TherapyBot – Mental health manager usingnatural language processing unit

Increases participation in activities: Although one may

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Abstract

One of the major health concerns in this Covid-19 pandemic is depression and stress. Millions of people throughout the world are suffering from a mental health disorder. Suicide is a quite common thing seen among depressed people. As a result, it is critical to provide self-aid to mentally stressed people early on. This research aims to create a mental assist chatbot that can evaluate the user's mode of operation as well as the sentiment of the user's contact and provide personal virtual psychoanalyst service. Additionally, it will guide in a personal and ethical manner to provide timely and effective self-help. It uses an efficient natural language processing unit to assess the textual input provided by the user and recommends a prompt and effective course way to heal the individual.

The purpose of this health care manager is not to replace the physical therapy with psychiatrist but compliment it and enhance the experience. we hope to reduce the stigma towards seeking help by integrating virtual therapy with proper therapy.

Key Words: Psychiatric counselling, Rasa Chatbot, Rasa NLU, Rasa Core, Natural Language Understanding/ Preprocessing, Mental health Application, Android Application, Postman, ngrok.

1. INTRODUCTION

Stress is a significant aspect that can influence a person's mental state. According to the NCBI, mental diseases are projected to account for 14.3 percent of all deaths worldwide, or nearly 8 million deaths per year [1]. As a result, it may be deduced that depression, stress, and anxiety are the primary causes of suicide in the general population. As a result of this research, an attempt has been made to assist those suffering from depression by providing them with a personal virtual psychologist A chatbot is a piece of software that facilitates communication via the use of audio or written prompts. While a chatbot can fulfil a user's fundamental informational needs by impersonating a friendly individual, a therapy chatbot can also fulfil the user's emotional needs by impersonating a therapist. Additionally, it is known as "online counselling" Because a person suffering from mental health issues is resistant to sharing intimate problems with another person for fear of being misled or criticised, the most acceptable channel for sharing is a virtual one

• Some people are hesitant to share their personal tragedies or troubles with others out of fear of being judged or mocked. Thus, in these instances, chatbots or dialogue systems can be employed to fulfil the user's usual informational needs by posing as a friend or well-wisher.

• Communication facilitation: Chatbots are available to users, addressing issues of affordability and availability.

•Confidentiality is a vital consideration when any breach of personal information in these cases might have fatal effects, which is why a chatbot is advantageous, as no personal information is collected. Experience anger, engaging in leisure activities helps reduce stigma. The more activities a person participates in, the better they feel. It provides a type of mental relaxation and might act as a much-needed respite.

• The demand for more patient-centered apps capable of taking on the role of a health care professional, as opposed to generic ones, prompted us to pursue the idea. It is not only necessary but also urgent, as the topic is at is delicate it is important that the app is capable of handling such sensitive issues.

The following sections comprise the paper: Section II provides the project's literature review. The Methodology is explained in Section III. Section IV discusses Pre- processing Data. Section V represents the model being trained and assessed, while Section VI depicts the results. And Section VII brings the paper to a close.

2. LITERATURE SURVEY

A Chatbot to Aid in Psychiatric Counselling in a Psychiatric Facility Based on the 2017 IEEE 18th International Conference on Mobile Data Management paper, Emotional Dialogue Analysis and Sentence Generation [2], a conversational service for psychiatric counselling is proposed that utilises high-level natural language understanding (NLU). Additionally, emotion recognition is tested utilising a multi-modal technique. It is based on bidirectional RNN, which means that it only considers text from start to finish.

Digital Psychiatry - Using a Therapy Chatbot and Depression Analysis to Combat Depression: (ICICCT 2018) IEEE [3] - This article proposes a cognitive behavioural treatment system, or Therapy Chatbot, that collects a user's health and informational demands. It determines an individual's level of depression. Additionally, it provides methods for reducing an individual's depression level. It examines text to ascertain the user's state beginning with the first word of the phrase.

A self-aware Chabot built with deep learning, bidirectional RNNs, and an attention model (NCIBI 2021) [4] - In this paper, a chatbot is created using a Bidirectional Recurrent Neural Network (BRNN) with attention layers. The Bidirectional Recurrent Neural Networks (BRNN) are used to ensure that the chatbot responds appropriately to the user's input message, which can comprise between 20 and 40 words, and the model was trained using the Reddit dataset.

A Sequencing-to-Sequencing AI Chatbot with an Attention Mechanism: (arxiv.org 2020) [5]- This article shows how an intelligent chatbot is created using an encoder-decoder attention mechanism architecture that combines Recurrent Neural Networks with LSTM (Long-Short-Term Memory) cells. In this case, the Encoder is used to construct a fixed-length vector representation of the user's input message to the chatbot, which is then used as the preliminary hidden state of the Decoder, which creates the desired response..RASA: An Analytical Study and Review (IJERT 2020) [6]

The Rasa chatbot is examined in this article; it is an open source, conventional AI assistant made up off components such as: Rasa NLU and Rasa Core. Additionally, this article discusses how a Rasa chatbot may connect with a database, APIs, and Tracker Store, as well as various Rasa files such as domain.yml and config.yml.

3. METHODOLOGY

Various elements of our app's architecture can be seen in Fig. 1:

• The chat section is where the user can communicate with the chatbot.

• Meditation section- Users can choose to meditate and relax in this section.

• Learn section- Users can read online articles about mental health and well-being in this part.

• A to-do list allows the user to keep track of the things that need to be completed throughout the day.

The user can also access the meditation and article sections from the chat section.

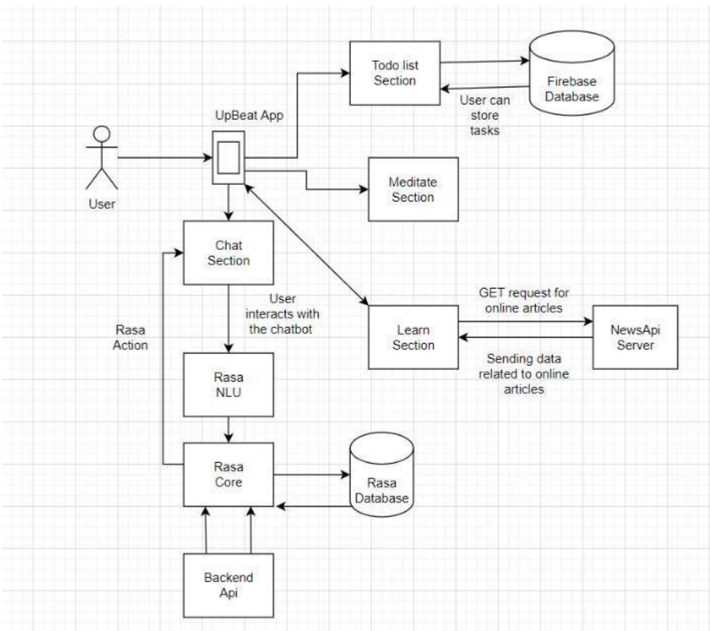

Fig 1. Application architecture

3.1 Chatbot Section:

This portion uses Rasa NLU for intent classification and entity extraction [7]. Rasa NLU parses incoming text and converts it to structured data, while Rasa Core keeps track of the discussion and decides how to proceed. Both Rasa Core and NLU use machine learning to learn from real- world conversations. This section will be central hub of sorts as the user will be able to not only speak their mind but also book, accesses therapy appointments as well as keep track of progression made.

Fig.2 illustrates the Rasa Open-Source design. Rasa consists of two basic elements. Natural Language Understanding (NLU) and Dialogue management. The natural language understanding component is responsible for tasks such as purpose classification, entity extraction, and response retrieval. In Fig.2, this is depicted as the NLU Pipeline, and then there is the dialogue management component, which, based on the environment, chooses the next step in a dialogue, as represented in Fig.2.

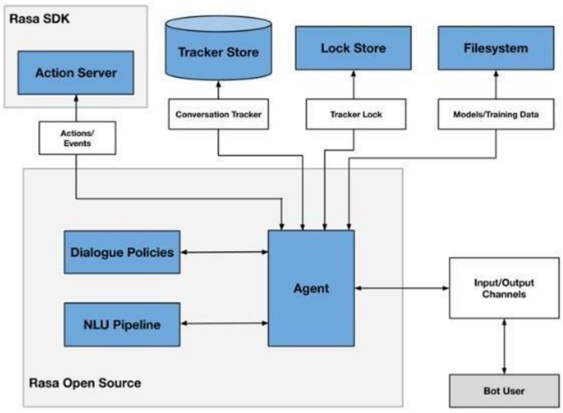

Fig 2. Rasa architecture

The Rasa NLU Pipeline is defined in the "config.yml" file. This file contains all of the pipeline steps that Rasa will use to classify the intents and take the relevant action. Each component that we used in this project is described in detail below.

- **Whitespace-Tokenizer**: Using whitespaces as separators, the tokenizer generates a token for each whitespace-separated character sequence.

- **RegexFeaturizer**: This component generates a collection of regular expressions defined in the training data format. RegexFeaturizer creates a feature for each regex that will be set to indicate whether or not the expression was found in the user message. Then, all of these features will be given into an intent classifier or entity extractor to facilitate classification (provided the classifier learned during the training phase that this set of features signals a particular intent / entity). At the moment, only the CRFEntityExtractor and DIETClassifier components enable these Regex-based entity extraction functionalities.

- **CountVectorsFeaturizer**: Constructs a bag-of-words model of user communications, intents, and replies, together with characteristics for intent categorization and response selection.

- **HFTransformersNLP**: With the help of HuggingFace's Transformers library and a pre-trained language model, this module generates sequence and sentence level representations for each sample in the training data. via language model-specific tokenization and featurization.

- **DIET Classifier**: By default, Rasa contains a DIET Classifier (Dual Intent and Entity Transformer).. This classifier is capable of handling both intent classification and entity extraction. Its architecture is depicted in Figure 3**.**

- **Rasa NLU and Core**:

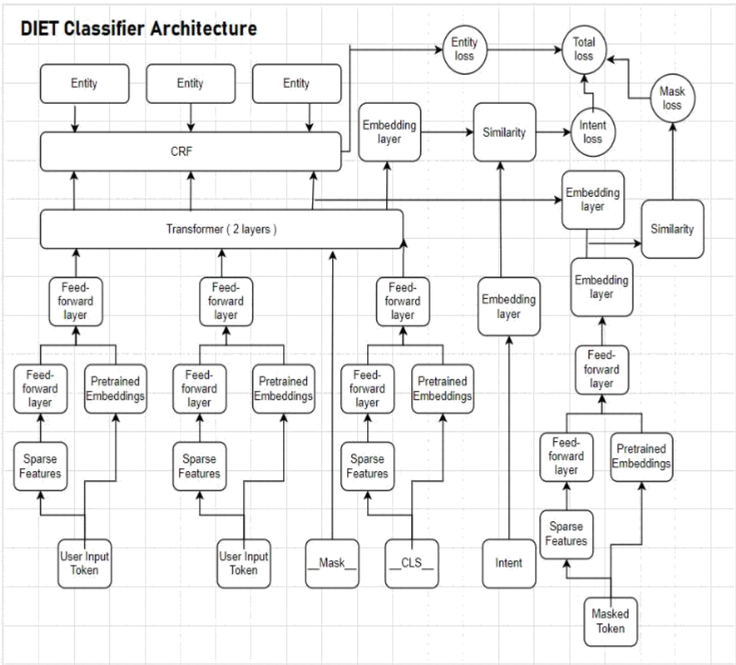

Fig 3. DIET Classifier architecture

_ _context" comes from user input tokens and the " cls "token, both of which have a significant effect on the intent. As a result, the gradient created by the Intent Loss is provided to the Transformer, which then passes it on to these tokens.

- The primary advantage of this design is that it can be customised to meet the specific requirements of your project.

3.2 Meditation Section:

This section is intended to assist the user in developing a daily habit of meditate ion while listening to soothing peaceful music provided by our App. By meditating, the user can improve his or her concentration and calmness. This will assist the user in regaining control of his mind in difficult situations, allowing him to avoid panic and make sound and rational decisions.

Rasa DIET Classifier Architecture, although rasa gives the programmer complete freedom to choose any classifier, the default one provided by rasa is termed DIET Classifier.

- Now that the user's response to the chatbot has been tokenized, it is delivered to the DIET classifier. These tokens are converted to sparse vectors using One-Hot Encoding and then to a dense numeric vector using pre- trained word embeddings such as BERT, GloVe, and ConVert.

- We used BERT word embeddings for this project. The sparse vectors are fed into a Feed Forward Layer, and the output is mixed with the dense word vectors from the pre-trained word embeddings and fed back into the Feed Forward Layer. Rasa starts with sparse Feed Forward Layers and eliminates 80% of the connections. In fact, these Feed-Forward layers are identical in weight and are kept sparse.

- Thus, we have a vector from this procedure, which is essentially a feature extracted from the input token, which is then sent to the Transformer. The DIET classifier applies this process to all input tokens. Rasa summarises the input tokens in this fashion.

- Now, Rasa utilises the " cls " token to summarise the full input sentence. As you can see, we have a Sparse Features block. This block calculates the sum of the Sparse Features of the input tokens. Then there's the block for Pre- trained Embedding, which will take care of sentence embedding while we're using BERT.

- This produces a vector representing the summarization of the user input sentence, which is subsequently provided to an Embedding layer for the purpose of predicting the user input sentence's intent. The output of this is compared to actual intent to determine the degree of resemblance, which yields Intent Loss.

- At the heart of Rasa Architecture is a Transformer block that utilises the Attention mechanism. Rasa comes with two levels of Transformer by default.

- Because we did not use entity extraction and masking in this project, the overall loss will consist solely of intent loss. Thus, the Transformer is the central block that assists in identifying these losses, which are then improved toincrease the chatbot's accuracy.

- Within the Transformer, all of the Token Blocks' output vectors have impact, and when we use the Transformer's output vectors, these vectors have some additional context. Now take the scenario of Intent Loss; the "additional

3.3 Learn Section:

This section was created to educate users about their mental health and well-being; here, users can read online articles on a variety of topics related to mental health, leadership, self- improvement, and positivity. This will contribute to the user developing a positive attitude. The online articles in this section were retrieved via an HTTP GET request to NewsApi Api and cover topics such as mental health, positive attitude, and leadership.

3.4 User Profile Section:

This is the section where the user can view his or her progress, such as how many tasks were completed in the previous week and how the user's emotional state was on those days. This enables the user to self-assess his or her level of activity.

3.5 To-Do List Section:

This section is intended to help the user keep track of all the tasks he or she wishes to complete throughout the day. Our primary objective is to assist users in developing an effective schedule that will enable them to complete their work on time. The Firebase Realtime Database is used to store all tasks entered in this section. Firebase Realtime Database is a type of BaaS, or Backend as a Service. For this project, we used Firebase Realtime Database and FireAuth for user authentication.

3.5.1 User Authentication and Database:

We used FirebaseAuth and Firebase Realtime Database for user authentication and database storage, respectively. OAuth2 is supported by Firebase Auth for Google, Facebook, Github, and Twitter. Additionally, it includes the fundamental email-Password user authentication method; in this project, we used Email-Password Authentication. Firebase Realtime Database isa NoSQL database that is extremely fast and dependable.

3.6 Connection of user with chatbot server:

The chatbot will not be present locally within the mobile application but will be hosted on a server. Thus, all communication will occur via HTTP GET/POST requests from the mobile app to the chatbot server. Thus, we used Ngrok [9] for this purpose, which exposes the local server hidden behind NATS and firewalls to the public internet via secure tunnels.

•ngrok is a cross-platform tool that connects a local development server to the Internet. No requirement for a public IP address or domain name on the local PC..

• It can avoid NAT Mapping and firewall constraints by constructing a permanent TCP tunnel from ngrok.com to a localworkstation..

4. DATA PROCESSING

We created data with various intents such as greet, goodbye, affirm, deny, happy, unhappy, and so on. In a chatbot's settings, "intent" defines what the user wants to communicate with the chatbot. Separate files "stories.yml" and "actions.py" are used to reference different stories and actions. The "stories" section defines how the chatbot should manage conversations, while the "actions" section contains all the actions that the chatbot can perform. Finally, there is the "policy" section, which is referenced in the "config.yml" file. This section assists in making accurate predictions of the actions that the chatbot must perform; inthis project, we used the "TED policy." All of this helps trainthe chatbot [10] to produce the desired output. The training and testing data sets are split in an 80-20 ratio. The rules that the chatbot must follow are specified. These rules are defined to ensure that the chatbot correctly responds to specific types of queries.

VI. Result

TRAINING AND TESTING MODEL

Initially, we did not use any pre-trained word embeddings such as Bert, GloVe, or ConVert. As a result, theresults of the testing are shown in **Fig.4**

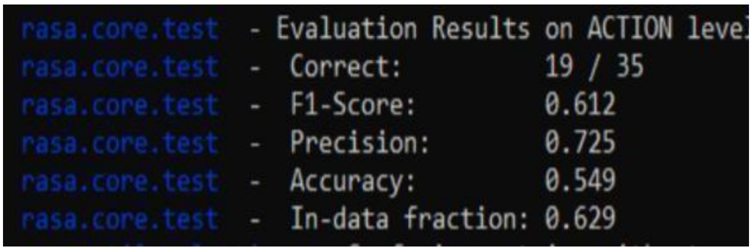

Fig 4. Testing the model without using any pre-trainedword embeddings

In Fig.4, you can see the Evaluation Results at the ACTION level, which indicates how many of your chatbot's actions were correctly executed in comparison to the total expected actions. At the moment, our model's accuracy is 54%.

To improve the model's accuracy, we combined it with pre- trained BERT word embeddings. This aided in improving the model's accuracy, as illustrated in Fig.5. The accuracy ofthe model was increased by using it, and this time we also used Rasa's end-to-end learning, which means that rasa can now predict the next action that needs to be performed based on the user's input message. Rasa's end-to-end learning is a new feature introduced in version 2.2.

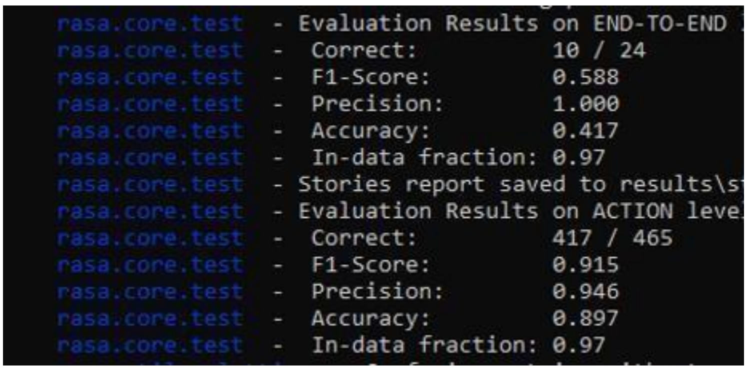

Fig 5. Testing the model using pre-trained wordembeddings BERT

This is a chatbot that will run on different operating systems and will be connected to the user via an Android application.

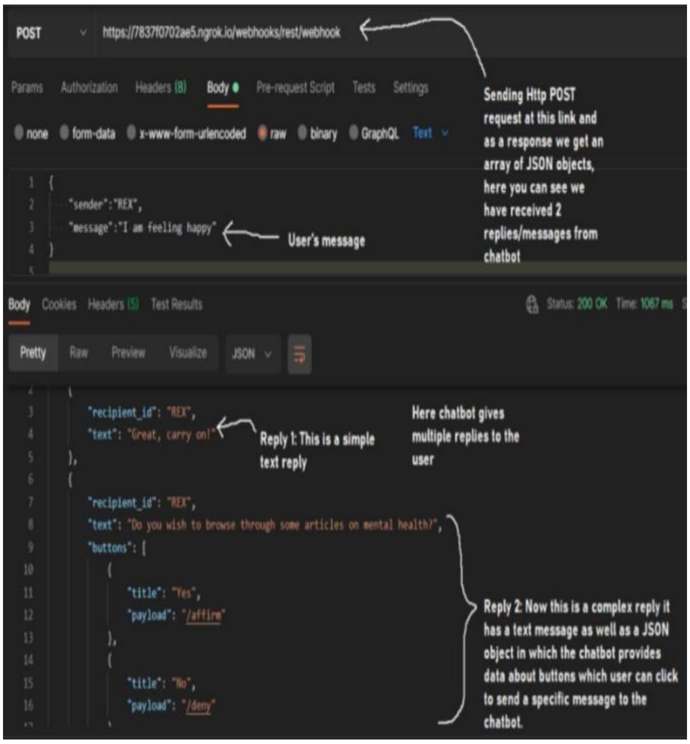

Fig 6. Postman showing request and response from the chatbot.

As a result, we assessed this using the Postman tool, which is commonly used for API testing. As shown in Fig.6, the Http post request is sent to the URL first, followed by the user's message. The chatbot communicates with the user by sending a reply that is essentially a JSON Array. This array contains a JSON object containing the response itself. As shown in Fig.6, the chatbot provides a text response and then a nested JSON object for the key "buttons," which contains the "affirm" and "deny" buttons. This message will be displayed as actual buttons on the frontend.

VII. Conclusion

Thus, we have created a contextual chatbot that converses with or responds to the user based on their mood. We designed this chatbot in such a way that it responds to the user's anxiety or loneliness, as well as his happiness. By doing so, we do not intend to convey the message that a chatbot can take the place of a trained professional in psychiatric counselling. This chatbot will assist users in developing a more positive outlook on life and in breaking the recursive cycle of negative thoughts.

VIII. Future

Our project successfully converses with a user, attempting to ascertain his mood and assisting him in lifting it. The future of this project is contingent upon advancements in the field of natural language processing, which will aid in maintaining a proper flow of conversation and automate all dialogues. By increasing the epochs, we can improve the chatbot's accuracy. Epochs are the number of times your machine learning model will encounter each training example during the training process. Additionally, you could consider adding spaCy embeddings to the pipeline, which would add additional features that would benefit the DIET classifier. One can use a spaCy-trained pipeline such as en_core_news_md or en_core_news_lg for

XI. References

1. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4461039/#:~:text=We%20estimate%20that%2014.3%25% 20of,are%20attributable%20to%20mental%20disorders.

2. 2017 IEEE 18th International Conference on Mobile Data Management-A Chatbot for Psychiatric Counselling in Mental Healthcare Service Based on Emotional Dialogue Analysis and Sentence Generation.

3. International Conference on Inventive Communication and Computational Technologies (ICICCT 2018) IEEE - Digital Psychiatry – Curbing Depression using Therapy Chatbot and Depression Analysis.

4. An intelligent Chatbot using deep learning with Bidirectional RNN and attention model. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7283081/

5. Seq-to-Seq AI Chatbot with Attention Mechanism: (arxiv.org 2020) https://arxiv.org/ftp/arxiv/papers/2006/2006.02767.pdf

6. An Analytical Study and Review of open Source Chatbot framework, RASA (IJERT 2020) https://www.ijert.org/an- analytical-study-and-review-of-open-source-chatbot-framework-rasa

7. https://rasa.com/docs/rasa/

8. https://firebase.google.com/products/realtimedatabase?gclid=Cj0KCQjw4ImEBhDFARIsAGOTMj9JhFp HSAT2m9XtZfwXFBnjJ2f7OGUZmWbaHbGytd6lhYk

9. https://ngrok.com/docs

10. https://rasa.com/docs/rasa/training-data-format

11. Fitzpatrick KK, Darcy A, Vierhile M. “Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial”. JMIR Ment Health. 2017;4:e19. 1FDs3kwaAgg8EALw_wcB&gclsrc=aw.ds

12. Basha, Syed Muzamil, Ravi Kumar Poluru, and Syed Thouheed Ahmed. "A Comprehensive Study on Learning Strategies of Optimization Algorithms and its Applications." In *2022 8th International Conference on Smart Structures and Systems (ICSSS)*, pp. 1-4. IEEE, 2022.

13. https://firebase.google.com/products/storage?gclid=Cj0KCQjw4ImEBhDFARIsAGOTMjYSmjnZBHYAgXmwXgyp1i-Io8y2NW6nVQ_og8RUdNJmA8gcIbbpZgaAt12EALw_wcB&gclsrc=aw.d

14. N. Nagashree, Premjyoti Patil, Shantakumar Patil, and Mallikarjun Kokatanur, "InvCos Curvature Patch Image Registration Technique for Accurate Segmentation of Autistic Brain Images", Springer Nature Singapore Pte Ltd. 2022 V. S. Reddy et al. (eds.), Soft Computing and Signal Processing, Advances in Intelligent Systems and Computing 1340, https://doi.org/10.1007/978-981-16-1249-7_62, pp 659-666.

15. Nagashree N, Premjyoti Patil, Shantakumar Patil, Mallikarjun Kokatanur, "Performance Metrics for Segmentation Algorithms in Brain MRI for Early Detection of Autism", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2S, December 2019.