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Machine Learning in Public Health: A Review

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Abstract- In recent years Machine learning has been used for disease diagnosis and prediction in the public healthcare sector. It plays an essential role in healthcare and is rapidly being applied to education. It is one of the driving forces in science and technology, but the emergence of big data involves paradigm shifts in the implementation of machine learning techniques from traditional methods. Computers are now well equipped to diagnose many health issues with large health care datasets and progressions in machine learning techniques. Researchers have been used several machine learning techniques in public health. Several methods, including Support Vector Machines (SVM), Decision Trees (DT), Naïve Bayes (NB), Random Forest (RF), and K-Nearest Neighbors (KNN), are widely used in predictive model design research, resulting in effective and accurate decision-making. The predictive models discussed here are based on different supervised ML techniques and various input characteristics and data samples. Therefore, the predictive models can be used to support healthcare professionals and patients globally to improve public health as well as global health. Finally, we provide some problems and challenges which face the researcher in public health.

Keywords: machine learning, prediction, classification, public health, disease.

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Abstract- In recent years Machine learning has been used for disease diagnosis and prediction in the public healthcare sector. It plays an essential role in healthcare and is rapidly being applied to education. It is one of the driving forces in science and technology, but the emergence of big data involves paradigm shifts in the implementation of machine learning techniques from traditional methods. Computers are now well equipped to diagnose many health issues with large health care datasets and progressions in machine learning techniques. Researchers have been used several machine learning techniques in public health. Several methods, including Support Vector Machines (SVM), Decision Trees (DT), Naïve Bayes (NB), Random Forest (RF), and K-Nearest Neighbors (KNN), are widely used in predictive model design research, resulting in effective and accurate decision-making. The predictive models discussed here are based on different supervised ML techniques and various input characteristics and data samples. Therefore, the predictive models can be used to support healthcare professionals and patients globally to improve public health as well as global health. Finally, we provide some problems and challenges which face the researcher in public health.

Keywords: machine learning, prediction, classification, public health, disease.

I. Introduction

Machine learning, a method of developing a prototype that learns to enhance its quality through experience, belongs to the context of artificial intelligence and is increasingly being used in various fields of science [1]. Such algorithms can be applied to help track the progress of a person, what variables make their symptoms worse, predict how long they would take etc. [2]. It is likely to deliver technically superior results, but it is not going to be perfect. While machine learning can deliver technical performance, inequities can be compounded [3]. The intervention was particularly among the group with a moderate likelihood of participation. Targeting the results of the prediction model using the machine-learning method has been identifying suitable intervention targets [4]. Traditional machine-learning approaches have been successful because the complexity of molecular interactions has been reduced by investigating only one or two dimensions of the molecular structure in the feature descriptors. Several different ML classifiers are experimentally validated into the data set in the present study [5]. Machine learning is involved in many of these, but streaming data is only addressed in a few plays. The machine learning library consists of common learning algorithms such as classification, clustering, collaborative sorting, etc. useful when dealing with problems with machine learning [6].

Machine learning typically extends these methods to cope with high dimensionality and nonlinearity, which in wearable sensor data is of particular importance. It overlaps with artificial intelligence, but traditional biomedical statistics usually recognize the problems it seeks to solve. Extraction of the function renders machine-learning traceable because it reduces the number of data dimensions [7]. These techniques can help enhance the ability to discriminate by combining multiple metabolites' predictive abilities. However, these methods are monitor, and therefore, various validations are key factors in preventing over fitting [8]. In this paper, a new approach is proposed to automatically identify fund us objects. The method uses pre-processing techniques for images, and data to improve the performance of classifiers for machine learning [9]. Machine learning techniques are applied to these data, which are useful for data analysis and are used in specific fields [10]. Recently it can use to analyze medical data, and for medical diagnosis to identify various complex diagnostic problems. We can improve the accuracy, speed, reliability, and performance of the diagnosis on the current system by using machine learning classification algorithms for any particular disease [11]. It is used to estimate vegetation parameters and to detect disease, with less consideration give to the effects of disease symptoms on their performance [12].

II. Machine Learning in Public Health

Machine learning plays a role in the healthcare field and it is rapidly apply to healthcare, including segmentation of medical images, authentication of images, a fusion of multimodal images, computer-aided diagnosis, image-guided therapy, image classification, and retrieval of image databases, where failure could be fatal [15]. Statistical models developed using machine-learning methods can view in many ways as extensions from epidemiology and health econometrics of more conventional health services research methodologies [16]. Given the wide availability of free packages to support this work, many researchers have been encouraged to apply deep learning to any data mining,

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and pattern recognition topic related to health informatics [17]. In medical fields, machine learning has also shown promise when the aim is to discover clusters in the data, such as therapeutic choice imaging research. Here, the new features can check with a radiologist or neurologist expert assessment which varies from the prediction environment where observed marks exist in the data [18]. Screening and prognosis of patients with cancer use methods for pattern recognition and identification such as machine learning [19].

The repository should highlight the specifications of clinical machine learning tasks and motivate the ML community by providing a platform for the publication, collection of data sets, benchmarking of statistical evaluators, and methods for challenging machine learning problems [19]. The main of applying the classification method is to allow healthcare organizations to provide accurate medication quantities [20]. At every stage of development and application of machine learning in advancing health, ethical design thinking is essential. To this end, honesty and innovation physicians will work closely with software and data scientists to re-imagine clinical medicine and foresee its ethical implications. It is crucial that data from mobile health and consumer-facing technologies be systematically validated, especially when dynamic intervention is provided [22]. Three developments in machine learning may be of interest to public health researchers and practitioners [25]. Machine Learning techniques have shown success in the prediction and diagnosis of numerous critical diseases. Some sets of features use in this strategy to represent each instance in any dataset [26]. Research comparing the quality of different prediction methods to predict disease, disease etiology, or disease subtype is minimal. For many types of medical diagnoses, a good machine learning approach to classification will apply [27].

III. Challenges in Public Health

Overall, health systems face multiple challenges: rising disease burden, multimorbidity, and disability drove by aging and epidemiological transition, increased demand for health services, higher social expectations, and increased health spending [3]. Healthcare offers unique machine learning challenges where the requirements for explaining ability, model fidelity, and performance, in general are much higher than in most other fields. Ethical, legal, and regulatory challenges are unique to health care since health care decisions can have an immediate impact on a person's well-being or even life [28]. The primary focus in health informatics is on computational aspects of big data, including challenges, current Big Data Mining techniques, strengths and limitations of works, and an outline of directions for future work. A challenge is pose the high volume of healthcare data, the need for flexible processing, and support for decentralized queries across multiple data sources. Global health as an approach to the current situation and challenges, and the use of digital health as an ideal way to address health challenges associated with conflict-affected environments [30]. There are several ways in which the proposed models of machine learning can help address public health challenges. The regularity, reliability, and granularity of available data is a challenge in tracking population health. Model estimates can play a role in strategic decision-making if they can achieve sufficient precision, and machine learning models can provide a route to this required level of precision [31]. Several writers describe different challenges in public health.

Table 1: Public health Challenges

Challenges	Description	References
Development	Challenges in the acquisition of talent and growth capital	[64]
Data schema	Increasing the burden of disease, multimorbidity and disability driven by aging and epidemiological transition	[3]
Ethics, laws and regulations	Health care choices can have an immediate impact on a person's well-being or even life.	[28]
Epidemic	Social health inequalities, a small number of local healthcare professionals, and a weak infrastructure for healthcare.	[13]
Big Data	Data mining methods, advantages and weaknesses of current works and recommendations for future work	[29][32][19][61]
Treatment effect	Treatment of patient outcomes in order to select the correct treatment	[16]
Clinical Data	Real clinical information environment, incomplete and erroneous data.	[65]
Data regularity, timing and reliability	The regularity, pacing and granularity of available data is the control of population health.	[31]
Characteristics identifying	The features of communities, ecosystems and policies are defined in population health	[47]

Health Tackling	Health as an approach to the existing situation and challenges.	[30]
Dataset imbalance	Forming an ensemble of multiple models with matched numbers of positive and negative slides trained on data subsets.	[66]
Biomarkers identify	Build diagnostic, prognostic or guided therapy predictive models	[19][59]
Screening	The area of early detection of cancer is packed with highlighting cautionary tales.	[67]
Diagnosis	The nuanced essence of the disease and its patient heterogeneity	[68][69]
Image data	Modern imaging technology will surpass the capabilities of human pattern recognition	[70]
Diagnosis, treatment and monitoring	The growing number of patient data in the form of medical images	[9]
Decision making	Prediction of disease is one of the most important medical problems because it is one of the leading causes of death..	[26]
Monitoring of disease	The progression of the disease and the estimate of the level of fibrosis of the patient	[71]
High- dimension image data	Imaging evidence was a problem in the treatment of diseases based on brain imaging.	[72]
Accurate prediction	Things that recur within a binary outcome	[69]

IV. Problem Statement

In public health, they are reducing constraints such as lack of resources (human and logistic) in healthcare centers, high population dispersion, and lack of infrastructure. One problem with the concept of "data health" is the lack of a practical idea of effective and efficient healthcare programs: each insurer has sought effective strategies through trials and errors [4].The main problem is the unstructured of the medical reports. High complexity and noise issues result from the multisource and multimodal nature of healthcare data. Additionally, the high-volume data also has problems with impurity and missing values. These issues are to handle in terms of both size and reliability, although a range of methods has developed to improve data accuracy and usability [29].Machine learning methods are the leading option for achieving a better result in classification and prediction problems. In a wide range of machine learning (ML) problems, classification plays a role. Another major issue with the collection of data is the potential lack of label accuracy. Overfitting is a potential problem in machine learning. The general problem is that several existing datasets are difficult to use in terms of permission [34]. Table 2 displays the numerous public health issues facing them.

Table 2: Problem Statement in Public Health

Problem	Description	References
Classification	The situation was linear in nature for all armed and unarmed group datasets	[57][33][42][50][19][5][21][55][73][74][60][75][76][77][69]
Scalability	Exists with two of the most widely used interpretable machine learning models	[28]
Lack of infrastructure	Lack of resources in health care centers (human and logistic), high population dispersion	[13]
Effective and Efficient	Through trial and error, every insurer tried effective strategies	[4][78]
Exchange health information securely	Scientists and clinicians across institutional, provincial, or even national jurisdictional boundaries across a given healthcare organization.	[29]
Overfitting	Because of its storage limitation, it may not be appropriate for very large datasets with high dimensional features	[29][32][17][34][24][79][80]
Data Imbalanced	Which are commonly used to resolve big data clinical databases.	[29][81][27]]82][83]
Clinical unstructured notes	The multisource and multimodality of health care data leads to high complexity and noise problems	[29]
Impurity and missing	The high-volume data also has problems with impurity and missing values	[29]
Missing variables	This results in the normal multivariate methods, while	[16]

	machine-learning approaches can still be appealing for other reasons	
Prediction	The computer is equipped with a set of data to improve the classification model after it can be used for future predictions	[33][82]
Mobility	The problem of visual, hearing, flexibility also affects the disease.	[50]
Dose management	Use machine learning approaches to the SCD drug problem	[20]
Segmentation	That pixels can be marked as belonging to a particular segment or category	[84]
Multicollinearity	Reduction of measurements and management of experimental data	[73][80]
Dimensionality	Less likely than other classifiers to suffer from this problem.	[60][11][72]
Class imbalance	The number of samples from one class outweighs the other classes significantly	[59][83]
Sampling	Data collection is a possible lack of label accuracy	[7]
Scoring	Functions for use in models of prognosis estimation	[85][82]
Diagnosis		[86]
Missing data and Class imbalance	For the context, the performance metrics selected are most often inappropriate.	[46]

V. Dataset

To generate the most effective results, machine learning algorithms use to analyze data repeatedly. Machine learning currently provides the machine for scrutinizing imaginative information. Today, medical clinics very well equippe with fully automatic machines, and these machines produce tremendous amounts of data, then collect, and exchange these data with information systems or doctors to take the necessary steps. Machine learning methods can used to examine medical data and various technical diagnostic conditions in medical diagnosis. Using machine learning, systems take patient data as an input such as symptoms, laboratory data, and some of the at tributes and produce reliable diagnostic results. Depending on the reliability of the test, the computer must determine the information for the future reference will be used as a learning and qualified dataset [11]. Different Authors are used to several data determine the quality of the proposed classifiers which display as.

Table 3: Summary for data used in various research paper

Data Description	References
Patient data	[2]
Parkinson's Disease Data	[35]
Clinical Data	[3][87][88][55][24][89][10][71][90][91][38][92]
RGB-D Data	[8]
Diabetes Data	[54][93][52][81][23][36][86][43]
Malaria Data	[1]
TB Data	[13]
Health Data	[4][29]
Biomedical Data	[94]
Heart Disease Data	[62][95][48]
EMR data	[16]
Chronic Disease Data	[96]
Breast Cancer Data	[33][42][46]
Stress Data	[65]
S1,BRFSS & ACS Data	[31]

Cleveland Data	[47]
GDS Data	[50]
EHR Data	[97][18][39][98][56][99][100][77]
Medical Data	[30][20][75][24][61][11]
Meta Data	[66][19]
Image Data	[101][84][102][103][34][104][70][9][105]
TCGA Data	[67]
CKD Data	[5][51][106][26][69]
Physiological Data	[107][53]
Health Care Data	[6][108][79]
OASIS Data	[44]
Sensor Data	[40][7]
IMU Data	[74]
ADNI Data	[60][59]
RNA Data	[68]
UCI Cardiac Data	[41]
CAD Data	[85]
AF Data	[109]
Metabolites Data	[57]
MRI Data	[110][111][72]
Social Media Data	[112]
Thyroid Data	[76]
Dengue Case Data	[113]
NHANES Data	[80]
Dementia Data	[37]
DIARE-TDBI Data	[58]
ECG Data	[114]
Wisconsin Breast Cancer Data	[115]
SW Data	[116]
Genomics Data	[82]
Clinical & Image Data	[117]
PH^2 Data	[118]
WBC Data	[119]
Spectral Data	[120]
ISIC Data	[72]
ILPD Data	[83][45]
NHA-NES Data	[121]

VI. Classification Technique

In many real-world issues, classification is one of the most decision-making techniques. The higher number of samples selected for many classification problems, but does not lead to higher classification accuracy [35]. Supervised machine-learning algorithms are mainly use for classification or regression issues where the patient sample class label is already available [19]. Classification tasks are found in a various decision-making tasks in various fields such as medicine, science, industry, etc. Several approaches are suggest in the literature on how to solve classification problems [5]. In the medical context, the identification quality of commonly used machine learning models, including k-Nearest Neighbors, Nave Bayes, Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression [36]. In this research paper, we conclude various research papers in a tabular form (Table-4) showing different methodologies and compare the accuracy

Table 4: Techniques are used in Public Health

Technique	Disease Name	Highest Accuracy	References
SVM,RF,KNN,DT	Parkinson's	SVM=97.22%	[2]
NB,KNN,C4,5DT,RF,SVM	Liver Disease	KNN=98.6%	[57]
LR,Adaboost,SVM,DT,	DB	SVM=94.4%	[54]
SVM,ANN	Malaria	SVM=89%	[63]
DNN	Diabetes	DNN=83.67%	[62]
MLP, KNN, CART, SVM, NB.	Breast cancer	MLP=96.70%	[33]

NB,LS-SVM,Adabag,Adaboost, RF,SVM,Logit,LDA	Breast cancer	Adaboost=99.08%	[42]
BN,LR,MLP,SMO,DT	Liver cancer	SMO=93.33%	[50]
NB,SVM,RF,LR,ANN	Heart disease.	SVM=97.53%	[39]
MLP,SVM,KNN,C4.5,RF	Cancer	RF=99.45%	[5]
LR,NN,VM	Chronic kidney	VM=97.8%	[51]
,FR,MVS,NNKAdaboost	Heart Disease	95.24=FR%	[21]
,MVS-ACP,NNK-ACP EM-PCA-Fuzzy Rule-Based	Breast Cancer	EM-PCA-Fuzzy Rule-Based93.6=%	[73]
SVM, GEPSVM, TSVM	Alzheimer's	TSVM=92.75%	[44]
SVM,L1-Logistic,L2-Logistic,RF,RUSRF	Alzheimer's	SVM=73.33%	[59]
RF,SVM,AB,BT,GL	Diabetes	RUSRF=90.60%	[52]
LR,RF,SVM,SGB	Heart Disease	RF=89.97%	[41]
LR,KNN,BaggedTree,CNN	CHD	LR=86.51%	[85]
SVM,KNN,DT,NB,LR	Diabetes	KNN=85.29%	[23]
SVM,RF,ANN	Post-Traumatic stress	LR=77.61%	[109]
RF,C5.0,SVM,KNN	Glaucoma	RF=97.17%	[89]
RF,NB,SMO,RBF,MLPC,SLG	CKD	RF=98.00%	[26]
NB,KNN.ANN,DT	Diabetes	RF=99.35%	[36]
BN,NNK	Thyroid	NB=88%	[10]
PLM,NB,BN,BNB,FR,RL,MVS	Dementia	93.44=NNK%	[37]
NNK,BN,MVS,4.5C	Breast Cancer	73.98=MVS%	[115]
FBR,MVS,BN	Suspicious Thyroid	95.99=BN%	[91]
MVS,BN,NNK,NN	Brain Tumor	83.92=FBR%	[111]
MVS,NNK,FR,BN,RL	Diabetes	98=MVS%	[100]
TD,NNK,MVS,NNA	Skin Lesion	98=FR%	[118]
MVS,BN,RL	Kidney	92.50=NNA%	[38]
TRL-4,tsooBadA,MVS,RL	Heart diseases	76.70=MVS%	[77]
MVS,BN	Liver Disease	82=MVS%	[45]
BN,FR,TD,MVS,NNA	Cancer	79.66=MVS%	[92]

VII. Cross-Validation Technique

The predictive performance of the models is evaluated using the Cross-Validation technique to estimate how each model performs outside the sample to a new dataset also identified as to test data. The reason for using the cross-validation techniques is to fit it into a training dataset when we fit a model [33].Cross-validation was applied to achieve the best results to measure the numerical performance of a learning operator [10]. This was not achieved to properly isolate and compare the performance of the different methods concering the weighting of the propensity score. Through several steps, we measured the quality of the various propensity score matching methods [53].The classifier's accuracy calculation is the average accuracy of k-folds. Subsampling is done in bootstrap validation with equivalent substitution from the training dataset [59]. Effective use of the 10-fold cross-validation was found to be a good and reasonable compromise between offering accurate performance estimates and being computationally feasible and preventing overfitting [57].

Table 5: Summary of validation Technique in Public Health

Disease Name	Validation Methods	References
Parkinson Disease	10 fold	[35]
Liver Disease	10 fold	[57][45]
Diabetes Disease	10 fold	[54][52][23]
Malaria Disease	5 fold	[1]
Heart Disease	5 fold	[7]
Breast cancer Disease	10 fold	[33][73][115]

Breast cancer Disease	5 fold	[42]
Liver cancer Disease	10 fold	[50]
Heart disease	10 fold	[39][41][77]
Cancer Disease	5 fold	[5]
Chronic kidney disease	10 fold	[51]
Heart Disease	5 fold	[21]
Alzheimer's Disease	10 fold	[44][59]
CHD	5 fold	[85]
Post-traumatic stress Disease	10 fold	[109]
Glaucoma Disease	10 fold	[89]
CKD	10 fold	[26]
Diabetes Disease	5 fold	[36]
Thyroid disease	10 fold	[10]
Dementia Disease	10 fold	[37]
SuspiciousThyroid Disease	5 fold	[91]
Brain Tumor Disease	10 fold	[111]
Diabetes Disease	5 fold	[100]
Skin Lesion Disease	10 fold	[118]
Kidney Disease	5 fold	[38]
Cancer Disease	10 fold	[92]

VIII. Model Evaluation Technique

After the estimation, the performance of the predictive models is evaluate in terms of accuracy, accuracy, and recall of unseen data using the k-fold cross-validation technique to test their abilities [33]. Classification performance is evaluating the precision, sensitivity, and specificity of each system as it is a widely accepted tool of classification performance evaluation and generalization error estimation [60]. It is mention that the F1 score can be affect distorted class ratios when used as a quality indicator. Both AUC and F1 scores are compared using paired t-tests to updated Bonferroni inference thresholds [59].Here we can summarize different methods of performance evaluation as below,

Table 6: Summary of Performance Evaluation Methods

Performance Evaluation Method	References
Specificity, Sensitivity, F-Measure, Accuracy, Precision, Cohen-Kappa Statistic	[8]
RMSE,ROC	[10]
Specificity, Sensitivity, F-Score,Accuracy,ROC,K-S Test	[18]
Accuracy, Precision, Recall	[24]
MSE,MAE,NMSE	[44]
RMSE,RSE,RAE,MSE	[45]
Specificity, Sensitivity,PLR,NLR,DP.PPV,NPV	[57]
Specificity, Sensitivity, Accuracy	[60]
AUC, Specificity, Sensitivity,F1-Score,Precision,Recall	[61]
Specificity, Sensitivity,ROC	[63][68]
Fishers Exact Test	[64]
ROC	[69][115][98][75]
Accuracy, Recall, Precision, TP rate, Precision, NPV, FP rate, RME, F1-measure, G-mean	[70]
MAE,RAE,RMSE,RSE	[71]
FROC	[74]
Accuracy, Specificity, Sensitivity, Precision, (ROC)	[75]
F1 score, Precision, and Recall,NPV	[81]
DR, Specificity, Sensitivity	[95]
RRSE,Accuracy	[96]
RMSE,R-Square	[114][91]

IX. Limitations

While the application of machine learning approaches to healthcare problems is unavoidable given the complexity of processing massive amounts of data, the need to standardize standards of interpretable ML in this field is critical [28]. Although very broad, these data sets can also be very limited (e.g., system data can only be accessible for a small subset of individuals). Several machine learning methods effectively address these restriction but are still subject to the usual sources of bias commonly found in experimental studies [62]. The limitation of using SVM is its interpretation, computational costs for larger datasets, and SVM is essentially a binary classifier. A Simplified decision tree with four attributes for a multi-class decision problem [16]. A model that is overfitted is more complicated than the data can explain. For a genuine disease-related structure, an overfitted model may have too many free parameters and thus risk confusing random noise or another confounding in the training data. This is a pervasive problem in numerical machine learning because it is often possible to set the complexity of the model as high as required to achieve arbitrarily high prediction accuracy [7]. Some limitations of traditional medical scoring systems are the presence of the input set of intrinsic linear combinations of variables, therefore they are not able to model complex nonlinear interactions in medical domains. In this study, this weakness is addressed by using classification models that can implicitly detect complex nonlinear associations between independent and dependent variables as well as the ability to identify any potential correlations between predictor variables [63].

X. Conclusion

To inform clinicians and policymakers, systems powered by machine learning will have to deliver results of interest in action through clinical trials or real-world performance observations. Eventually, classification approaches such as clustering and artificial neural networks would require a complete set of experiments. Most of the researchers used the traditional machine learning algorithm to analyze public health data like SVM, RF, NB, LR, NN, KNN, ANN, and DT and 10-fold cross-validation provide the better results. But in public health, the challenge is pose the high volume of healthcare data. As a result, the challenge in public health to handle big data. Besides, there are a lot of public health researchers facing problems. Most of that found in a different research paper are classification problems in public health data. Overfitting and data imbalances are problems in public health. In our review paper, we find some challenges which keep in mind every public health researcher because most of the research paper discussed these problems, and most of the researchers have faced these problems.

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