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EMERGING TRENDS IN SCIENCE AND TECHNOLOGY (ETIST-2021)

27th October 2021

Jointly Organized by

Department of Biological Science, Physical Science and Computational Science

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ABOUT THE INSTITUTION

A nations's growth is in proportion to education and intelligence spread among the masses. Having this idealistic vision, two great philanthropists late. S.P. Nallamuthu Gounder and Late. Arutchelver Padmabhushan Dr.N.Mahalingam formed an organization called Pollachi Kalvi Kazhagam, which started NGM College in 1957, to impart holistic education with an objective to cater to the higher educational needs of those who wish to aspire for excellence in knowledge and values. The College has achieved greater academic distinctions with the introduction of autonomous system from the academic year 1987-88. The college has been Re-Accredited by NAAC and it is ISO 9001 : 2015 Certified Institution. The total student strength is around 6000. Having celebrated its Diamond Jubilee in 2017, the college has blossomed into a premier Post-Graduate and Research Institution, offering 26 UG, 12 PG, 13 M.Phil and 10 Ph.D Programmes, apart from Diploma and Certificate Courses. The college has been ranked within Top 100 (72nd Rank) in India by NIRF 2021.

ABOUT CONFERENCE

The International conference on "Emerging Trends in Science and Technology (ETIST-2021)" is being jointly organized by Departments of Biological Science, Physical Science and Computational Science - Nallamuthu Gounder Mahalingam College, Pollachi along with ISTE, CSI, IETE, IEE & RIYASA LABS on 27th OCT 2021. The Conference will provide common platform for faculties, research scholars, industrialists to exchange and discus the innovative ideas and will promote to work in interdisciplinary mode.

LIST OF ARTICLES

Analysis and Treatment for Mentally Retardation Using Machine Learning

Ms. S.S.Shanthi[1] - Ms. R.Sasikala[2]

ABSTRACT:

Globally, there is a huge unmet need for effective treatments for neurodegenerative diseases. The complexity of the molecular mechanisms underlying neuronal degeneration and the heterogeneity of the patient population present massive challenges to the development of early diagnostic tools and effective treatments for these diseases. Machine learning, a subfield of artificial intelligence, is enabling scientists, clinicians and patients to address some of these challenges. In this Review, we discuss how machine learning can aid early diagnosis and interpretation of medical images as well as the discovery and development of new therapies. A unifying theme of the different applications of machine learning is the integration of multiple high-dimensional sources of data, which all provide a different view on disease, and the automated derivation of actionable insights.

1.INTRODUCTION

Enhanced technology in computer and internet has driven scale and quality of data to be improved in various areas including healthcare sectors. Machine Learning (ML) has played a pivotal role in efficiently analyzing those big data, but a general misunderstanding of ML algorithms still exists in applying them (e.g., ML techniques can settle a problem of small sample size). This paper reviewed the research of diagnosing mental illness using ML algorithm and suggests how ML techniques can be employed and worked in practice and also provides useful information of the properties and limitation of each ML algorithm in the practice of mental health.

The exponential expansion of data has emerged in every field from the rapid advancement of computer and internet technology such as a considerable number of students data from Organisation for Economic Co-operation and Development(OECD) in educational area and customer-related data from Walmart and Facebook in industrial side. Such a huge growth of data also has occurred in the health domain as well. Various personal health information on patients and population started to be digitized in the Electronic Health Record (EHR) system in many countries. In 2012, the EHR produced around 500 petabytes of data, and its size is expected to be 26,000 petabytes by 2022.

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Moreover, the growth is not restricted to its quantity. Developments of medical technology enable measuring various forms of human biology such as a gene, cerebral blood flow, and EEG, at a relatively lower cost but with higher accuracy than before. This big quality data has a high potential to advance healthcare sector by deepening our understanding of human disease mechanisms but requires a different approach from traditional one for their efficient analysis.

Machine Learning (ML) has been acknowledged as an appropriate method for the analysis of big data. ML, conceptually suggested by Allan Turing and coined by Arthur Samuel in 1950s, has been in widespread use in various field including medical area since 1990s, due to incessant efforts of ML researchers along with expeditious developments of computing power.

In addition, some ML techniques enable their machine to learn properly from the data of numerous variables compared to a small number of cases. Thus, ML can be regarded as 'an essential part of big data analytics,'and has contributed to resolving issues in healthcare such as early diagnosis of disease, real time patient monitoring, patient centric care, and enhancement of treatment.

In our recent mental health research, a clinician expected that ML algorithms could be a remedy for small sample size or gave a proper diagnosis without expertise's diagnosis even for training. In addition, Deep Learning or Neural Networks algorithm, well-known as the main algorithm of Artificial Intelligence (AI), was thought of as all about ML. These sorts of confusion obstacles clinical researches using ML techniques which are usually conducted collaboratively by domain experts and ML researchers.

Despite their great advantages, it is obvious that ML techniques are 'not a panacea that would automatically' yield a solution of generalizability or higher accuracy without large quality dataset nor any human instruction for training. There are huge numbers of ML algorithms used for the analysis of clinical data other than deep learning, and each of them has its own advantages. Therefore, it is meaningful to organize and offer the prior knowledge about the ML algorithms necessary for applied clinical research with empirical examples of how ML has actually been employed in the clinical field. This information can be a useful guideline to facilitate communication between clinical and ML researchers and help their collaborative research more efficient.

Neuroscientists and clinicians around the world are using machine learning to develop treatment plansfor patients and to identify some of the key markers for mental health disorders beforethey may set in. One of the benefits is that machine learning helps clinicians predict who may be at risk of a particular disorder.

There is so much data available that we are now able to compile data for mental health professionals so they may do their job better. What makes machine learning so helpful today is that in the past, understanding of diagnoses were based off group averages and statistics over populations. Machine learning gives clinicians the opportunity to personalize."Machine learning allows us to get at individual predictions in a way we haven't been able to before." — David Benrimoh, MD, CM, a psychiatry resident atMcGill University.

Machine learning is helping change the face of mental health in two key ways:

1. Identifying Biomarkers / Developing Treatment Plans
2. Predicting Crises

Identifying Biomarkers and Developing Treatment Plans -When patients are diagnosed with a mental illness today there is a trial and error process to achieve the right dosage of medication and adopting the right treatment plan. Each patient's symptoms will be different from the next patient. An example of a biomarker is blood cholesterol being a biomarker to coronary heart disease.Just as the human body has physical biomarkers, it has behavioral biomarkers to conditions such as depression and anxiety. Machine learning algorithms could help to determine key behavioral biomarkers to aid mental health professionals in deciding if a patient is at risk of developing a particular mental health disorder.

"These algorithms can identify patterns that can help us cluster patients on markers outside of what we currently do — cluster based on severity or specific symptoms," says Benrimoh. Machine learning algorithms provide a rich opportunity for psychiatrists and mental health professionals to identify sub-types of different disorders and develop more catered treatment plans and medication dosages.

Predicting Crises -For patients who have already been diagnosed with mental health conditions, their conditions are monitored to help them go about their daily lives. But certain conditions such as Schizophrenia and Bipolar disorder have a higher risk of crises occurring.

2. TYPES OF MACHINE LEARNING TECHNIQUES

Primary purposes of ML techniques are to analyze data, to predict target features of data, or to derive meanings of the given data. Here, we introduce two main types of ML, **supervised learning and unsupervised learning**, in terms of given data and the purpose of analysis. The ML algorithms used in previous works for mental health data are mostly categorized into these two types.

Besides those two main types mentioned above, another main type of ML is **reinforcement learning (RL)**. The main purpose of RL is for agents to learn optimal behaviors about given environments through repetitive simulations of interacting with environments. This is not applicable to our case where given data is a set of attributes and the corresponding values.

Researches about mental illness diagnostic using ML techniques were carefully reviewed. Five traditional ML algorithms-Support Vector Machines (SVM), Gradient Boosting Machine (GBM), Random Forest, Naïve Bayes and K-Nearest Neighborhood (KNN)-frequently used for mental health area researches were systematically organized and summarized.Based on literature review, it turned out that Support Vector Machines (SVM), Gradient Boosting Machine (GBM), Random Forest, Naïve Bayes, and K-Nearest Neighborhood (KNN) were frequently employed in mental health area, but many researchers did not clarify the reason for using their ML algorithm though every ML algorithm has its own advantages. In addition, there were several studies to apply ML algorithms without fully understanding the data characteristics.

Supervised learning - The supervised learning (SL) is the most commonly used way in MLbased diagnosis. In the supervised learning setting, given data should be labeled. In other words, all data instances should be represented with attributes and corresponding values. Attributes are a set of features, representing data instances. For example, personal characteristics such as height, body weights, eye color, etc. can be attributes to describe a person, or a da instance. A label is the value of a data instance's specific target attribute that we want to predict from other attributes' information. The main purpose of supervised ML model is to predict labels, or values, of unseen instances with their corresponding given attributes.

An example of a SL setting is described: In case of classifying diseases of patients, each patient is a data instance, a patient's measured conditions are attributes, and the patient's disease is a class. The ML algorithm employs attributes to predict a disease class. Given the measured data of a number of patients, the ML model can be built and then can be used to pre-screening of patient's disease before medical professionals' diagnosis.

Unsupervised Learning -The unsupervised learning requires no supervision, unlike the supervised learning that requires target labels of data instances for the model to predict. The main purpose of unsupervised learning is not to predict target attributes but to handle data without supervision. Some examples of unsupervised learning are figuring out similarities between data instances, discovering relationships of attributes, reshaping attributes to reduce dimensionality, etc. We can bring the example described in the previous section for supervised learning as an example of unsupervised learning. Although disease types are labels for supervised learning, the label information can be neglected, and the extra analysis can be conducted with the unsupervised learning. In case of grouping data instances with a smaller number of groups than the number of diseases, from given data, generated groups can be viewed as an indicator to check similarities of diseases.

Supervised Learning Examples -In this paper, we focus on the SL setting as described in the example for the supervised learning above. The supervised learning fits to the purpose of diagnosis since diagnosis can be viewed as evaluation/prediction of patients with measured quantities. We do not cover details of all supervised learning algorithms due to the large number of existing SL methods. Instead, we briefly describe representative SL algorithms frequently used in many works: **Support Vector Machines** (SVM), **Gradient Boosting Machine** (GBM), **Random Forest**, **Naïve Bayes**, and **K-Nearest Neighborhood** (KNN).

The **SVM** is one of the most famous and utilized supervised learning methods. The fundamental concept of SVM is based on the binary classification case. For the binary classification, we want to divide given data points into two classes. Given data points distributed on the feature space, SVM finds a margin that divides feature space most well.

GBM is a boosting method, which is an ensemble technique that leverages a set of weak learners to create a strong learner to obtain better performance. Generally, decision trees, which use a set of hierarchical conditions to divide given data by stages, are used as weak learners due to its simplicity. For example, a set of weak learners may not fit well to given data. We add another weak learner that works well on a part of data that the current set of weak learners do not work well. Then, the new set of weak learners including the newly added weak learner perform better on the given data.

Random Forest is another ensemble technique using decision trees. Unlike GBM which is a boosting method, Random Forest is a bagging method that handles weak classifiers in a different way. The basic procedure that the model uses weak learners and adding new weak learners is same. However, when adding a new weak classifier, the bagging method including Random Forest searches for the best feature among a random subset of data, instead of specific data that are difficult to the current set of weak classifiers. In other words, many randomly generated different decision trees are merged into one learner, and this is why it's called Random Forest.

Naïve Bayes is a naïve probabilistic model to find the value that achieves the maximum probability computed from a conditional probability chain. This model is called 'naïve' because it assumes independency between all measured attributes. In Naïve Bayes model, the model designer is required to decide which attributes to view as dependent attributes to other attributes when computing conditional probabilities. The model solely depends on characteristics of data.

KNN is a type of instance-based learning, where no computations are required before actual classification or regression. In other words, given data itself can be considered as 'learnt' model and then computations are conducted when actual predictions are needed. The basic idea is that a label of a data point can be predicted from same/similar labels of nearest neighbor data points. Therefore, in order to use this algorithm, the selection of parameter K and attribute-distance computation metric to compute which other data points are nearest neighbors are required. However, this algorithm is usually not best because of its simplicity to model real world settings.

3. INTERNATIONAL CLASSIFICATION OF DISEASE SYSTEM (ICD)

The International Classification of Diseases (ICD) is published by the**World Health Organization**(WHO) and used worldwide for**morbidity**and**mortality**statistics, reimbursement systems, and automated decision support in medicine. This system is designed to promote international comparability in the collection, processing, classification, and presentation of these statistics. The ICD is a core classification of the WHO Family of International Classifications. The diagnosis of a mental disorder is a process that begins with a qualified licensed practitioner.

Mental disorders are unique medical conditions because there are no laboratory tests that can be administered in order to help the clinician make an accurate diagnosis. The two most widely used psychiatric classification systems are the**International Classification of Disease System (ICD)**and the **Diagnostic and Statistical Manual of Mental Disorders** (DSM). In the United States, the DSM is used as the standard diagnostic tool.

The five axes of the DSM are labeled as the primary clinical problem, personality disorders, general medical conditions, social and environmental stressors, and global assessment of overall functioning. Collectively, evaluation among all five axes attempt to give clinicians an overall idea of an individual to ensure a holistic treatment approach.

Axis I: Primary Clinical Problem - Axis I includes all mental health conditions exceptpersonality disordersandmental retardation. This axis describes clinical symptoms that cause significant impairment.

Axis II: Personality Disorders -Axis II includes mental retardation and personality disorders. This axis describes long-term problems that are overlooked under Axis I. Many of these disorders, such as autism, are typically first evident in early childhood.

Axis III: General Medical Conditions - Axis III addresses any major medical conditions that may be relevant to treatment of the mental health disorder and includes physical and medical conditions Some examples may include HIV or AIDS, hypothyroidism, celiac disease and brain injuries.

Axis IV: Social and Economic Stressors - Axis IV is used to report psychosocial and environmental factors affecting the person that can result from or contribute to Axis I, II, and III disorders. Some examples of these factors includes problems with primary support group (divorce), problems with social environment (death of a friend), educational problems,housing problems, economic problems, occupational difficulties, legal difficulties, and transportation difficulties.

Axis V: Global Assessment of Overall Functioning - Axis V codes the "level of function" the individual has attained at the time of assessment, and, in some cases, is used to indicate the highest level of function in the past year.

4. CONCLUSION

Machine learning currently provides an opportunity to parse disease models in complex, multi-factorial disease states (e.g. mental disorders) and could possibly inform treatment selection with existing therapies and provide bases for domain-based therapeutic discovery. Recent years have witnessed an increase in excitement and exploratory research on potential applications of ML for mental health.

Our review has offered an overview of this area of research and highlighted current trends and challenges. Aiming to shape the future direction of work, we have discussed current approaches and potential steps toward achieving ML systems that are effective and implementable for mental health care. Specifically, we have examined how constraints and requirements for access to large-scale, high-quality data can pose challenges to study design and urge researchers to extend efforts to gain more in-depth understanding of the specific needs or challenges that are faced by MHPS and people with lived mental health experiences.

Deeper and more creative explorations of the design space can meaningfully inform future research questions and problem scenarios for ML to ensure the domain can truly benefit from novel data tools. This may extend beyond more obvious ML applications for mental health. Bound-up with data access is the need to better assist people in assessing potential benefits of data sharing and how potential risks are mitigated or outweighed by potential benefits (e.g., effectiveness of interventions), such that they can make more informed choices about data uses and to aid their trust in, and acceptance of, data applications.

Furthermore, since the field of ML in mental health is still in its infancy, we have urged for more cautio presentations of ML development to avoid premature claims on the potential usefulness and real-world impa new models. This is especially important considering the complexity and difficulties involved in generating ro as well as technically and clinically reliable ML outputs. So far, the majority of models are rarely tested for us clinical environments, leaving gaps in assessments of their practicality, acceptance, and effectiveness for improv mental health-related outcomes, or services.

Finally, we argued that helping the field achieve its many ambitious visions for ML in mental health requi continued efforts in conducting basic, multi-disciplinary research in deep collaboration with health partne developing and testing new ML-interventions, and studying their effectiveness within real-world use contexts. Th includes a key focus on the challenges of designing new ML-enabled systems that are sufficiently interpretable a (clinically) useful to its target users or recipients. It also requires that research and development efforts recogni and carefully respond to the broader practical and ethical implications that the use of ML systems could have f people, health care, and society

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