COMPARATIVE STUDY OF ANXIETY SYMPTOM'S PREDICTIONS FROM DISCORD CHAT MESSAGES USING AUTOML

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ABSTRACT

Anxiety is a chronic illness especially during the Covid and post-pandemic era. It's important to diagnose anxiety in its early stages. Traditional Machine learning (ML) methods have been developmental intense procedures to detect mental health issues, but Automated machine learning (AutoML) is a method whereby the novice user can build a model to detect a phenomenon such as Generalized Anxiety Disorder (GAD) fairly easily. In this study we evaluate a popular AutoML technique with recent chat engine (Discord) conversation dataset using anxiety hashtags. This multi-symptom AutoML Random Forest predictive model is at least 75+% accurate with the most prevalent symptom, namely restlessness. This could be a very useful first step in diagnosing GAD by medical professionals and their less skilled hospital's IT area using pre diagnostic textual conversations. But it lacks high quality in predicting GAD in most symptoms as found by a low 50% precision on most symptoms (except 5). The AutoML technology is quicker for IT professionals and gives a decent performance, but it can be improved upon by more sophisticated ANN methods like Convolution neural networks that plug AutoML's symptom's deficiencies with at least 80+% precision and 0.4+% in F1 score, namely in detecting poorly predicted symptoms of concentration and irritability.

KEYWORDS

General Anxiety Disorder, machine learning, Discord chat. AutoML, Convolutional neural network

1. INTRODUCTION

Feelings of worry, nervousness, or unease about uncertain outcomes are usually associated with an emotion called anxiety. Anxiety is a feeling many people experience throughout their lives in varying degrees of intensity. However, there are individuals with anxiety so severe it impedes their day-to-day functioning. Those with general anxiety disorder (GAD) experience this worry and unease chronically, and they are unable to control the behaviors that come along with it [1].
The prevalence of GAD in the general population ranges from 1.9% to 5.4% [2]. The prevalence in the United States was 3.1% in 2014 and 5.7% over the course of a patient's lifetime, according to epidemiological surveys [1]. While the age of onset is highly variable, there is a higher rate of females having GAD compared to males at a rate of 2:1 [1]. Risk factors of GAD include low socioeconomic status, exposure to childhood adversity, and being female; twin studies have also shown anxiety has a moderate chance (about 15-20%) of being inherited through genetics [1].
General anxiety disorder also commonly co-occurs with major depressive disorder, with many of their symptoms overlapping, thus making it difficult to distinguish the two diagnoses [1]. Although the inability to experience pleasure does not overlap with GAD, individuals with this condition feel hopelessness like patients with major depressive disorder. According to the NCS, 65% of patients with GAD also had at least one other disorder at the time of their assessment [2].

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Additionally, patients with GAD have a higher risk for other mental health disorders and physical symptoms such as chronic pain and asthma [1]. About 35% of those with GAD turn to alcohol and medications to reduce their symptoms of anxiety, which can increase the risk for substance and drug-related problems [1].

This research focuses on the following questions:

- How can one get a complete picture of GAD using symptoms?
- Can we predict the severity of GAD using symptoms as the guiding post?
- How can social media conversations help with diagnosing GAD?
- Can Auto ML be a quick way to model GAD?
- What intelligent techniques are there beyond Auto ML to better predict GAD?

The main contributions of this research are to:

- Analyze GAD symptoms with the help of popular chat engine conversations.
- Predict severity GAD based on symptoms.
- Evaluate off the shelf Auto ML techniques to predict GAD.
- Build a dataset for Anxiety to be used for further research purposes.

2. RELATED WORK

Machine learning algorithms are present in the process of diagnosing and predicting future outcomes related to mental health. The science field uses machine learning algorithms in a variety of areas because they can apply solutions without human input [4]. They have also been used to detect the prognosis of various mental health disorders such as bipolar disorders and panic disorder [3]. In the context of anxiety disorders, these machines have been used to predict and detect anxiety. More specifically, they can potentially be used to diagnose anxiety, predict future risk of anxiety, and predict responses to medical treatment. [4] Prior studies have made use of a Bayesian network, a probable graphic model that represents certain attributes amongst others; Artificial Neural Networks (also known as ANNs), adaptive processing units made for discovering new knowledge; Support Vector Machines (also known as SVM), supervised learning models meant for analyzing and classifying data based on training data it has been provided with; decision trees, they predict responses and branches based on specific features present in data; linear regression (also known as LR), explains the relationship between the outcome and another variable, and Neuro-Fuzzy Systems (also known as NFSs), combines neural networking and fuzzy logic to develop new fuzzy rules or functions of the inputs and outputs in the system [3].

Individually, these algorithms and machines can do little. This is why the scientific community has turned to hybrid models, models that combine two or more existing methods to create a more efficient product [3,11]. The community has made use of logistic regression, Naive Bayes, and a Bayesian Network while feeding the machines input data based on inferred heart-rate measurements. [12] used a Bayesian joint model paired with a linear mixed effects model and a generalized linear model to analyze input data from self-esteem data and anxiety diagnosis in regards to examining the development of self-esteem on adult onset anxiety disorder. [13] used ANN to analyze a dataset of patients. [14] used ANN, RF, NFS, and SVM to predict affective states of an individual based on five defined classes without any input data. [15] used a SVM nestled within a leave-one-out-cross-validation framework to separate GAD diagnoses from healthy subjects and major depressive disorder with input data from questionnaires, cortisol release and white and grey matter volumes.

[11] found the Bayesian Network model was the most accurate machine learning algorithm they had tested with an accuracy of 73.33%. [12] found the joint-model to be more effective with a 75% accuracy rate. [13] found an overall 82.35% accuracy rate using ANN. [14] found the NFS to be the most accurate than the other models with a 84.3% being the highest accuracy level. Taking all the data into account, 15 found an improved accuracy in detecting GAD from healthy individuals and differentiating it from major depressive disorder at 90.10% and 67.46% respectively. According these results, ANN was concluded to be the most accurate in predicting GAD [3].

Recent studies [16, 17] have given rise to more accurate machine learning algorithms in detecting anxiety with an accuracy of 90% – 96%. But these are cumbersome for hospital IT staff to implement. AutoML [8] is a recent technique to enable novice users to build ML intelligence. This has several advantages to evaluate the traditional ML models fairly quickly and focus on the optimizations and business question at hand. However, they have a severe limitation: "But although automation and efficiency are among AutoML's main selling points, the process still requires human involvement at a number of vital steps, including understanding the attributes of domain-specific data, defining prediction problems, creating a suitable training dataset, and selecting a promising machine learning technique" [8].This study evaluates the efficacy of AutoML using recent technique (Navigator by Pyxeda [9]) in building a high performance machine learning model for GAD diagnosis. Secondly, the study digs deep into symptoms with the anticipation that ML techniques using AutoML would not be as performant as per observation in [18]. Finally, there is no such in-depth study in recent times leveraging AutoML. The study aims to validate the hypothesis that AutoML techniques can be a low hanging fruit for hospital IT staff to use to diagnose GAD and similar mental health problems.

3. THORETICAL FRAMEWORK

The DSM-IV [7] highlights six symptoms of tension/negative affect which are associated with symptoms of anxiety and for consideration when making a diagnosis for GAD. Three of the six symptoms (only one for children) must occur along with excessive anxiety being present for more days than not, for at least six months to qualify. This iteration of the DSM also indicates these symptoms and worry connected to them must be perceived by the individual to be difficult to control. According to [2], this revision from the previous edition of the DSM was made due to evidence showcasing the difference between the anxiety of the general population and those with GAD; while they both had worries about similar content, the controllability of the worry was reported to be vastly diminished in individuals with GAD [2]. More criteria explain that the anxiety, in order to qualify for a diagnosis, should cause distress and/or impairment in important functioning and should not be the result of substances or their side effects.

In the DSM-V, the criteria have not changed significantly, but there is a short addition: "the disturbance should not be better explained by another mental disorder" as per American Psychiatric Association. From DSM [7], the six criteria of anxiety are specified as:

1. restlessness or feeling on edge
2. being easily fatigued
3. difficulty concentrating or the mind going blank
4. irritability
5. muscle tension
6. sleep disturbance

One of the ways to diagnose GAD is via non-elicited speech (e.g. chats). Text chat can be used as a source for both the second and third ways, both elicited and non-elicited speech. Our plan is to create a corpus of sentences from ‘Discord’ anxiety health conversations, tag them for each of the six text-based criteria, and create a prediction model for each.

4. DATA COLLECTION

The study uses Discord [8] to collect the data related to anxiety. Discord is a free audio, video, and text chat service used by tens of millions of individuals aged 13 and above to communicate and socialize with their communities and friends. People use Discord on a regular basis to discuss a wide range of topics, from art projects and family vacations to homework and mental health. The vast majority of servers are private, invite-only locations where friends and communities may communicate and spend time together. Because all discussions are opt-in, users have complete control over who they connect with and how they interact on Discord. It's a place where they can be themselves while still spending time with others who share their interests and hobbies.

The public chats are communities of "servers." Servers are groups of persistent chat rooms. The channel #R/SocialAnxiety and #Kai Havanon Discord as in specified in Table 1is a popular place to express and discuss anxiety. Almost 42,000 posts and comments have been downloaded from various individuals. The data has been preprocessed as per Table 2 to correlate a user's sentences to anxiety.

Table 1: Discord Original Uncondensed Dataset

Channel	Totals	Collection date
#Kai Havan	10,482	02/09/2022 – 04/10/2022
#R/Social Anxiety	31,959	05/20/2021- 04/18/2022

Pre-processing

After Data Collection, the study involved looking at distribution of each variable (all the six symptoms) as well as the Anxiety Intensity variable to understand the spread of the data. Once the data gaps were identified, the data was balanced using SMOTE techniques. Then feature engineering was performed to create new variables using the existing data provided. Using Natural Language Processing, techniques were performed, such as the removing stop words, analysing the errors using spell checker, and cleaning the suspected errors by correcting their spellings. During explorations, visualizations were generated for the content variable to understand distribution of text length and build a word cloud to understand the top or the most common words used by the people during anxiety.

5. EXPERIMENTATION

5.1. Tagging & Labeling

The first involved tagging the individual data pieces and required a clear foundation for what qualified for each of the six symptoms. This would assist the study and future researchers as well. The symptoms were described as the following: “edginess or restlessness,” “tiring easily; more fatigued than usual,” “impaired concentration or feeling as though the mind goes blank,” “irritability (which may or may not be observable to others),” “increased muscle ache or soreness,” and “difficulty sleeping (due to trouble falling asleep or staying asleep, restlessness at night, or unsatisfying sleep).” The process involved looking out for behaviors that fit the symptoms such as descriptions of not knowing what to say which implies feelings of the mind going blank, tones of voice to attribute to edginess or irritability, expressions of exhaustion or hints of fatigue to ascribe to the easily fatigued and/or difficulty sleeping symptoms, and more. During tagging the data, it was found noticeable edginess and the mind going blank were frequent occurrences, as they were both strongly related to social situations in which the individual did not know how to converse with other people, this topic being a common topic of discussion amongst the messages.

However, there were messages that described symptoms not covered clearly within the six categories that had been defined, such as experiencing shaky hands, inability to maintain eye contact, general shyness, nausea and dizziness, panic attacks, and extensive worry about other anxiety-related thoughts and behaviors. While there were some that could fit into the defined symptom categories, some could not qualify for any, despite the display of behavior/content of the message clearly showcasing anxiety or being a result of anxiety. Additionally, many messages giving advice to others expressing concerns over their anxiety could not properly be accounted for, as they did not provide a clear understanding of how the individual experienced their symptoms of anxiety, even if they did reference their own personal experiences; furthermore, these messages were very general and mainly provided emotional support.

A number of messages spoke about medication use and feelings surrounding different brands of prescription medications, as well as feelings of depression that occurred alongside symptoms of anxiety. Many of these messages could not properly be categorized within our defined categories due to the symptoms being more aligned with depression rather than anxiety in the provided context. Medication use also appeared to not be related to our categories as the messages only vaguely mentioned increasing or decreasing dosage or generally if the medication did or did not help with managing symptoms. While a majority of messages talked about general anxiety, a vast portion of them concerned social anxiety, and our categories of symptoms were not equipped to properly assess symptoms related specifically to social anxiety.

Finally, an intensity scale 1-5 (*0 none) was assigned to curate the level of anxiety based on the severity of the symptoms as in specified in Table 2.

Table 2: Severity of GAD based on symptoms

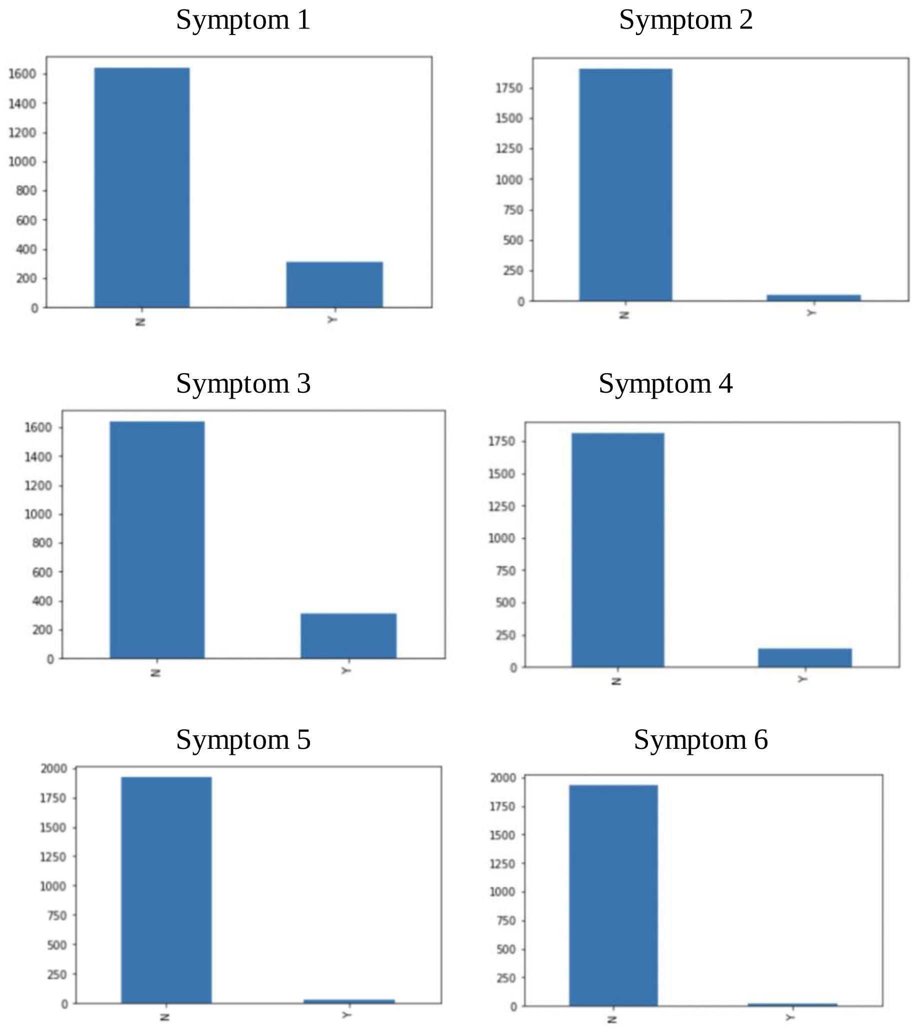
Intensity Level	%
1	11.6
2	3.85
3	1.54
4	0.62
5	0.15
0*	82.2

5.2. Data Analysis

The Discord dataset has a majority of the sentences which do not have any symptoms as shown in Table 2. But symptom #1 (restlessness) is more prominent amongst the comments where there is some symptom. The distribution of the records when the symptoms are exhibited is shown in Figure 1.

Figure 1: Symptoms distribution

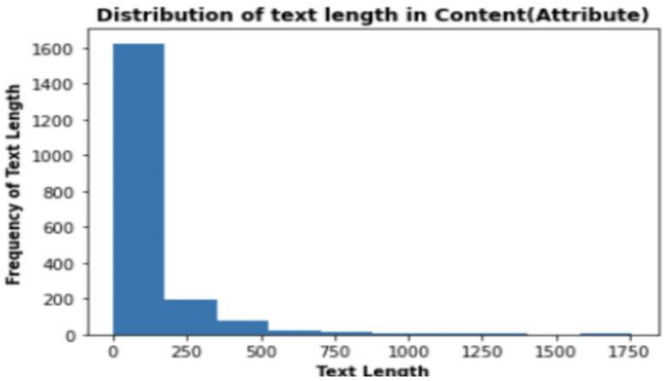
1: restlessness or feeling on edge
2: being easily fatigued
3: difficulty concentrating or the mind going blank
4: irritability
5: muscle tension
6: sleep disturbance
*7: None



Thus, restlessness is the most prominent symptom followed by difficulty concentrating. Sleep disturbance is the least prominent symptom in this dataset. This seems consistent with the general observations in patients suffering GAD and leads us to believe our dataset from discord has merits in diagnosing GAD.

Figure 2 shows that lengths of text in each labelled user comment is roughly 0-500 (ignoring long tail). So, the comments are fairly long which gives us confidence in the expressivity of the users in their deliberation on the depression topic in Discord.

Figure 2: Distribution of text length in Content



The plot below (in Figure 3) shows top N words after removing the stop words vs number of occurrences of each word. As seen in the plot, the top words now are ‘anxiety, feel, talk, not’ with high frequency. The word ‘anxiety’ has a frequency close to 276 and negativity expressed by ‘not’ is amongst the top. This is again indicative that this is a good dataset to develop GAD models.

Figure 3. Distribution of Top N words (after removing stop words)

```
from collections import Counter
Counter(" ".join(Anxiety["Content"]).split()).most_common(30)
```

```
[('not', 391),
 ('like', 326),
 ('anxiety', 276),
 ('people', 261),
 ('feel', 234),
 ('know', 212),
 ('social', 194),
 ('get', 175),
 ('anyone', 151),
 ('talk', 144),
 ('really', 144),
```

Figure 4 shows the word cloud of top frequent words after removing stop words from users’ comments. We see that ‘people’ occurred more followed by ‘feel,’ ‘anxiety,’ ‘help,’ and ‘anyone’. These indicate that the users want to discuss depression and are looking for help.

Figure 4: Word Cloud showing top words after lemmatizing and stopword processing

6. MODELING

6.1. Auto ML

Pyxeda Navigator [9], as in Figure 5, is an Auto Machine Learning (AutoML) tool that uses the Amazon Web Services cloud. Using this tool, a basic model was created. First, “Create an AI service” was chosen.

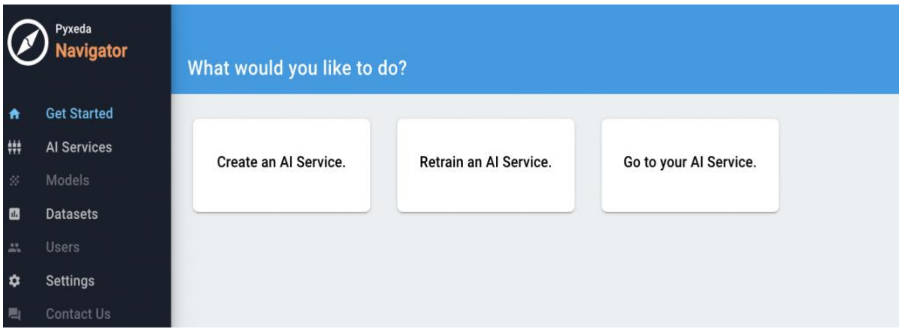
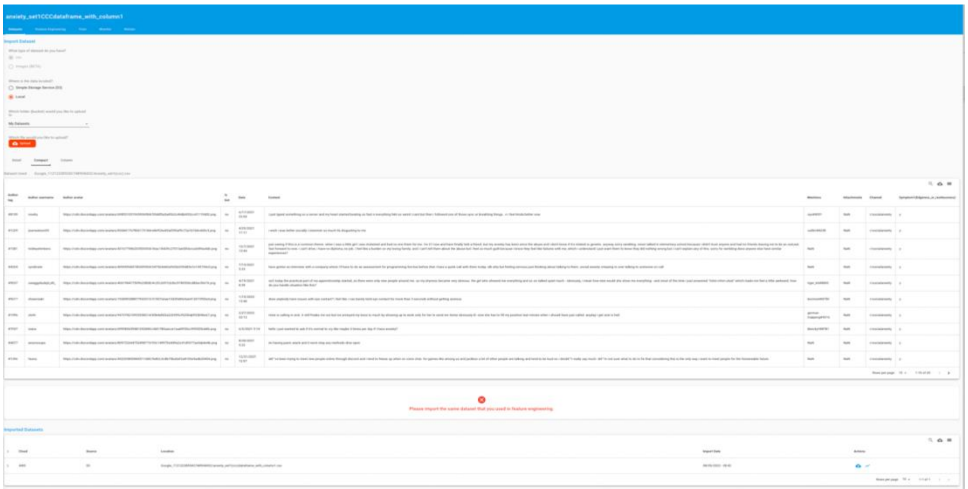


Figure 5: Home screen of Pxyeda Navigator

A CSV file “Anxiety set” was then preprocessed as in Figure 6. Using pandas coding, data frames were created for each of the symptoms, excluding the “Anxiety Intensity Scale.” Then one of the resulting CSV files with the feature “Corrected_Content” and label “Symptom1(Edginess_or_restlessness)” was uploaded and stored on the navigator.
Figure 6: CSV file “Anxiety_set” uploaded onto the AutoML tool



Feature Engineering was then done automatically as in Figure 7. Data was formatted and cleaned, and the relevant label, “Symptom1(Edginess_or_restlessness)” was selected.

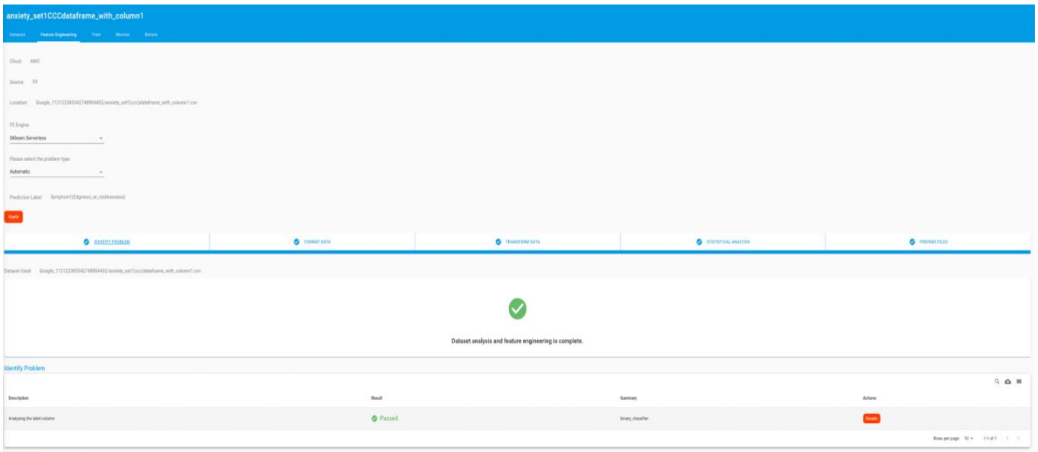


Figure 7: Feature Engineering in Pyxeda (Navigator)

Next, training occurred using Random Forest Classifier, MLP Classifier, and Logistic Regression as in Figure 8.

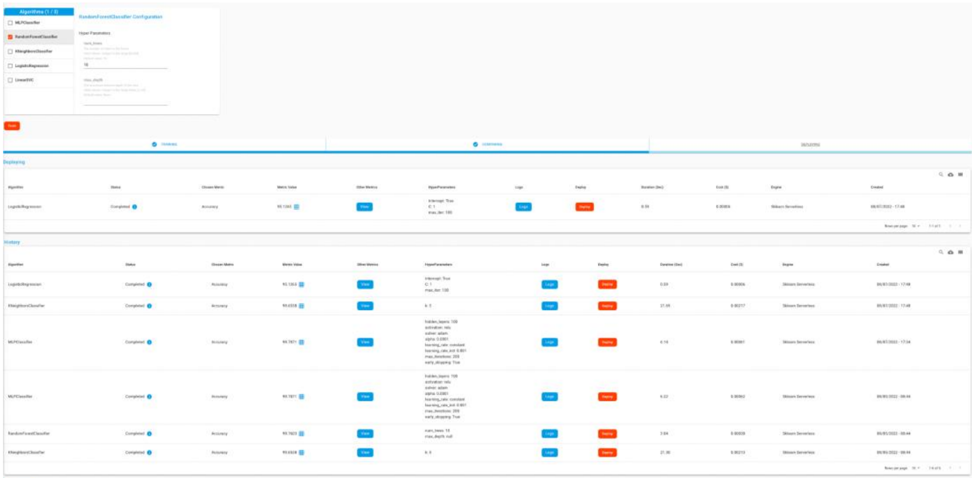


Figure 8: Training in Pxyeda (Navigator)

Source Code was then generated as Figure 10. Then, the methodology included creating a separate validation data set of 300 records of unseen data for testing the models. Finally, the source code was modified to test on unseen data to get final results.

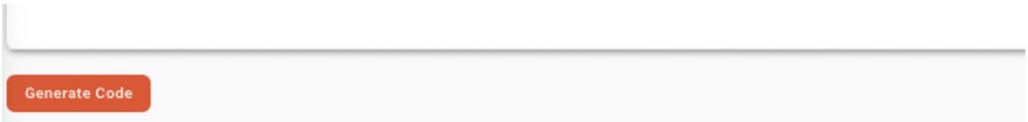


Figure 9: Generate Code button

7. RESULTS

7.1. Auto ML Results

The study evaluates Auto ML as in Table 4 (https://github.com/sneka/anxiety) based on accuracy precision, recall and F1 score. We focus on these metrics as our dataset consists of potential GAD patients. So, it's more important for us to use precision as this model can serve as a guiding post. Tables 3, 4, and 5 shows the resulting metrics for the AutoMl generated models using the algorithms Random Forest Classifer, MLP Classifier, and Logistic Regression. The algorithms were tuned with max_text_features set to 20, 200, 2000, and 5000.

Symptom with max_text_features determined for best output	Accuracy	Precision	Recall	F1 Score
Symptom 1 (5000)	75.0	0.789	0.174	0.286
Symptom 2 (5000)	95.333	1.000	0.125	0.222
Symptom 3 (2000)	84.333	1.000	0.041	0.078
Symptom 4 (2000)	85.33	0.500	0.023	0.043
Symptom 5 (5000)	98.33	0.000	0.000	0.000
Symptom 6 (5000)	98.0	1.000	0.250	0.400
Symptom 7 (200)	75.67	0.784	0.874	.827

Table 3: Metrics for the Random Forest Classifier model

Symptom with max_text_features determined for best output	Accuracy	Precision	Recall	F1 Score
Symptom 1 (200)	76.33	0.632	0.419	0.503
Symptom 2(200)	94.66	0.500	0.250	0.333
Symptom 3(2000)	84.67	0.600	0.184	0.281
Symptom 4(200)	78.33	0.216	0.182	0.198

Symptom 5(5000)	98.33	0.000	0.000	0.000
Symptom 6(5000)	98.0	1.000	0.250	0.400
Symptom 7(2000)	72.0	0.731	0.915	0.812

Table 4: Metrics for the MLP Classifier model

Table 5: Metrics for the Logistic Regression Model

Symptom with max_text_features determined for best output	Accuracy	Precision	Recall	F1 Score
Symptom 1 (200)	76.33	0.632	0.419	0.503
Symptom 2(5000)	95.33	1.000	0.125	0.222
Symptom 3(5000)	84.67	0.667	0.122	0.207
Symptom 4(200)	79.0	0.268	0.250	0.259
Symptom 5(5000)	98.0	0.000	0.000	0.000
Symptom 6(5000)	98.0	1.000	0.250	0.400
Symptom 7(200)	75.33	0.808	0.824	0.816

*Symptom 5's low positive samples affected its metrics as shown by the Table 3, 4, and 5.

7.2. Deep Learning Model Results

As pointed by [8], AutoML has its challenges. This study looks beyond into Artificial Neural Networks to evaluate them as compared to Auto ML models. Notably, the study evaluates Feed forward networks and convolution neural networks.

Feed forward ANN

Keras is an open-source Python framework used for creating and analyzing deep learning models. It is part of the TensorFlow library and allows us to define and train neural network models. After loading the dataset, we split the data into input (X) and output (y) variables and then create a Sequential model and add layers to our network architecture. Fully connected layers are defined using the Dense class. One can specify the number of neurons or nodes in the layer as the first argument and the activation function using the activation argument. Also, one can use the rectified linear unit activation function referred to as 'relu' on the first two layers and the Sigmoid function in the output layer. By using a sigmoid on the output layer, one can easily transfer our network output to a probability of class 1, or, with a default threshold of 0.5, snap to a hard classification of either class. After adding the layers, one can compile the model because it has been specified. For training and producing predictions on our hardware, such as CPU, GPU, or even distributed, the backend automatically determines the appropriate method to represent the network. There are a few more characteristics that must be specified during compilation in order to train the network. Keeping this in mind, we can determine the optimal set of weights to translate our dataset's inputs to outputs while training a network.

The study used cross entropy as the loss justification. This loss, known in Keras as "binary crossentropy,". The study uses the effective stochastic gradient descent method "adam" to define the optimizer. This variant of gradient descent is well-liked since it automatically fine-tunes itself and produces effective solutions to a variety of issues. The classification accuracy described by the metrics argument will be collected and reported because it is a classification problem. Now we build the model with 85% training data. By using the fit() method on the model, one can train or fit our model using the loaded data. The training process runs for a fixed number of epochs (iterations) through the dataset that will be specified using the epochs argument. The study used 15% validation dataset to assess its performance. The evaluate() function returns loss, accuracy, f1, precision and recall for the validation dataset.

Symptom	Accuracy	Precision	Recall	F1 Score
Symptom 1	76	0.8	0.20	0.31
Symptom 2	93	0.10	0.10	0.10
Symptom 3	85	0.5	0.18	0.25
Symptom 4	85	0.43	0.18	0.24
Symptom 5*	95	0.000	0.00	0.00
Symptom 6*	94	0.0	0.00	0.0

Table 6: Feed forward metrics for GAD symptoms

*Symptom 5's & 6's low positive samples affected its metrics as in Table 6.

Convolutional neural network - CNN

In Keras, one may simply add the necessary layer one at a time to build up layers. The Sequential object's add method is then called to add layers. The layers themselves are examples of classes like Dense, which denotes a layer that is fully linked and uses a certain number of neurons with a certain activation function. The study adds a first convolutional layer using Conv1D (). The rectified linear unit activation function, often known as relu, was then to be used on the first layer. Next, were added the max-pooling layer with MaxPooling1D() and so on. The last layer is a dense layer that signifies sigmoid activation. After the model is created, it was compiled using Adam optimizer, one of the most popular optimization algorithms, and subsequently used cross entropy as the loss justification. This loss, known in Keras as "binary cross-entropy,". Similar methods like previous sections on 15% validation dataset were used to generate accuracy, f1, precision and recall.

Symptom	Accuracy	Precision	Recall	F1 Score
Symptom 1	76	0.8	0.20	0.32
Symptom 2	96	0.4	0.25	0.29
Symptom 3	**87**	**0.8**	0.29	**0.41**
Symptom 4	**92**	**0.9**	0.51	**0.62**
Symptom 5	98	0.1	0.10	0.10
Symptom 6	99	0.5	0.45	0.46

Table 7: CNN metrics for GAD symptoms

As in Table 6 basic Feed forward Neural networks performance is not way superior to Auto ML, but as in Table 7 when more sophisticated Convolutional Neural networks were adopted, symptoms 3's 4's & 6's detection was well above the Auto ML capabilities with F1 score north of 0.4+. Thus additional sophistication gets to detect more difficult to detect symptoms.

For the final GAD prediction, we used the regressor model stacked on top of previous symptom model using Random Forest regressor to get the predicted GAD intensity. The ground truth symptom labels were regressed as well using the same model to compare its efficacy over the predicted symptom label's ones. A 19% discrepancy was observed in MAE as in Table 8 which indicates that we can predict GAD intensity using symptom models within 80% error rates.
Table 8: Anxiety intensity model

Model	**MAE diff w. Ground Truth**
RF Regressor	0.19

8. CONCLUSION

This research recommends an Auto ML approach to predict General Anxiety symptoms to get a complete picture of depression. Such methods are simpler and easy to use by less technical IT folks in Hospitals. Social media conversations, especially in Discord chat engine, can help fuel and seed an accurate analysis of GAD symptoms. The multi-symptom's AutoML random forest model predicts GAD with 50+% precision (except 5) and is at least 75+% accurate including the most prevalent symptom of restlessness. This could be very useful in diagnosing GAD by medical professionals using pre diagnosis chats as recommended by DSM. The AutoML technology gives quick and gives decent performance, but it can be improved upon by more sophisticated ANN methods like Convolution neural networks that plug rest of AutoML's Symptom's deficiencies with at least 80+% precision and 0.4+% in F1 score, namely in detecting concentration and irritability lapses symptoms.

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