2018 Year in Review: Machine Learning in Healthcare.

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INTRODUCTION

The purpose of this synopsis is to provide a comprehensive review of publications related to machine learning (ML) or artificial intelligence (AI) applications in healthcare for the year 2018. We appreciate the work of researchers and authors who have contributed significantly to the advancement of science in this area.

METHODOLOGY

We did a PubMed search using the terms, “machine learning” or “artificial intelligence” and “2018”, restricted to English language and human subject research. This search resulted in an initial pool of 2274 articles.Each of these were reviewed individually and exclusions were made based on errors in the PubMed search and low scientific or clinical relevance of the individual articles. A large majority of the excluded publications were either focused on robotic surgeries which did not have ML/AI context, certain gene studies with limited impact and short commentaries.

1068 publications were finally selected, reviewed and categorized into one or more medical specialties. Majority of the drug discovery related and review/editorial articles were placed into the “General” category.

REVIEW

In 2018, oncology and imaging were the big areas of machine learning/artificial intelligence research and related publications. Significant number of **Oncology** related imaging and gene studies were highly relevant especially in breast and lung cancer research. **Imaging** also had special focus on overall use of machine learning/artificial intelligence with significant number of editorials or review articles. Imaging studies prominently used Convolutional Neural Network (CNN) for diagnostics. Whereas, Support Vector Machine (SVM) was the method of choice for **Genetic** studies focused significantly on cancer gene detection.

Ophthalmology research used rich data from optical coherence tomography and retinal imaging for early diagnosis of diabetic retinopathy. In **Neurology**, complex electroencephalogram waveform data interpretations and classification saw a huge interest. Many of the studies in the field of **Psychiatry/behavioral Science** used brain imaging data for diagnostics. **Cardiovascular medicine** had few studies related to EKG interpretation, especially focused on atrial fibrillation and a few others related to Imaging for cardiovascular disease. **Pathology/lab medicine** saw significant number of publications related to cancer diagnosis, cell imaging and applications related to pathology reports. **General** as a category contains most of the review articles, drug discovery related studies, articles related to challenges and ethics of machine learning application in healthcare along with articles describing various machine learning techniques. It was interesting to see adoption of ML techniques in specialities such as **Reproductive sciences, Physiotherapy/rehabilitation, Dentistry** and **Education** amongst others.

Despite a big focus in areas of early warning scores and sepsis scores in healthcare, studies related to application of machine learning for predictive analytics were limited. Also, we didn't see much work in key areas of healthcare such as stroke, telemedicine, population health and healthcare cost and economics.

LIMITATIONS

Search was limited to PubMed and with the restrictions mentioned in the methodology section. It is possible that some significant studies or articles might have been missed. BrainX Community's "LEARN" (https://www.brainxai.org/learn/) section provides an extensive supplement to the review provided here. We welcome any suggestions to include publications that might have been missed.Please contact us via BrainX Community LinkedIn group, BrainX Community webpage or directly using email (pmathurmd@gmail.com).

MEDICAL SPECIALITY

[Numbered Bibliographic references]

General
[1-207]

Administrative/Quality Improvement
[208-242]

Anesthesiology
[243-253]

Cardiovascular
[4, 211, 373, 481, 654, 711, 726-762]

Critical Care
[263, 298, 712-725]

Dermatology
[278-299]

Education
[251, 934-942]

Endocrinology
[70, 307-323]

Emergency Medicine
[225,300, 306]

Gastroenterology
[15, 324-354]

Genetics
[34, 355-444]

Geriatrics
[274-277]

Head & Neck/Dental
[1059-1068]

Nephrology
[518-521]

Neurology
[210, 246, 256,261, 324,445-517]

Ob/Gyn/Reproductive science
[120, 522-532]

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