Chapter 1

Influence of Machine Learning in Disease Prediction in Healthcare Sector

1.1 Introduction

The healthcare sector is a very critical service section, wherein the services need to be quick, otherwise leading to catastrophes [1]. In healthcare, identifying disease is the most crucial part of the treatment. Many methods and techniques have been proposed to use Machine Learning (ML), and Deep Learning (DL) to leverage the services in healthcare which efficiently identify ailments and prescribe the appropriate treatment. A lot of recent works, using ML and DL algorithms, have been proven to be effective in identifying the disease and suggesting a cure. However, most of these methods, except a few, depends on the structured, annotated data of patient records to deliver accurate predictions [2] [3]. A greater number of tests, using ML algorithms, for disease diagnosis reveals the huge need for suitable, annotated data [4] [5] [6] [7] [8]. This necessity of structured data, from which algorithms learn to perform well, paved the path to innovation, and create novel learning methods which require no data or less annotated data. Some of the promising domains of learning in this category are self-supervised learning [9], contrastive learning [10], discriminative learning etc [11]. In this paper, we review the previous works of ML in disease diagnosis including the performance, limitations, advancements and other methods which performed well. We also try to extend the applications of contrastive learning by applying it in medical services including pathology image classification, medical image segmentation, and disease detection from WSIs (whole slide images) and others. Self-supervised learning method applied using contrastive learning, for digital histopathology [12], has proven to be effective. The method [12] performed well on the digital histopathology relative to the previous methods of ML such as SVMs (Support Vector Machines) [13], DTs (Decision Trees) [14], etc.

According to [15], the major challenges faced during the analysis of medical images are the curse of dimensionality and heterogeneity of function sources [16] [17] [18]. These challenges lead to delays or inaccuracies in the diagnosis of the disease which thereby, leads to inadequate care for patients. An end-to-end systematic approach enables diagnosis of the diseases including the physician's decision-making [19] a little ahead of time, eventually leading to better results. In recent times, many ML methods were proposed and deployed in the healthcare sector, serving vital functionalities including small-specialized diagnostic problems [20, 3], and differentiating patients between stable and unstable (patients with Parkinson's disease) [21]. Since traditional paradigms failed, such as statistical, medical, and computer fields, to prognosis and diagnosis of diseases, novel approaches were explored and found to effectively perform the functions such as ML algorithms.

1.2 Overview

Machine Learning has been very successful in serving critical functionalities or decision making, otherwise, requiring huge resources. In the past decade, a major part of ML literature has also focussed on applications in medicine. Fundamentally, ML has four sub-domains, and each of them suits a different set of problems to solve in the field of medicine. The four sub-domains of ML have Supervised Learning, Unsupervised Learning, Semi-supervised Learning, and Reinforcement Learning [22]. Other techniques like self-supervised learning (for example, contrastive learning), and evolutionary algorithms, used for [23], are also part of ML. To improvise the services in healthcare, ML aids to deploy a systematic procedure replacing the traditional method to automate the processes and enhance the decision making. The sub-domains of ML also extend their application into healthcare services to make things seamlessly fast. Supervised learning is very useful in disease prediction, for which structured data is available. Unsupervised and Semi-supervised learning techniques can be applied for decision-making in which the availability of annotated data is rare and tough to gather. Reinforcement learning, since inspired by the natural behaviour of humans which learn in course of time (opposite to the immediate and effective decision-making required in the medical field), doesn't contribute much to modelling solutions in medicine. ML techniques that suit the diagnosis of ailments vary from ailment to ailment. Some of the traditional ML techniques used for medical data analysis are, SVMs, k-NN, Logistic Regression, Decision Trees, Naïve Bayes, Deep Learning, CNN, Lasso Regression and etc. These algorithms can be applied to diagnose various diseases including pneumonia detection, ailment segmentation, heart disease prediction, malignant growth of the lungs, medical imaging, protein-protein collaboration, and multiple ailments [24].

The application of ML is applied on wide range of diseases in the field of medicine. However, a single ML algorithm can't generalize to all the diseases, hence multiple algorithms are good at detection or diagnosis of different diseases. The ML algorithms can be classified into some of the major problems in medicine, such as classification, detection, anomaly detection and etc. The figure below shows some of the major areas of problems solved by ML algorithms.

Figure 1: Most common application of ML algorithms in medicine [40].

1.3 Previous Works

There are multiple recent kinds of literature which proposed advanced techniques of unsupervised learning to model decision-making systems that are robust to unlabelled or unstructured data. The [25] has found that AP datasets were better than the UCLA datasets, evaluated using multiple ML algorithms. [26] used multiple ML models such as Naïve Bayes, k-NN, and another method uses SVM with Radial base function (RBF) [27] to analyse thyroid disease and learn the problem of classification. This method was claimed to be achieving the highest accuracy. The [26] used two datasets of thyroid disease in which, one is from the UCI machine learning repository [28] and the other one is from Imam Khomeini hospital by the Intelligent Device Laboratory of the K.N.Toosi University of Technology [29]. SVM was proven to work outstandingly well in the diagnosis of various diseases such as Parkinson's disease [30], morphological feature extraction [31], breast cancer [32] and a few others, on which the SVM method scored higher than 94% at least. Some of the other literature also proposed regular MI ECG beats detection using CNNs [33]. A lot of research on machines' diagnosis of the disease shows that most of the ML or DL methods were performing worse compared to CNN's algorithms. Some of the algorithms over which, CNN outperforms others are, mSVM-RFE-iRF (Elimination of Machine

Recursive Function and Enhanced Random Forest) and varSeIRF. The work [34] on applying CNNs, mSVM-RFE-SiRF, varSeIRF, and SVMs modelled and evaluated on cancer classification (gene minimization in cancer prediction), UCI system repository dataset revealed that CNNs perform better than the other algorithms. Moreover, the SVM algorithms performed better than backpropagation algorithms using neural networks in the diagnosis of multiple diseases including liver disorders, tumours, etc. ML algorithms such as LR, DA, DT, SVM, k-NN, and ensemble learners are used to diagnose a wide range of diseases such as diabetes disease detection, a few advanced versions of traditional ML algorithms were also modelled to train on liver disorder prediction. One of the modified versions is the Gaussian SVM method which acquired an accuracy of 65.5%. Algorithms performing outstandingly well on specific diseases or domains, outperforming existing generic state-of-art algorithms are more reliable in safety-critical domains such as medicine. Algorithm J48 performed well with an accuracy rate of 95.04% in feature selection. The tumour classification (using MRI brain images, with details of various characteristics of the brain such as multifocal, gliomatosis, and multicentric) task modelled using the SVM algorithm performed well, with a precision rate of 90% or higher compared to other traditional algorithms such as k-NN, RF (Random Forest), LDA. Techniques of time series analysis also help to model or analyse multivariate data or anticipate the expansion of hematoma ICH using SVMs, in other words, model the relation between Intracerebral haemorrhage sources leading to high mortality. Random Forest regression or recursive function 180 elimination were used for feature selection, which is used in the selection of patients in thrombolytics procedures. Various ML algorithms came to the rescue during the COVID-19 pandemic to trace, test, and treat people who were infected. Some of the algorithms used during those unprecedented times are ES, LASSO, LR, and SVM with higher sensitivity, specificity and accuracy. In most recent times, due to insufficient annotated data, many deployed ML algorithm-based applications failed to perform to the safety critical criteria. Self-supervised, unsupervised, contrastive learning algorithms, discriminative algorithms. The [35] proposed a state-of-art algorithm to model machine learning applications better in generalizability, which is relatively higher than existing traditional ML or DL algorithms. Multiple techniques are also generalized and extended to the domain of disease diagnosis and pathology detection in medical images from contrastive learning, and discriminative learning. On an overview, ANNs performed significantly better than the traditional statistical or ML models on detection, and diagnosis of disease, especially the CNNs algorithms worked out well in real-time for the fact that they use fewer parameters to learn complex relations in the medical data either structured or unstructured.

1.4 Diseases & ML Techniques

Various diseases in the field of medicine are very complex and unique so, a single ML method can't generalize to perform or diagnose all the diseases or at least a wide range of diseases. For this reason, many methods have been proposed to build state-of-art models to automate the entire process of diagnosing diseases using ML. Many proposed ML-based algorithms, which performed well on a particular dataset, failed to generalize on multiple other datasets on similar tasks. This signifies, the diversity and complexity of diagnosing diseases. The summary table below describes the ML algorithms that best suit a specific disease diagnosis.

Authors	Diseases	Dataset	Methods	Accuracy	Research Objective
Javeed et al., 2019	Heart Disease	Cleveland heart failure dataset by Meng et al., 2018	RSA, R	93.33%	To build an accurate model that predicts weather heart of patient is either failed or infected based on his/her past medical records.
Rustam et al., 2020	Covid-19	Wissel et al., 2020 on GitHub	LR, ES, LASSO, SVM	NA	The research reveals the potential of ML algorithms to predict the number of patients that may get affected by COVID-19, which is one among the biggest threats to human lives.
Zeebaree et al., 2018	Cancer disease	Various cancer datasets	CNN	100%	To diagnose the disease using the capabilities of ANN to an extreme extent.
Cinarer & Emiroglu 2019	Brain tumour	TCIA dataset from Scarpace et al. 2015	k-NN, RF, SVM, and LDA	SVM – 90%	Build a model to classify algorithms by wise decisions.

Hariharan el at., 2014	Parkinson's Disease	UCI dataset on PD from the UCI machine learning repository	SVM	100%	In order to build state-of-art approaches that helps in early detection of PD in patients.
Kousarrizi et al., 2011	Thyroid Disease	UCI dataset on diabetic disease from the UCI machine learning repository	SVM	99% appx	A state-of-art model to thyroid disease classification, diagnose.
Kumari and Chitra, 2013	Diabetic Disease	UCI	SVM	78%	A better approach for early breast cancer detection. An complete overview of diagnosing breast cancer patients
Acharya et al., 2018	Myocardial infarction	Control: 40 CHD: 7	Convolutional Neural Networks	98.9%	The research aimed and fulfilled at proposing a diagnosing Myocardial infarction using deep CNN layers of above 10.
Naqi et al., 2020	Lung cancer	LIDC-IDRI by Meng et al., 2018	Deep Learning	96.9%	The work offers an automated detection system for classification to promote diagnosis by radiologists.
Liu et al., 2019	Brain stroke	1157 patients	SVM	83.3%	A time series model can be used to forecast expansion of spontaneous

					ICH. However, in this example a SVM is used and developed with good accuracy.

To summarize the previous works on applying ML algorithms to safely tackle the complex problems in medicine such as identification, precaution recommendation, treatment, and medicine prescription helped the field to serve better, making the lives of people better. The earlier works, not only helped to aid the services in the medical field but also form the foundation for the latest and advanced techniques, architectures, and algorithms. There are various other diseases whose diagnosis has been made easy using ML algorithms.

1.5 Application of Contrastive Learning

Contrastive learning, unsupervised learning, and self-supervised learning algorithms are being applied in domains similar to medical disease diagnosis. Contrastive learning has already been applied to digital histopathology, extending the benefits of contrastive learning to leverage the performance of the model on various diseases. In this paper, we propose a tuned contrastive learning approach used in diagnosing various diseases and compare the existing state-of-art ML algorithm, which is summarized in the above table. In the coming section, the results post the evaluation of the contrastive learning are proposed, compared to existing state-of-art models. The contrastive learning can be applied to all the diseases diagnosed such as Thyroid Disease, Cancer Disease, Brain tumours, Covid-19, heart disease etc for its efficacy to learn well from a smaller size dataset. Since the necessity for identifying disease in its early stages i.e., detection and treatment of diseases as soon as possible lead to higher quality lives of people hence, ML algorithms fuel the exhaustive research to automate and leverage processes of disease diagnosis.

The experiments on histopathology using contrastive learning proved its efficacy by performing well which inspired our work to experiment with the learning method of contrastive learning using a slightly modified architecture on the other popular medical disease diagnosis such as tumour disease, thyroid disease, and others. In the current research, we applied contrastive learning to detect brain tumours from MRI images of the brain. The architecture used is a standard contrastive learning method [10], that trains an encoder to encode a sample or image into a lower dimensional space. Additionally, VAE (Variational Auto-Encoder) [36] loss is used to ensure that model learns an accurate representation that not only encodes the latent space of the brain tumour image, but also the hidden features differentiating the brain tumour and non-brain tumour images.

1.6 Implementation Details of Contrastive Learning on Various Disease Diagnosis

Contrastive learning is a subset of unsupervised learning, which is becoming extensively popular for its efficacy to learn from complex data, which has a lot of complexities. Contrastive learning was proved to generalize well on complex data, with a relatively smaller number of samples. By taking the advantage of contrastive learning, which requires relatively fewer data and a smaller number of resources to train, the model is implemented using a VAE encoder with a contrastive loss defined as the sum of cosine similarities between the encoded latent space of an example with both a negative example's latent space and a positive example's latent space. The contrastive loss function is defined to lower the cosine similarity between an example with its negative sample and increase the cosine similarity between an example and its positive sample.

The code used to build and evaluate a contrastive learning method is open-sourced on GitHub to work on further improvements. The current version indicates the efficacy of the model to learn with limited resources, with a fine-tuning over the statistical model, employed to use the latent space of the images, output from trained encoder, to classify brain tumour prediction. The additional statistical model is employed instead of a deep network in order to lower the computational cost further. The statistical model could perform well to classify based on the latent space from the encoder network (VAE encoder). In the current version, RandomForestClassifer is used, from the sklearn.ensemble.

1.7 Evaluation

Contrastive learning applied to the dataset, one among those mentioned in the above table on brain tumour diseases. There are a few other diseases like Parkinson's disease, Alzheimer's disease, and others to which contrastive learning can be applied to assess the capability to generalize to other diseases or domains, however, the current scope is to experiment with the capability of contrastive learning to diagnose diseases effectively without using any pre-trained or state-of-art model. In order to train and evaluate the approach using contrastive learning, similar kind of datasets are used, which are also used in the earlier state-of-art methods, mentioned in the table. To be particular, a brain tumour dataset is used to evaluate a model, which learnt the patterns from scratch without using any pre-trained or existing state-of-art models. The average accuracy obtained upon evaluation; the score is 79.9%. The accuracy of the model is comparatively lower than the previous methods using VGG-16 [37], Resnet-50 [39], VGG-19 [38], and other state-of-art pre-trained models, but the efficacy of contrastive learning is unleashed by its potential to acquire close to 80% accuracy with not much hyperparameter tuning and with a smaller number of epochs. The contrastive learning model, presented in this paper, is learned from a smaller dataset and is able to generalize well. The trained model used very limited resources but could able to extract as much as it can from the existing smaller collection of data. One of the intuitions behind using contrastive learning is its mechanism of learning an encoding not only from an example but also trying to learn from a negative example and extract the most out of it. This mechanism is highly helpful to learning multi-class problems in which, contrastive learning can learn by forming a huge number of pairs with negative examples hence, contrastive learning is highly advantageous if the data is small. In other words, the mechanism of contrastive learning itself consists of an internal method of data augmentation to increase the data for learning.

The learning curve obtained, when a contrastive learning model is trained, using a VAE encoder to learn the latent space with a combined loss function of VAE loss and contrastive learning loss is shown in the below figure 2.

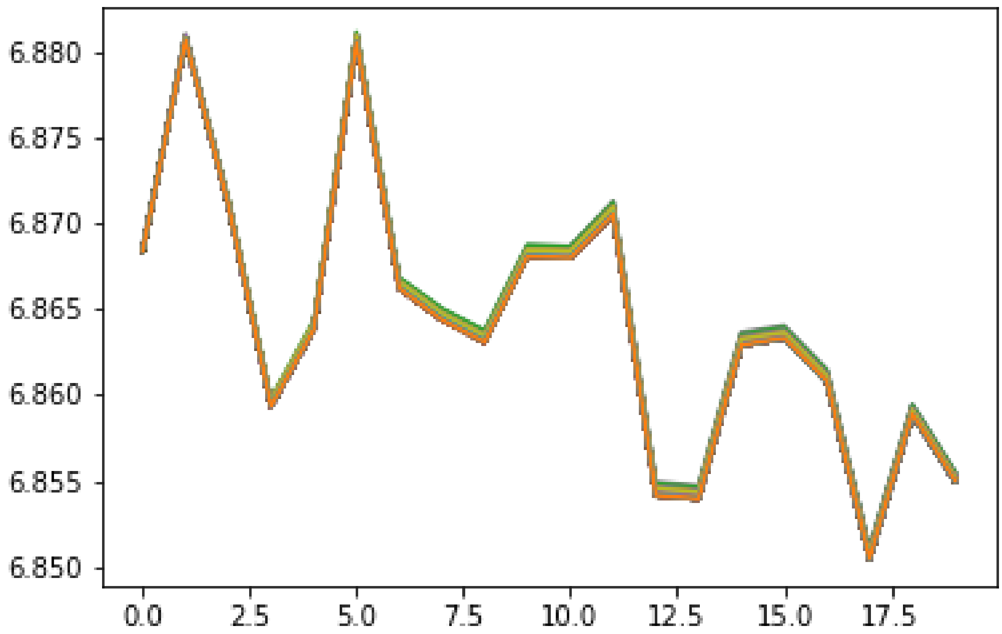

Figure 2: Learning Curve of the Contrastive Learning

1.8 Conclusion

Medicine is a huge domain of complex problems that need efficient aid from technology to diagnose the disease at early stages, which otherwise might lead to catastrophes. Since many ML algorithms were proposed and deployed in real-time applications aiding the doctor or professionals to deliver much better service. The overview in this article aims to acknowledge the efforts of the ML community toward helping the field of medicine and also outlines a better understanding of the kind of ML algorithms that works for the kind of disease. The table [5] briefly explains the progress so far and in this article, we attempted to apply contrastive learning to aid the field more. The evaluation of contrastive learning on digital histopathology using a similar dataset was reproduced but, the tuned method is applied and evaluated on another disease diagnosis. Based on the results, contrastive learning, by taking the advantage of neural networks, performed well but hopefully has a lot more potential to do better. The efficacy of the model to learn the pattern in image efficiently with limited resources heavily suggests its capabilities to generalize to any domain, for that matter, any disease of medicine.

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