Artificial Intelligence in Mental Healthcare

Joseph Killian Jr.

Abstract - This paper describes how artificial intelligence is being utilized in mental healthcare. The issues and obstacles in place for this type of research and development are discussed along with the many positive aspects and applications that this technology can have. This paper focuses on the use of scikit-learn and pandas in python to classify whether patients had received treatment for a mental illness, with a supporting KNIME workflow. Fuzzification of some of the parameters that contribute to depression was also completed in python. These programs demonstrate some of the artificial intelligence algorithms currently in use, along with the hurdles and problems that stand in the way of widespread adoption and acceptance of the use of artificial intelligence in mental healthcare.

Index Terms - Artificial Intelligence, Machine Learning, Mental Health

1. Introduction

With the advent of the COVID-19 pandemic, and the ensuing lockdowns, mental health is at the forefront of many people's minds. The mental health of healthcare workers in particular has been adversely affected with their risk of mental illness increasing [1]. More than 300 million people worldwide suffer from depression alone [2] and the prevalence of mental illnesses in general will surely increase as a result of the measures necessary to combat COVID-19. Many Psychiatrists also struggle to accurately predict these cognitive disorders [3]. That is where Artificial Intelligence (AI) can assist the experts in this field, since data can be used in conjunction with AI systems to predict mental illness with high accuracy [4]. All of these systems, whether they be Neural Networks, Fuzzy Expert Systems [5], Natural Language Processing Systems (NLP), or Chatbots [2], rely upon large amounts of data to be available to them. The biggest hurdle that modern medicine faces in general with integrating these AI systems lies in providing adequate data in order to solve these complex clinical problems [5]. These data based AI's can only perform as well as the data that they have been trained on [6]. This is a particularly challenging problem to solve with the ethical issues that surround collecting large amounts of data, especially in regards to medical information. For mental health specifically, much of the available data comes from self reporting of patients suffering from a cognitive disorder [7], which can be difficult to verify. If this data is also not gathered carefully, the biases already present in healthcare can be exacerbated [8]. The problem with using these systems on their own also raises many potential questions with the consequences that result from a diagnosis. Those suffering from cognitive disorders, often deal with these issues for life, so a misdiagnosis can have serious ramifications for the patients involved [7]. In order for these decisions made by AI systems to be trusted, they need to be clear to not only the healthcare professionals and the researchers, but to the patients as well [7]. Thus, the need for high quality data, and for transparent construction of the architecture of the system, make this a complex issue.

Although there are some drawbacks to the use of AI in the field of mental health, it also has shown its potential to improve care, and more accurately predict a mental illness [2,4,5,9,10,11,12,13]. There have been many examples of different types of systems being used successfully for various applications. The advances in AI and machine learning have allowed for more personalized care that takes the more granular details into account[4]. Use of data from smartphones and social media in particular has provided positive results [6,9]. Researchers have been able to use things such as touchscreen typing patterns [2], sensor and usage data [6], and data scrubbed from social media [9] as predictors for various cognitive disorders such as anxiety and depression. Much of this data can also be looked at as more objective, since much of it is passively collected, and relies less on self reporting [11]. Chatbots which have been around since the 1960s with ELIZA [6] being one of the first NLP systems, have also found success in more recent times. One paper in particular utilized the Tess chatbot [10] with students who had suffered from depression, and found that it was able to reduce the symptoms of both depression and anxiety. This care can traditionally be very cost prohibitive, but systems like Tess provide a more cost friendly alternative [10]. Both fuzzy inference systems(FIS), and neuro fuzzy systems have been shown to be able to model the clinical diagnosis of depression [13], and to accurately predict depression risk levels in individuals based on biological markers [12]. Fuzzy systems seem to be relatively uncommon at the present moment with much current research focusing on the use of neural networks and chatbots, but they still certainly have a place in the development of AI for the field of mental health. There is a lot of vagueness and imprecision in attempting to diagnose cognitive disorders, and fuzzy logic can bring together human heuristics and computer assisted decision making[12]. The benefits of making progress in this area is clear, even though the barriers in place make it more difficult.

The main focus of this paper is to briefly demonstrate a sample of the methods that are currently being used in research today. In particular, the fuzzification of some biological parameters as detailed in [11] is shown in a jupyter notebook. The other method being demonstrated involves utilizing data from a survey of tech workers regarding mental health [14]. Another version of this same dataset [15] was also used in conjunction with the KNIME Analytics Platform for some initial testing and exploration of the dataset. After that initial scan of the data, it was then fed through machine learning algorithms in python using scikit-learn in an attempt to classify the survey participants who had received treatment for a mental health condition. This analysis is also contained in a jupyter notebook attached to this paper. The language used for both notebooks was python. The point behind these notebooks is not only to show the use of some of the AI algorithms, but to also demonstrate some of the issues surrounding the use of AI in mental healthcare.

2. Software/Data Challenges

The challenges did not lie as much in the software, as much of the software used in this project had already been installed from this course or previous courses. The main difficulty that arose was in finding relevant datasets that I could use to try and demonstrate some of the above methods. Mental health data, and medical data in general, is not as readily publicly available as other datasets due to the privacy issues surrounding it. With the fuzzy inference system detailed in [12], the only information about how it was set up was regarding how variables were fuzzified. The knowledge base and data used in this particular paper were not publicly available. To complete a system with this architecture more knowledge would be required concerning the parameters and their effect on the mental health of individuals. The other notebook, which goes through the classification of survey participants from [14], required some cleaning in order for it to be usable for the machine learning algorithms that were used. The notebook as described in [16] was used as a guide for the steps that needed to be taken to work with the data. Almost all of the data was originally in the form of strings, with various errors throughout the dataset. A few of the rows containing invalid ages for that particular survey had to be removed. The data had to be converted to floating point in order for it to be worked with. This process of cleaning up the dataset was more time consuming than the use of the machine algorithms themselves. The more simplified dataset from [15] was used with KNIME due to much of the cleaning and normalization already completed for me. I didn't know for sure what was done to clean the data, but it was only used for a preliminary look at what the data looked like and how some of the algorithms would perform, so it was less important for it to be as accurate. So overall the challenges were as a result of obtaining relevant data as opposed to working with any new software

3. Work Completed

The work completed for this project consists of two jupyter notebooks and a knime workflow, along with all of the research gathered for information on this topic. The first notebook that was completed was on the topic of fuzzifying some biological and self reported factors that contribute to depression [12]. The antecedents in question are age, body mass index(BMI), systolic blood pressure, and PHQ-9 scores(a patient health questionnaire used in diagnosing depression), with the consequent being depression risk. That is unfortunately as far as I was able to go with this system, since the knowledge base for creating the rules was not publicly available, as it was produced in conjunction with expert information in that field regarding how these risk factors contribute to depression. I was also missing a dataset to use, so this particular notebook only goes through the fuzzification process. This is a good example of how much background information and knowledge is needed to create a working AI system in the field of mental healthcare.

The next task that was completed was the knime workflow. KNIME is a free, and open source data analytics program, and was used in conjunction with the dataset from [15]. This dataset is identical to the dataset in [14], but much of the cleaning of the data is already done. This was used, because it made things much quicker in KNIME, and provided a much simpler version of the data before I fully dove into it with python. Some cleaning of the dataset still had to be done as yes/no answers had to be converted to binary values. Any columns that contained many possible answers/choices were simply dropped from the dataset. After all the initial cleaning and normalization was done, four machine learning algorithms were trained and tested, these being Logistic Regression, Support Vector Machine, Naive Bayes, and a Multi-layer Perceptron. Out of the four, Logistic Regression performed the best in terms of accuracy with SVM performing poorly. The point of using KNIME initially was to quickly and easily get a feel for the data and test these algorithms, to see if it would be worth using for further analysis and testing.

The final task completed consisted of taking the original dataset and working with it in python and a jupyter notebook. The goal being, to classify which survey participants had sought treatment for a mental illness, and those that have not. The data was read in and cleaned using pandas. After exploring and analyzing the data, it was then used to train the same four algorithms that were used in the above knime workflow. The Naive Bayes Algorithm was the worst performer on average with Logistic Regression, Support Vector Machine, and Multi Layer Perceptron, all achieving similar results. Some simplifying was still done in regards to this dataset, as the columns regarding the region the data was from, and any additional comments were stripped from the dataset. Overall, most of the columns were still used in the analysis of the machine learning algorithms, and to achieve an accuracy of around 80% was surprising given there were only around 1000 data points that these classifiers were trained on. This is a decent attempt at classifying the survey participants, but it also exemplifies some of the issues with this type of classification. The dataset is somewhat biased, as most of the survey participants were male. All of the respondents were also from tech companies, with the majority of participants living in the United States and the United Kingdom. How the classifier made the decisions that they made is also abstracted away, so it is unclear what the algorithms used in the decision making process. This program does a good job showing off not only the algorithm, but also some of the problems with AI and mental health.

4. Self Evaluation

The main goal of demonstrating some of the AI systems was accomplished. Due to the lack of data I was able to find and work with, I was unable to mirror as closely as I wanted to some of the current research going on in this field. But the notebooks and the knime workflow still do a reasonable job of showing off some of the machine learning algorithms that are used, as well as briefly touching on a fuzzy system. They also do an adequate job of exhibiting some issues that can occur when researching and working on using AI with mental health data.

The notebook demonstrating the classifiers in particular shows off some of the problems that this field of AI faces. Much of the data from that dataset is self reported and subjective, with only a few parameters being objective measures regarding mental health. So that problem is first shown in the dataset. Another issue present is the bias that is present in the data. Being that this data is from tech companies in 2014, most of the participants are men, which provides a skewed picture of how these factors may relate to mental health outcomes. This is a factor of bias in the data and is most likely reflected in how the classifiers made predictions. How the classifiers in scikit-learn, and machine learning and AI algorithms in general, make their predictions alone is a big problem that AI faces in regards to medicine in general. If the reasoning behind the decisions is unclear or abstracted to the practitioner, then there will be a lot less trust in the system. These decisions also need to be based off of the current knowledge regarding mental health, in order to avoid the AI making biased decisions. So in these respects, this notebook and the accompanying knime workflow do a very good job in showing the benefits with the relatively high accuracy, but also the flaws in regards to biased data, and abstraction of decision making by AI.

If more time was available to work on this project, ideally more variants of AI systems could be tested. Things such as a neuro fuzzy system, deep neural networks, and some natural language processing would all be relevant to demonstrate as they are very prevalent in research in this field. Working with different and more varied data would have also benefited this project, as only the single dataset is used for much of the project. Obtaining the guidance of some experts in the field of mental health could also be of use, when it comes to designing some of these systems, as was given in [12] to construct the particular fuzzy inference system. So if more time was given, these would be the most likely avenues that this project could use to improve.

5. Conclusion

Artificial Intelligence has the ability to greatly improve how cognitive disorders are diagnosed, and can provide a helping hand to psychiatrists and patients in terms of care. Some barriers in the way of adaptation of AI systems exist. The programs in this paper demonstrate those problems, such as the scarcity of quality unbiased data, the need for transparency on how the systems make their decisions, and that cooperation between AI researchers, psychiatrists/practitioners, and patients is necessary to establish trust and understanding. The benefits available from making progress in this area surely outweigh some of the potential drawbacks, and could improve the lives of millions suffering from mental illness.

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