Mental Health Patient's Continuity of Care using Machine Learning Models

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Abstract

The rise in mental health issues and the demand for high-quality medical care have prompted research into the use of machine learning in mental health issues. This article offers an overview of machine learning and its current applications in healthcare, a review of recent original research on ML focused on mental health, and a discussion of how ML can support clinical practice while taking into account its present limitations, areas that still require further research, and ethical considerations. Linking of ML and mental health that used electronic health records (EHRs), mood rating scales, brain imaging data, cutting-edge monitoring systems (such as smartphones and video), and social media platforms to predict, classify, or subgroup mental health illnesses like depression, schizophrenia, or other psychiatric illnesses.

Keywords Mental Health

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INTRODUCTION

Undoubtedly, a person's emotions, intellect, and ability to communicate with others are all affected by mental illness, which is a health issue. These problems have demonstrated that mental illness has major societal repercussions and necessitates novel prevention and therapeutic measures. Early mental health detection is a crucial step in implementing these techniques. According to Miner et al. [1], medical predictive analytics will fundamentally alter the healthcare industry. The typical method for diagnosing mental disease is based on the patient's self-report, which calls for the use of questionnaires created to identify particular emotional or social interaction patterns [2]. Many people with mental illness or an emotional condition should be able to recover with the right care and treatment [3]. Based on a multi-dimensional perspective of care continuity, this systematic review explores care continuity and care coordination concepts, models, and metrics. Synthesis shows agreement between diverse, independent models of care continuity, bringing out more details about the key components of the idea. Current research supports an association, but not a causal relationship, between care continuity characteristics and health outcomes. Practice implications: Clarifying care continuity in mental health services may help nurses who serve as care coordinators comprehend crucial facets of their jobs and offer direction for future service expansion.

RELATED WORK

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Understanding and strengthening the coordination of mental health and social services can benefit those who have mental health issues. The study's objectives were to determine which aspects of continuity of care are most important to service users and how they perceive continuity of care within and across services that are relevant to personal recovery. It also aimed to come up with suggestions for how to enhance service users' perceptions of continuity of care. ML has impacted a number of spheres that directly affect our daily life. With this development, ML for health—the use of ML in actual health care—has elevated to one of the most significant societal challenges of the day [3,4]. There have been numerous attempts to use AI and its applications in health care services [5, 6], with privacy and security serving as the cornerstones of ML-based health care. In the COVID-19 pandemic scenario, Rizwan Malik, a radiologist in the United Kingdom, used a novel AI-based chest X-ray technology to decrease patient waiting times [4].

Additionally, Microsoft [2] has contributed about $20 million to the data science/AI research teams that are working with healthcare professionals on COVID-19.

Intelligent systems are being utilised to help clinical decision-making, even though it is unlikely that they will ever totally replace physicians. Human learning is constrained by our capacity to learn, our access to sources of knowledge, and our lived experience, whereas AI-powered robots can quickly synthesis knowledge from an infinite number of medical information sources. Electronic health records (EHRs) are a good example of a very large dataset that may be computationally processed to show trends and relationships with human behaviours and patterns that are frequently challenging for humans to extract.

PROPOSED SOLUTION

Machine learning (ML) is the most widely applied branch of artificial intelligence in healthcare. In order to estimate or forecast outcomes from data, it uses data-driven algorithms.

Results for fresh information and/or upcoming events. ML is distinct from more conventional

The crucial steps from gathering patient data from many sources and biological levels to interpreting the knowledge to produce risk calculators have been detailed by the International Society for Bipolar Disorders Big Data Task Force (17). Similar to this, Park, et al. (26) discussed clinical research techniques for evaluating the efficacy of AI models in healthcare. A manual for interpreting ML-based publications and determining whether the ML model is acceptable for the number and type of input data was provided by Liu et al. (27)

Transfer learning, which enables the use of pretrained AI algorithms created for various purposes as a starting point, is one potential remedy for tiny samples. With less training data needed and without the need to create a new model from scratch, transfer learning is a cost-effective and effective approach. Transfer learning may be helpful for AI in mental healthcare given the relative scarcity of large psychiatric datasets.

Natural Language Processing (NLP): This comprises methods to convert text from unstructured to structured formats in order to facilitate further studies, such as speech recognition, sentiment, lexical, and semantic analysis, and optical character recognition. Language and speech are the key sources of information used to identify and treat mental diseases, making NLP techniques applicable to psychiatry. Unstructured mental evaluation records are easily obtained, reasonably priced, and full of details that can be used to pinpoint phenotypes and comorbidities. Applying

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NLP to the Clinical Record Interactive Search (CRIS) platform and predicting the risk of suicide and early psychiatric readmission using hospital discharge notes from the EHR are two instances that pertain to mental health.

In order to automate Journal Pre-proof 8 chart reviews, group patients into certain phenotypes, and forecast patient-specific outcomes, NLP can also be used more extensively to EHR or insurance claims data

Three categories of features were extracted for the model, namely: Age, gender, and ICD-10-coded diagnoses are examples of static or semi-static patient information, and variables that encode the most recent information available100 evaluations and interactions with the hospital (such as most recent risk evaluations or signs of wellbeing, severity, and number of89 crisis occurrences in the most recent episode and comparable events) and (iii) variables that measured the amount of time since the recorded events have occurred.

112 happened (such as crisis episode, contact, or a referral).

Data		
	Events	
ID	Type	Date
H120	Fever	
H121	Asthma	
H122		

Dignosis

Patient ID	Diagnosis	Date
H120	Fever	
H128	Asthma	
H122		

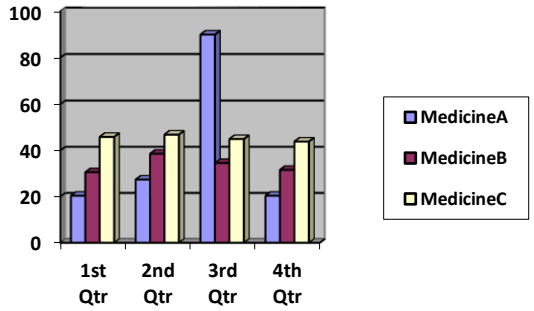
High Risk Patients

Patient ID	Diagnosis	Date

Patient Medicines

Patient ID	Medicines Prescribed	Date

Refill		
Patient ID	Refill Medicines	Date



Patient Info

Patient ID	Blood Group	Age
H120		
H128		
H122		

Accuracy of predictions for various illnesses, age groups, and data availability

We assessed the performance of the prediction model in patient subgroups according on their most recent disorder diagnosis, age , group, length of time from first visit, and length of time since last visit. We only used AUROC to assess the model performance for each subgroup because the AP is the wrong statistic to use when comparing groups with varied prevalence values.

By using machine learning approaches with longitudinally collected EHR and achieving an AUROC of 0.92 for the general model, we showed that it is possible to predict mental health crises. Even though there were 190 periods where there were no patient records in the EHR, which was sparse, the continuous (week by week) querying of the prediction model surpassed the baseline.

CLASSIFICATION RESULTS

AI is based on human intellect and can complete a variety of tangible tasks far more swiftly than a human by duplicating discrete human abilities.

Cognitive abilities like quickness of thought, memory, mathematical reasoning, and spatial reasoning

Ability, Auditory Processing, and Knowledge of Comprehension. AI will advance more. And grow to be super intelligent. However, it lacks the capacity to produce

decisions that are kind, just, and equitable. AI is unable to reflect, self-correct, or Think about the range of viewpoints, morals, and ethics. Changing such Artificial Wisdom (AW), which is what future AI will actually be, exposes the shortcomings of Health care

CONCLUSIONS

The XGBoost model yielded the best performance, including the highest accuracy, AUROC, and F1 score.

In this investigation, the model with the greatest AUROC, 0.92, performed better than the other models for patients with low COC levels.

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