, we propose Amigo, a web app that is meant to help people who are dealing with stress, anxiety, or depression. Whether you are looking to better understand your feelings, or you are experiencing anxiety, depression, or elevated levels of stress, Amigo is designed to help you feel better. Here is the gist of how it works: There is a questionnaire that will help you determine the severity of the symptoms. There is a cognitive-behavioral therapy (CBT) portion of the app that can teach you how to dispute overly negative thoughts. There is a thought record that provides strategies for modifying irrational thoughts so you can learn how to think differently. We also propose to make an anonymous chat section, where people from around the world could talk about their feelings without the fear of being judged.

# II. LITERATURE REVIEW

There are several existing methodologies available which work on diagnostics and help in curing depression in patients. We studied some of the existing solutions.

*A. Moodfit*

Moodfit is a mobile application that has features such as daily goal setting and self-care methodologies. It also has a mood journal and a gratitude journal to keep a track of users’ mood patterns. It also has meditation and therapy features on a paid basis. The app has a questionnaire that uses CBT to estimate the user’s state of mindfulness.

*B. Sanvello*

Sanvello is another mobile application that uses principles of CBT to provide therapy, coaching, expert help, and peer group support. The application is a paid application.

*C. Depression CBT Self-Help Guide*

Depression CBT Self-Help Guide provides education to be an informed consumer of mental health services and contains resources to use in collaboration with a health professional. The devices given in this app are inferred from the CBT inquire about base and created into a user-friendly arrange by Dr. Monica Frank, a clinical psychologist specializing in the cognitive-behavioral treatment of anxiety and stress-related disorders for over 30 years. It is as it were accessible for Android gadgets.

*D. Shine*

Shine is another mobile application that provides personalized self-care routines and a peer group for people who feel depressed. The app runs on a subscription model and uses a questionnaire to personalize the user experience.

*E. MoodMission*

MoodMission is an application that is backed by research evidence. It is also a mobile application, available for Android and iOS users [5]. The application uses CBT and claims to improve public mental health which is presented in research papers [6] and [7].

Furthermore, many researchers have worked on predicting anxiety and depression with machine learning algorithms, such as Random Forest Tree (RFT), the Support Vector Machine (SVM) and the Convolution Neural Network (CNN) for the collection and subsequent classification of data from blog posts. For encoding the text, various techniques have been used, that is topic modelling, Bag-of-Words (BOW) and Term Frequency–Inverse Document Frequency (TF– IDF). In addition, Python programming has been utilized for displaying tests, with the finest comes about among all the classifiers[8] being delivered by the CNN, whose precision and review scores were found to be 78% and 0.72, respectively.

Distinctive machine learning algorithms such as Logistic Regression, Catboost, Naïve Bayes, RFT and SVM were connected for classification in [9].In this study, 470 seafarers were interviewed and information on the occupations, socio-demographics and health of the participants was collected via 16 characteristics including age, academic qualifications, monthly income, employment status, BMI, duration of service, family type, marital status, presence (if any) of hypertension, diabetes or ischemic heart disease, job profile, rank within the organization, types of vessels posted to and dummy variables for academic qualifications and marital status. As a result, the researchers found that Catboost produced the highest levels of accuracy and precision among all the classifiers – i.e. 82.6% and 84.1%, respectively.

Reece et al. [10] focused on the predictors of depression and Post Traumatic Stress Disorder (PTSD) among Twitter users. The Hidden Markov Model (HMM) was used to recognize increases in the probability of PTSD. Of the entire dataset, 31.4% and 24% were observed to be affected by depression and PTSD. Braithwaite et al. [11] collected tweets from 135 participants recruited from Amazon Mechanical Turk (MTurk) and applied decision tree classification to measure suicide risk. The accuracy level for the prediction of suicide rate was observed to be 92%. Du et al. [12] extracted streaming data from Twitter and used psychiatric stressors to annotate tweets that had been deemed suicidal. The Convolution Neural Network (CNN) outperformed the Support Vector Machine (SVM) and extra trees (ET) etc. with a precision of 78% in recognizing tweets with suicidal tendencies.

# III. METHODOLOGY

*3.1 Survey and Questionnaires*

The research is focused on analyzing the performance of various machine learning algorithms in predicting the level of Depression, Stress or Anxiety in an individual. The dataset used for the research is made available by Kaggle Datasets Expert Yam Peleg which consists of data collected with an on-line version of the Depression Anxiety Stress Scales (DASS) [13].

Anyone may participate in the poll, and people were encouraged to do so in order to receive tailored findings. At the end of the test they also were given the option to complete a short research survey. This dataset comes from those who agreed to complete the research survey and answered yes to the question "Have you given accurate answers and may they be used for research?" at the end.

The survey consisted of the Depression, Anxiety and Stress Scale (DASS-42) questionnaire. along with time elapsed for each question and the order of occurrence in the survey. The following durations were also recorded (measured on the server's side):

Introelapse: The time spent on the introduction/landing page (in seconds)  
Testelapse: The time spent on all the DASS questions (should be equivalent to the time elapsed on all the individual questions combined)  
Surveyelapse: The time spent answering the rest of the demographic and survey questions

The Ten Item Personality Inventory (TIPI) questionnaire, 16 validity-check word definition questions (out of which 3 were imaginary words).A few more questions were asked related to the individual’s education, race, religion, gender, sexual orientation, age, native English speakers, marital status, family size, dominant-hand, neighborhood, major in university and voting status. Along with this on the server side, the country ISO code, network location (for checking duplicity) and source of redirection were also recorded.

*3.2 Dataset*

The dataset consisted of the recorded entries of 39775 participants and has 172 responses from each candidate represented by columns.

It consists of DASS-42 [14], a 42 item self-report scale designed to measure the emotional states of depression, anxiety and stress. The principal value of the DASS in a clinical setting is to clarify the locus of emotional disturbance, as part of the broader task of clinical assessment. The essential function of the DASS is to assess the severity of the core symptoms of Depression, Anxiety and Stress. Accordingly, the DASS allows not only a way to measure the severity of a patient’s symptoms but a means by which a patient’s response to treatment can also be measured. And the DASS scores were found to be reliable with only very modest influence of the demographic variable.[15]

Out of the 42 questions in DASS-42, 14 questions are allocated to each of the scales of Stress, Anxiety and Depression.

Table 1:- Questionnaires during quiz

|  |
| --- |
| 1.I had difficulty in swallowing. |
| 2.I found it hard to wind down. |
| 3.I felt down-hearted and blue. |
| 4.I felt terrified. |
| 5.I felt I was close to panic |
| 6.I was aware of of dryness of my mouth |
| 7.I felt sad and depressed |

The possible answers for each question – which could be given in text or numeric form – are as follows:

0 - did not applied to me

1 - applied to me to some degree, or some of the time.

2 - applied to me to a considerable degree or a good part of time.

3 - applied to me very much or most of the time.

Following the data collection, the participants’ responses were encoded using numeric values of 1 to 4, and the scores were then calculated first by reducing each value of scores by 1 and then adding the values associated with each question and the below formula:

score = Sum of rating points of each class

Once the final scores were calculated, these were labelled according to severity – i.e. Normal, Mild, Moderate, Severe and extremely severe (see Table 1)

Table2: Interpretation of DASS Scores

|  |  |  |  |
| --- | --- | --- | --- |
|  | Anxiety | Depression | Stress |
| Normal | 0-9 | 0-7 | 0-14 |
| Mild | 10-13 | 8-9 | 15-18 |
| Moderate | 14-20 | 10-14 | 19-25 |
| Severe | 21-27 | 15-19 | 26-33 |
| Extremely Severe | 28-42 | 20-42 | 34-42 |

These responsesare stored in variable A (e.g. Q1A). Along with it, the time taken in milliseconds to answer that question (e.g. Q1E) and that question's position in the survey (e.g. Q1I) were recorded in the variable E and I respectively. The following durations were also recorded (measured on the server's side):

Introelapse: The time spent on the introduction/landing page (in seconds)  
Testelapse: The time spent on all the DASS questions (should be equivalent to the time elapsed on all the individual questions combined)  
Surveyelapse: The time spent answering the rest of the demographic and survey questions

The Ten Item Personality Inventory was also administered which was developed by Gosling, Rentrfrow, and Swann[16]Completing this inventory takes less than a minute. And research on the psychometrics of this measure has demonstrated the validity of this measure in multiple studies. In short, it is very efficient and valid. It can actually provide someone with a quick snapshot of where they score on each of the Big Five personality attributes.

The "big five" are broad categories of personality traits as described by McCrae and Costa. They are as follows:

1. Extraversion(versus [introversion](https://www.psychologytoday.com/us/basics/introversion)) — The tendency to be outgoing and high in social energy
2. Agreeableness (versus disagreeableness) — The tendency to agree with people and to be generally kind in dealing with others
3. Conscientiousness (versus being disorganized) — The tendency to be meticulous and organized in all aspects of one’s life
4. Emotional Stability (versus neuroticism) — The tendency to be even in terms of emotions and to not experience much dispositional anxiety or sadness
5. Openness (versus close-mindedness) — The tendency to be interested in new ideas, people, art, and pretty much anything

The Ten Item Personality Inventory were stored in the following variables:

TIPI1 Extraverted, enthusiastic.  
TIPI2 Critical, quarrelsome.  
TIPI3 Dependable, self-disciplined.  
TIPI4 Anxious, easily upset.  
TIPI5 Open to new experiences, complex.  
TIPI6 Reserved, quiet.  
TIPI7 Sympathetic, warm.  
TIPI8 Disorganized, careless.  
TIPI9 Calm, emotionally stable.  
TIPI10 Conventional, uncreative.

Each TIPI items were rated "I see myself as:" \_ such that

1 = Disagree strongly  
2 = Disagree moderately  
3 = Disagree a little  
4 = Neither agree nor disagree  
5 = Agree a little  
6 = Agree moderately  
7 = Agree strongly

The TIPI scale scoring (“R” denotes reverse-scored items) is calculates as follows:  
Extraversion: 1, 6R

Agreeableness: 2R, 7

Conscientiousness; 3, 8R

Emotional Stability: 4R, 9

[Openness](https://www.psychologytoday.com/us/basics/openness) to Experiences: 5, 10R

The scores are reverse-scored by recoding a 7 with a 1, a 6 with a 2, a 5 with a 3, etc. Then the average of the two items (the standard item and the recoded is calculated, reverse-scored item) that makes up each scale.

In their 2003 paper, Gosling et al. [16] provided information on the means (averages) and standard deviations (SDs) for each of these five measures (on a sample of 1,813 adults). The results are shown in Table 2.

Table3: Mean and Standard Deviations of Five Personality Measures

|  |  |  |
| --- | --- | --- |
|  | Mean | Standard Deviation |
| Extraversion | 4.44 | 1.45 |
| Agreeableness | 5.23 | 1.11 |
| Conscientiousness | 5.40 | 1.32 |
| Emotional Stability | 4.83 | 1.42 |
| Open-mindedness | 5.38 | 1.07 |

Compare the scores with the means. For dimensions where the score is below the mean, that individual will be “low” on that dimension. For instance, one might have scored a 3 on extraversion, which would correspond to being below the mean of 4.44, thus making them somewhat of an introvert.

The average scored for each personality trait was calculated and stored in new variable for each five personality trait.

For validity check, 16 words were presented to the subjects as checkbox out of which three of them, stored in variables VCL6, VCL9 and VCL12 were imaginary words. The dataset recorded a check as 1 when the subjects were familiar with definition of the word and an uncheck as 0 for unfamiliarity of the word.

A few more responses were recorded related to the individual’s education, race, religion, gender, sexual orientation, age, native English speakers, marital status, family size, dominant-hand, neighborhood, major in university and voting status. Along with this on the server side, the country ISO code, network location (for checking duplicity) and source of redirection were also recorded.

When the data was further explored, it was found that 11407 values were missing from the major column and 2 values from the country column. Around 500 of the participants skipped few questions in the DASS-42 Questionnaire.

**Model Training**

For the training and testing of our model, we have divided the transformed dataset in the ratio of 80:20. The shape of the training and the testing dataset is (31820, 177) and (7955, 7644), respectively.

we have used Logistic Regression and Random Forest Classifier for training our model. Scikit Learn has been used for all the implementations mentioned in section 4.3.

3.4. **Classification**

We used the machine learning language applied in python programming language using google colab which helps us to predict the percentage of people suffering from stress,anxiety and depression according to the level of seriousness. The dataset was divided into the ratio of 80:20 representing the trainig and test sets,respectively. The following algorithms which we use describe in the following ways:-

3.4.1 **Random Forest Classifier**

It use the Decision tree to creates a sets from a randomly selected subset of the training dataset.Basically it is a set of decision tree from a randomly select data from training set and then collects the votes from several or different trees to gives the final prediction.

3.4.2 **Logistic Regression**

It is most commonly used machine leaning algorithm for two classification.Easy to implement and used as the baseline for any binary classifiction problem.

3.4.3 **Decision Tree**

It is most powerful and commonly used tool for classification and prediction. It is like a tree structure where each internal node indicates a test in attribute and each branch indicates outcome of the test and leaf node holds a class label

3.4.4 **ADA BOOST**

It is called as Adaptive boosting. It is a technique in ML ueas as an Ensemble method.It used decision tree with one level that means decision tree with 1 split only

3.4.5 **XG BOOST**

It is one of the famous gradient boosting techniques(ensemble) having enhanced performance and speed in tree-based (sequential decision trees) machine learning algorithms.

3.4.6 **Support Vector Machine (SVM)**

It is simple supervised machine learning algorithm. It is mainly used for classification and regression.It is mostly preferred for classification.It is used to find a hyper-plane that creates a boundary between the types of data.

**IV.RESULT AND DISUSSION**

We get an accuracy of 53% from Random forest Classifier , 46% from Logistic regression, 53% form Decision Tree, 53% from Gaussian Naive Bayes, 53% form Support Vector Machine, 53% from ADA BOOST and 53% from XG BOOST.

A more detailed overview of the various evaluation metrics is shown in table 4.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Evaluation Matrix** | | | | |
|  | **Accuracy** | **Precision** | **Recall** | **F1-score** |
| **1.RFC** | 53% | 0.70 | 0.54 | 0.39 |
| 2.LR | 46% | 0.29 | 0.47 | 0.36 |
| 3.DT | 53% | 0.70 | 0.54 | 0.39 |
| 4.GNB | 53% | 0.70 | 0.54 | 0.39 |
| 5.SVM | 53% | 0.70 | 0.54 | 0.39 |
| 6.ADA BOOST | 53% | 0.70 | 0.54 | 0.39 |
| 7.XG BOOST | 53% | 0.70 | 0.54 | 0.39 |

Table 5: Evaluation metrics for different models implemented

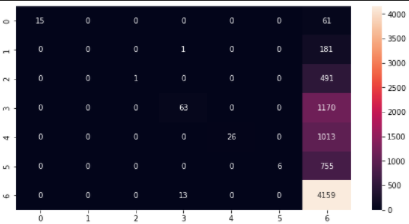


Image 1: Confusion Matrix of Random Forest Classifier

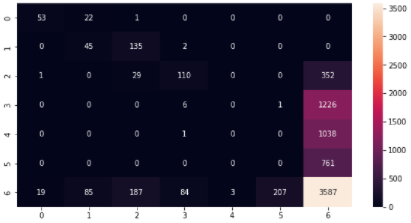


Image 2: Confusion Matrix of Logistic Regression model

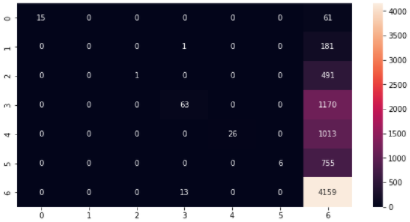
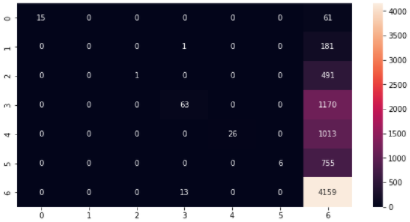
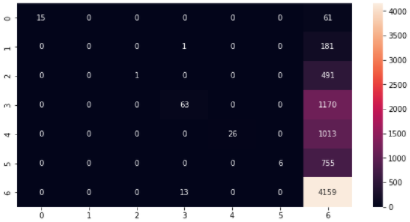


Image 3: Confusion Matrix of Decision Tree Classifier

##### hahahh1.png

##### Image 4:Confusion Matrix of Gaussian Naïve bayes

Image 5: Confusion Matrix of Support vector Machine



##### Image6: Confusion Matrix of Ada Boost

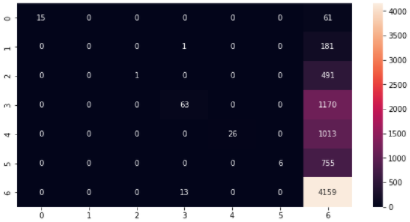


Image 7:Confusion Matrix of XG boost

##### REFERENCES

1. Fight depression, <https://fightdepression.quora.com>
2. Everything You Want to Know About Depression And How to ..., <https://mumuhealth.com/everything-you-want-to-know-about-depression/>
3. Social factors affecting old age -, <https://www.slideshare.net/Drraveesoni/social-factors-affecting-old-age>
4. Loneliness is a disease, <https://pjn.sbvjournals.com/doi/PJN/pdf/10.5005/pjn-7-1-18>.
5. David Bakker, Nikolaos Kazantzis, Debra Rickwood, Nikki Rickard, A randomized controlled trial of three smartphone apps for enhancing public mental health, Behaviour Research and Therapy, Volume 109,2018, Pages 75-83, ISSN 0005-7967, https://doi.org/10.1016/j.brat.2018.08.003.
6. David Bakker, Nikolaos Kazantzis, Debra Rickwood, Nikki Rickard, Development and Pilot Evaluation of Smartphone-Delivered Cognitive Behavior Therapy Strategies for Mood- and Anxiety-Related Problems: MoodMission, Cognitive and Behavioral Practice, Volume 25, Issue 4, 2018, Pages 496-514, ISSN 1077-7229, https://doi.org/10.1016/j.cbpra.2018.07.002.
7. Aizenstros, A., Bakker, D., Hofmann, S., Curtiss, J., & Kazantzis, N. (2021). Engagement with smartphone-delivered behavioral activation interventions: A study of the MoodMission smartphone application. Behavioral and Cognitive Psychotherapy, 49(5), 569-581. doi:10.1017/S1352465820000922
8. Tyshchenko, Y. (2018)"Depression and anxiety detection from blog posts data."Nature Precis. Sci., Inst. Comput. Sci., Univ. Tartu, Tartu, Estonia
9. Sau, A., Bhakta, I. (2018) "Screening of anxiety and depression among the seafarers using machine learning technology."Informatics in Medicine Unlocked :100149
10. Reece, A. G., Reagan, A. J., Lix, K. L. M., Dodds, P. S., Danforth, C. M., Langer, E. J.(2016) "Forecasting the Onset and Course of Mental Illness with Twitter Data."Scientific reports 7 (1): 13006.
11. Braithwaite, S. R., Giraud-Carrier, C., West, J., Barnes, M. D., Hanson, C.L. (2016) "Validating machine learning algorithms for Twitter data against established measures of suicidality."JMIR mental health 3 (2): e21.
12. Du, J., Zhang, Y., Luo, J., Jia, Y., Wei, Q., Tao, C., Xu, H. (2018) "Extracting psychiatric stressors for suicide from social media using deep learning."BMC medical informatics and decision making 18 (2): 43.
13. <http://www2.psy.unsw.edu.au/dass/>
14. Lovibond, S.H., Lovibond, P.F. (1995). Manual for the Depression Anxiety Stress Scales (2nd ed.). Sydney: Psychology Foundation.
15. Crawford, J. R., & Henry, J. D. (2003). The Depression Anxiety Stress Scales (DASS): Normative data and latent structure in a large non-clinical sample. British Journal of Clinical Psychology, 42(2), 111–131.
16. Gosling, S. D., Rentfrow, P. J., & Swann, W. B., Jr. (2003). A Very Brief Measure of the Big Five Personality Domains. Journal of Research in Personality, 37, 504-528.
17. Costa, Paul & McCrae, R.R.. (1999). A five-factor theory of personality. The Five-Factor Model of Personality: Theoretical Perspectives. 2. 51-87.