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METHODS FOR ENHANCING MEDICAL DECISION SUPPORT WITH MACHINE LEARNING

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Abstract:
According to estimates provided by the World Health Organization, the cost of medical care is going up all over the world. Because of this, health care systems need to improve their capacity to treat patients in a timely and cost-effective manner in order to slow the rate at which costs are increasing. Nowadays, motivators are all the rage. I will argue that the use of machine learning techniques to healthcare will improve treatment outcomes, and I will be in a position to construct health care information systems. The results of my research highlight creative new methods for promoting collaboration. Skills in machine learning and in working with medical professionals, in addition to cutting-edge methods for simulating the responses of patients to therapy.

Adapting is a necessary aspect of my collaboration with other therapeutic providers. Biopsies taken for breast cancer that turn out to be benign are being used to address the challenging challenge of identification using machine learning algorithms. I began by becoming a student of inductive logic programming in order to choose rules that do erroneously identify cancer cases and display encouraging outcomes that do not serve to in service of the clinical goal and shine light on the work that needs to be done. I then provide a platform for communication and collaboration between AI researchers and medical practitioners. By drawing on the experience of doctors, a model may be developed and modified in such a way that the objective of conservatism is to miss no cases of malignancy.

The things that I've discovered through the course of my work include calculating individual responses to treatment in the marketing discipline, which is where uplift modelling is being utilized to perform the two most important roles in the field of medicine. Priority should be given to identifying those patients within a patient population who are most likely to suffer a heart attack. Because of COX-2 inhibitor medication, and the second reason is learning about the distinctive characteristics of in situ breast cancer that affects older women. I will begin by presenting a statistical learner that constructs Bayesian networks with the goal of minimizing the arithmetic mean squared error (RMSE). I will then show that trained networks are capable of capturing the clinically significant characteristics of breast cancer that is relatively slow-growing and in situ. After that, I will present a support vector machine that I developed expressly for the purpose of boosting AUU. I will also display some encouraging results for COX-2 drugs and breast cancer duties, in addition to a synthetic version of a marketing assignment.

Keywords: Machine Learning , Artificial Neural Network

I. Introduction:

Access to high-quality medical treatment is among the most important factors that play a role in determining a person's likelihood of living for a longer period of time, as well as their sense of safety and happiness in today's society. To make a bad situation even worse, the cost of medical care is very high. It is managed by the World Health Organization (WHO), which estimates that the total expenditure of health care in the United States was 17.0 trillion dollars in 2012, making it the world's largest economy according to GDP (World Health Organization) (2015). GDP in relation to expenditure in the same estimate for 1990 places growth in the United States at 13.1%. The United States is not the only country to see an increase in their pricing.

According to the World Health Organization (WHO), in 2012 France spent 11.6% of its GDP on medical care, which is significantly more than the country's spending of 10.1% in the year 1990. Germany boosted its spending to 11.3%, up from 10.4% in the previous year. Canada expenditure grew from 8.7% to 10.9%. The budget for government spending in the United Kingdom was increased from 6.9% to 7.1%, bringing the total to 9.3% of GDP. The pattern can be seen all throughout the world, albeit with a few significant exceptions here and there.

The cost of medical treatment cannot proceed to increase at the current rate for much longer. In order to simultaneously meet the objectives of delivering care and reducing costs, health care systems everywhere will need to enhance the efficiency with which they do it. The Health Information Technology for Economic and Clinical Health Act (HITECH Act) was passed in the United States in 2009 in order to solve this issue. This act was a component of a larger plan to address the problem.

Providers now have an incentive to make better use of in terms of both efficiency and effectiveness. Developing a healthcare system that is based on information that is more recent in order to create a healthier population through the widespread adoption and utilisation of HER (Blumenthal, 2010). Since that time, data collectors have amassed vast volumes of information, both organised and unstructured, but we are just now beginning to make productive use of this information.

The possibility that cutting-edge data and technology developments may lead to improvements in patient treatment.

1.1 Accuracy Medication

The Precision Medicine Initiative was first established under Barack Obama's watch as President of the United States.

Activities to be carried out within the framework of the State of the Union address For the purposes of this paper, we shall adhere to the definition provided by the National Research Council (2011).

The process of tailoring a patient's medical care to their specific set of circumstances is referred to as "precision medicine," and the phrase "precision medicine" describes this technique. It is not so much the ability to produce medications and medical devices that are specific to individual patients that makes this possible; rather, it is the capacity to segment the population into groups with varied degrees of vulnerability to a disease.

Concerning the ailment at hand, namely with regard to its biology and/or prognosis Diseases they may contract, or how they may react to a specific treatment Concerning the ailment at hand, specifically with regard to its biology and/or prognosis

The concept of selecting a course of treatment while also taking into account several other medical concerns

It is not a new concept that personalized medicine takes into account the specific characteristics of each individual patient; however, with the proliferation of electronic health records (EHRs), the decline in the cost of genome sequencing, the rise in the prevalence of genetic disorders, and the availability of computing power, there has never been a better time to launch a programme like that (Collins and Varmus, 2015). It is a rallying cry to aim for perfection in the healthcare endeavour, and in order to make this a reality and maximise the potential it already possesses, it will take the united efforts of researchers from a wide range of fields. The programmer is only available in the United States, despite the fact that it has global significance and may have repercussions worldwide.

1.2 The Application of Machine Learning to Medicine

The development of a health care system that is information-based is supported by a number of financial incentives. System, but the next challenge for scientists is to figure out how to effectively use all of that data. There will be an increase in the amount of information and tools that may be accessed. Larger and more abundant medical datasets that include more relations, timestamps, unstructured data, and other types of information are needed. Due to the fact that data is becoming more difficult and is originating from a wide variety of sources, there is an increasing demand for novel approaches to the process of working with heterogeneous datasets. Machine the accumulation of new information grants access to untapped resources, which ultimately results in improved patient care (Page, 2015). Machine teaching (Mitchell, 1997) is an area of artificial intelligence that comprises the automation of once manual processes.

The focus of this approach is on computer programmers who "learn" from data by constructing models, which can then be used to generate predictions and draw conclusions. What the majority of people encounter on a day-to-day basis, possibly even without their knowledge, as a result of machine learning For example, the search engine that Google uses makes predictions about the results that are most relevant to the user's search keywords by using a technique called machine learning. As an illustration, Amazon uses an automated system to determine which products to recommend to a user based on the information obtained from the customer's previous transactions. This data is collected automatically.

Who are the consumers who are most inclined to make a purchase? Machine learning has demonstrated its influence on the business world alongside industry heavyweights such as Google and Amazon, but it has been unable to match its success in healthcare settings.

II. Literature Survey

1. **Siyabend Turgut et al., "*Microarray Breast Cancer Data Classification Using Machine Learning Methods*" [IEEE 2018]**

The paper uses microarray breast cancer data for classification of the patients using machine learning methods. In the first case, eight different machine learning algorithms are applied to the dataset and the results of classification were noted. Then in the second case, two different feature selection methods such as Recursive Feature Elimination (RFE) and Randomized Logistic Regression (RLR) were applied on the microarray breast cancer dataset and 50 features were chosen as stop criterion. Again, the same eight machine learning algorithms were applied on then modified dataset. The results of the classifications are compared with each other and with the results of the first case. The methods applied are SVM, KNN, MLP, Decision Trees, Random Forest, Logistic Regression, Ad boost and Gradient Boosting Machines. After applying the two different feature selection methods, SVM gave the best results. MLP is applied using different number of layers and neurons to examine the effect of the number of layers and neurons on the classification accuracy [3].

2. **Varalatchoumy M et al.,** ***"Four Novel Approaches for Detection of Region of Interest in Mammograms - A Comparative Study"*** **[ICISS 2017]**

The paper compares Four Novel approaches used for detection of Region of Interest in Mammographic images based on database and Real time images. In Approach I histogram equalization and dynamic thresholding techniques were used for preprocessing. Region of Interest (ROI) was partitioned from the preprocessed image by using particle swarm optimization and k-means clustering methods. In Approach II preprocessing was done using various morphological operations like erosion followed by dilation. For the identification of ROI, a modified approach of watershed segmentation was used. Approach III uses histogram equalization for preprocessing and an advanced level set approach for performing segmentation. Approach IV, which is considered to be the most efficient approach that uses different morphological operations and contrast limited adaptive histogram equalization for image preprocessing. A very novel algorithm was developed for detection of Region of Interest. Approaches I and II were applicable for Mammographic Image Analysis Society (MIAS) database images alone. Approaches III and IV were applicable for MIAS and Real time hospital images. The various graphs presented in the comparative study, clearly depicts that the novel approach that used a novel algorithm for detection of ROI is proved to be the most efficient, accurate and highly reliable approach that can be used by radiologists to detect tumors in MRM images

3. **Ammu P K et al.,** ***"Review on Feature Selection Techniques of DNA Microarray Data"*** **[IJCA 2013]**

This paper reviews few major feature selection techniques employed in microarray data and points out the merits and demerits of various approaches. Feature selection from DNA microarray data is one of the most important procedures in bioinformatics. Biogeography Based Optimization (BBO) is an optimization algorithm which works on the basis of migration of species between different habitats and the process of mutation. Particle Swarm Optimization (PSO) is an algorithm which works on the basis of movement of particles in a search space. Redundancy based feature selection approaches can be used to remove redundant genes from the selected genes as the resultant gene set can achieve a better representation of the target class. A two-stage hybrid filter wrapper method where, in the first stage a subset of the original feature set is obtained by applying information gain as the filtering criteria. In the second stage the genetic algorithm is applied to the set of filtered genes. Gene selection based on dependency of features where the features are classified as independent, half dependent and dependent features. Independent features are those features that doesn't depend on any other features. Half dependent features are more relevant in correlation with other features and dependent features are fully dependent on other features [5]

4. **Bing Lan Li et al., *"Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation"* [ELSEVIER 2010]**

A new Fuzzy Level Set algorithm is proposed in this paper to facilitate automated medical image segmentation. It can directly evolve from the initial segmentation by spatial fuzzy clustering where centroid and the scope of each subclass are estimated adaptively in order to minimize a pre-defined cost function. The controlling parameters of Level Set evolution are also estimated from the results of fuzzy clustering. The level set methods utilize dynamic variational boundaries for image segmentation. The new Fuzzy Level Set algorithm automates the initialization and parameter configuration of the level set segmentation, using spatial fuzzy clustering. It employs a Fuzzy-C means (FCM) with spatial restrictions to determine the approximate contours of interest in a medical image. Moreover, the Fuzzy Level Set algorithm is enhanced with locally regularized evolution. Such improvements facilitate level set manipulation and lead to more robust segmentation. Performance evaluation of the proposed algorithm was carried on medical images from different modalities. The results confirm its effectiveness for image segmentation [6].

III. Machine Learning Techniques:

3.1 Bayesian Belief Network is a graphical representation of different probabilistic relationships among random variables in a particular set. It is a classifier with no dependency on attributes i.e it is condition independent. Due to its feature of joint probability, the probability in Bayesian Belief Network is derived, based on a condition — P(attribute/parent) i.e probability of an attribute, true over parent attribute.

3.2 Naive Bayes Classifiers

- Naïve Bayes algorithm is a supervised learning algorithm, which is based on **Bayes theorem** and used for solving classification problems.
- It is mainly used in *text classification* that includes a high-dimensional training dataset.
- Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.
- **It is a probabilistic classifier, which means it predicts on the basis of the probability of an object**.
- Some popular examples of Naïve Bayes Algorithm are **spam filtration, Sentimental analysis, and classifying articles**.

3.3 Tree-Augmented Naïve Bayes

- Tree-Augmented Naïve Bayes (TAN) is a modification of Naïve Bayes with the strong independence assumption relaxed (Friedman et al., 1997). Specifically, all of the non-class variables are still dependent on the class variable, but may also be dependent on one other non-class variable. This relaxation is accomplished by constructing a maximum weight spanning-tree amongst all of the non-class variables. The weights of the edges used to construct the tree are the conditional mutual information of the two connected variables, conditioned on the class variable.

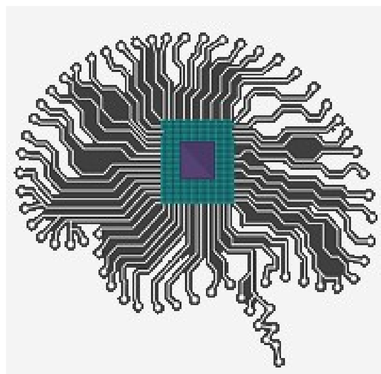
o By building the maximum-weight spanning-tree on the graph of conditional mutual information between non-class variables, and by allowing non-class variables to be dependent on at most one other variable, TAN accomplishes two important properties.

o

1. It produces the maximum likelihood tree, given the data.

o 2. The tree can be learned in polynomial time.

3.4 Artificial Neural Network



Artificial Neural Network Tutorial provides basic and advanced concepts of ANNs. Our Artificial Neural Network tutorial is developed for beginners as well as professions.

The term "Artificial neural network" refers to a biologically inspired sub-field of artificial intelligence modeled after the brain. An Artificial neural network is usually a computational network based on biological neural networks that construct the structure of the human brain. Similar to a human brain has neurons interconnected to each other, artificial neural networks also have neurons that are linked to each other in various layers of the networks. These neurons are known as nodes.

Artificial neural network tutorial covers all the aspects related to the artificial neural network. In this tutorial, we will discuss ANNs, Adaptive resonance theory, Kohonen self-organizing map, Building blocks, unsupervised learning, Genetic algorithm, etc.

3.5 Support Vector Regression:

Support Vector Machine is an algorithm for supervised learning that can be used for both classification and regression problems. So when we use it to solve problems involving regression, we call it Support Vector Regression.

Support Vector Regression is an algorithm for regression that works with variables that are always the same. Support Vector Regression uses the following words and phrases:

Kernel is a function that is used to map data with fewer dimensions to data with more dimensions.

In general, a hyper plane is a line that separates two classes. In SVR, however, it is a line that helps predict the continuous variables and covers most of the data points.
Boundary line: Boundary lines are the two lines apart from hyper plane, which creates a margin for data points. Support vectors are the points that are closest to the hyper plane and belong to the opposite class.

IV Medical Background

4.1 Quantifiable Conclusion Provision

Clinicians may have numerous patients and plenty of patient information. Clinicians must utilize the knowledge to diagnose and treat patients. Clinicians must learn about illnesses, treatments, outcomes, and more to use that information. Clinical trials and systematic reviews guide clinical practice, but the work is massive and crucial for optimal patient care. EHRs also help and strain practitioners. Clinicians must develop and maintain another skill set to capture information in more organized ways for subsequent use.

4.2 Clinical Trials

Estimating disease risk from exposures or treatments is a major public health and patient care issue. RCTs are the gold standard for determining average treatment effects in clinical trials (Friedman et al., 2010). (ATE). In an RCT, patients are randomised to treatment arms (e.g., treatment and control) and the rate or probability of a result is assessed (see Figure 3.1). Randomization balances confounding factors, ensuring bias-free treatment effect measurements. Equation 3.1 calculates the average treatment impact from outcome rate differences between treatment and control. Treatment success depends on the assessed outcome's desirability. The best-performing therapy is chosen.

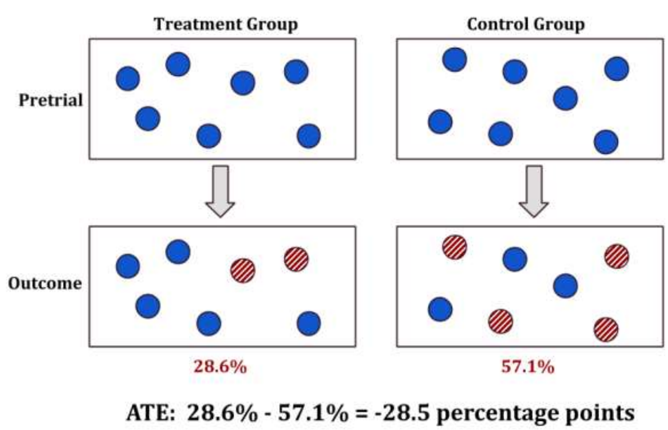


Figure 1: a randomized controlled trial's ATE. Striping implies a heart attack, but the others do not.

5. Datasets

There are undoubtedly a great number of conceivable applications of machine learning in the field of medicine; nevertheless, the majority of our effort has been concentrated on three specific tasks, two of which are associated with breast cancer, and one of which is associated with adverse medication events. Patients who have undergone breast biopsies and been given a non-definitive 1 diagnosis are the focus of one of the tasks, and the objective of this task is to identify the most suitable course of treatment for these patients. When it comes to predicting the development of breast cancer, another objective is to identify the variables that set older people' more placid in situ breast cancer apart from those of younger patients. Identifying the patients who are at the greatest risk of experiencing ill effects as a result of taking COX-2 inhibitors is the primary objective of our third task.

5.1 Upgrade Prediction

Diagnostic mammograms and ultrasounds are conducted on patients with suspected breast lesions. A core needle biopsy (CNB) is advised if the finding is worrisome.

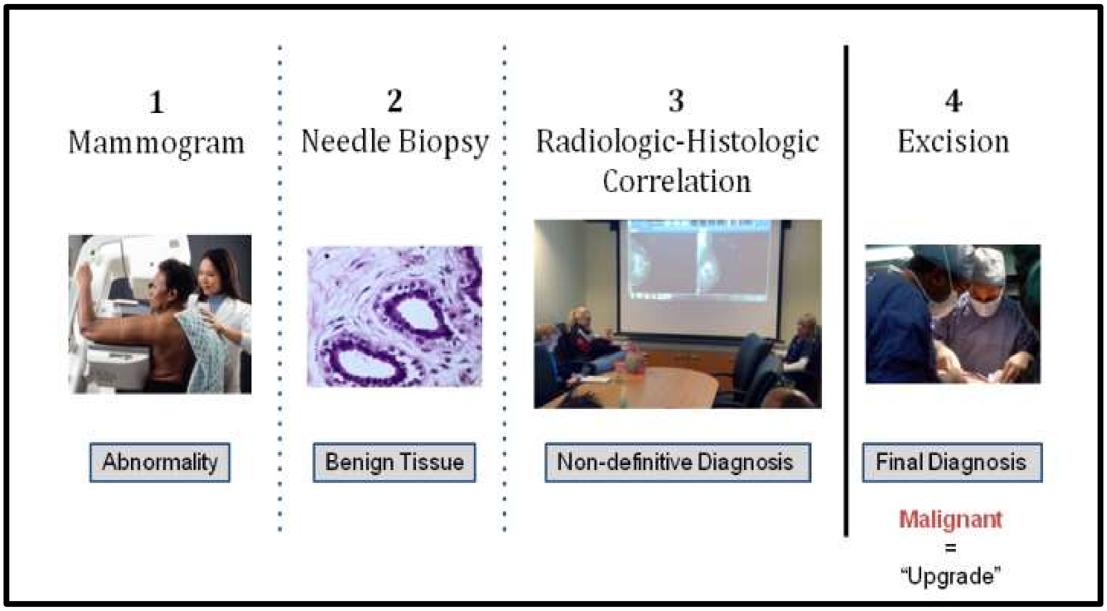


Figure:2 Non-definitive biopsy clinical method. Step 1: A lady has abnormal imaging and needs a needle biopsy. Step 2: Pathologist diagnoses biopsy as benign. Step 3: Radiologists and pathologists advocate surgery after finding no conclusive diagnosis. Step 4 involves surgery and the final diagnosis.

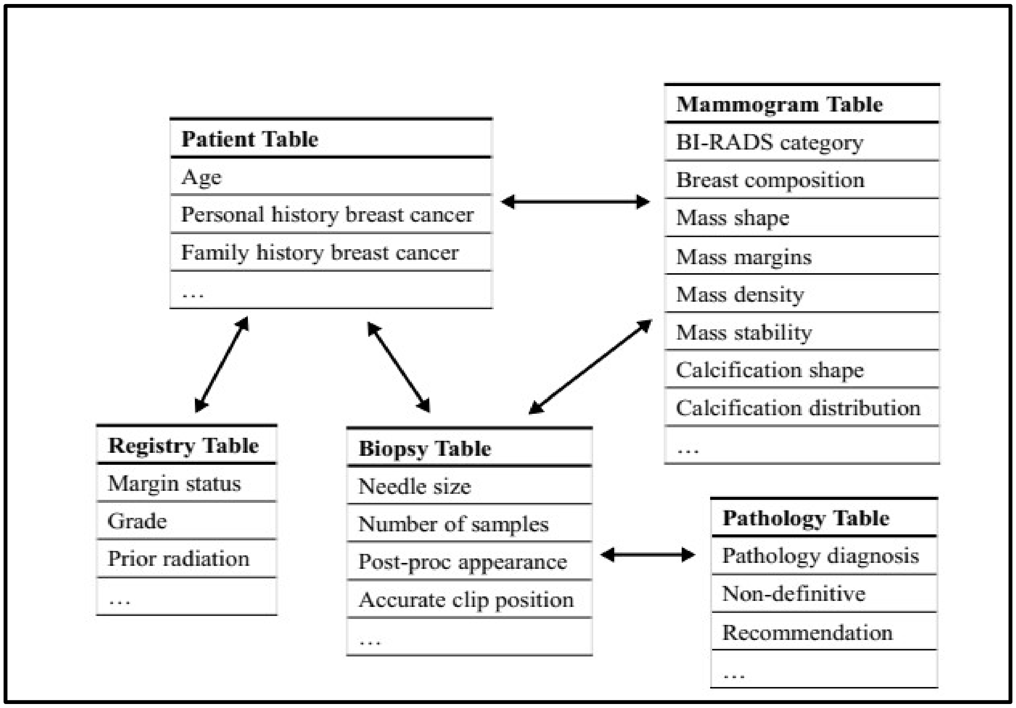


Figure 3: Our breast-imaging database. Gather our database tables are boxes with arrows related tables.

5.2 COX-2 Inhibitors

COX-2 inhibitors are NSAIDs that target the COX-2 enzyme to reduce inflammation and discomfort without impacting COX-1. This lowers NSAID-related gastrointestinal side effects, which is beneficial (Russell, 2001).

Thus, Vioxx, Bextra, and Celebrex were widely used in medicine. Unfortunately, new patient data indicated that COX-2 inhibitors also significantly increased the risk of myocardial infarction (MI), or "heart attack" (Kearney et al., 2006). Vioxx and Bextra were withdrawn, while Celebrex included a warning.

These medications must be prescribed more cautiously. Doctors avoid providing COX-2 medicines to individuals who are more likely to experience side effects. To identify at-risk individuals, estimate the customized MI treatment risk of COX-2 inhibitors versus no therapy.

	COX-2 Inhibitors		No COX-2 Inhibitors	
Features	MI	No MI	MI	No MI
12,496	184	1,776	184	1,776

Table: 1 Composition of the COX-2 dataset

5.3 Pretend Advertising Movement

Uplift modelling predicts when marketing activity makes a consumer more inclined to buy a product. Maximizing the uplift curve makes obvious sense, but since customer groups cannot be directly seen, it is hard to tell if it produces classifiers that can precisely identify Persuadable.

We created a synthetic customer population and simulated marketing activity to create a dataset 3 with ground truth customer groups to verify that maximizing uplift identifies Persuadables.

Algorithm 5.3 Marketing Campaign Simulation

```
BN ← GenBayesNet();                          ▷ Random Bayesian network
MarkCustomerNode(BN);   ▷ Select (four-value) customer type node
Pop ← SampleCustomers(BN);           ▷ Sample a customer population
for C ∈ Pop do
    if RandomTarget(C) then                  ▷ Choose to target or not
        MarkTargetResponse(C);
    else
        MarkControlResponse(C);
    end if
end for
```

5.4 Results

True positives are benign instances accurately detected, whereas false positives are malignant cases wrongly labelled as benign. False negatives are benign instances misdiagnosed as malignant, whereas genuine negatives are malignant ones appropriately discovered. Precision and recall—positive predictive value and sensitivity—are also reported. Each row shows the outcomes of the cases kept out from training in a single fold. Forman and Scholz recommend summary statistics (2010).

Each of the 17 folds provided a hypothesis that was reduced to a rule. Many folds yielded identical rules. The five distinct rules established by all folds are listed below each fold.

We personally translated them from first-order logic to English for readability. The performance of each unique rule on the whole dataset and the number of folds each rule was learnt can be found in.

Table 2 : 17-Fold Cross Validation Results

Fold	TP	FP	FN	TN	Precision	Recall	$F_{0.1}$
1	2	0	3	1	1.0	0.40	0.99
2	1	0	3	1	1.0	0.25	0.97
3	4	1	1	0	0.8	0.80	0.80
4	2	0	3	1	1.0	0.40	0.99
5	1	0	3	1	1.0	0.25	0.97
6	4	0	1	1	1.0	0.80	1.00
7	0	0	4	1	0.0	0.00	0.00
8	2	0	3	1	1.0	0.40	0.99
9	4	0	1	1	1.0	0.80	1.00
10	2	0	3	1	1.0	0.40	0.99
11	1	0	4	1	1.0	0.20	0.96
12	1	1	4	0	0.5	0.20	0.49
13	0	0	5	1	0.0	0.00	0.00
14	0	0	5	1	0.0	0.00	0.00
15	0	0	4	1	0.0	0.00	0.00
16	0	0	4	1	0.0	0.00	0.00
17	1	0	3	1	1.0	0.25	0.97
Summary	**25**	**2**	**54**	**15**	**0.93**	**0.32**	**0.91**

All five criteria predict many benign instances, and only two miss malignancies. Post-biopsy imaging (a common aspect of CNB), mass margin descriptors, and patient history are covered in many guidelines. Our interdisciplinary team—radiology, pathology, and surgery—confirmed that these findings have clinical significance. The cross-validation results suggest that we may reduce the number of patients with non-definitive diagnoses who undergo excision by 28%, with confidence that 93% of them do not have cancer.

Table.2: The five unique learned rules that predict a non-definitive case is benign.

1 The patient had no previous surgery, imaging showed no spiculated mass margin, and post-biopsy imaging showed the anomaly.

2 Imaging showed no unclear mass margin, spiculated mass margin, or disappearance of the anomaly post-biopsy.

3 Imaging showed no spiculated mass margin, and post-biopsy imaging showed the anomaly.

4 Imaging showed no unclear mass boundary, and post-biopsy imaging showed the abnormalities.

5 The patient had no breast cancer history, and post-biopsy imaging showed the anomaly.

Table 3 : Individual Rule Performance on Full Dataset (# Folds is the number of folds in which a rule was learned)

Rule	# Folds	**TP**	FP	FN	TN	Precision	Recall	$F_{0.1}$
1	10	**30**	0	49	17	1.00	0.38	0.98
2	4	**29**	0	50	17	1.00	0.37	0.98
3	1	**34**	1	45	16	0.97	0.43	0.96
4	1	**31**	1	48	16	0.97	0.39	0.95
5	1	**28**	0	51	17	1.00	0.35	0.98

Looking at the specific rules created yields further intriguing findings. Importantly, the two rules that missed single malignant instances were each learnt in a single fold, whereas Rule 1, which misses no malignancies, was learned in 10 (of 17) folds. Rule 2, the second-strongest rule that misses no cancers, was learnt four times. This suggests these two criteria capture a large signal throughout the sample. Clinicians select clinical rules.

favour cancer-detecting rules. Our results suggest that fold coverage and clinical judgement may be a criterion for selecting the best rules. Our project prioritises the first two guidelines. These rules may apply to fresh data.

Imaging-related predicates stand out. First, all criteria require that post-biopsy imaging shows the anomaly. This need is counterintuitive. If the anomaly fades, it shows that the needle biopsy sampled the whole abnormality, making it more likely to be benign. However, how non-definitive biopsy patients are selected may explain this. To confirm imaging abnormalities, all our patients had core needle biopsies. Clinicians may deem the biopsy non-definitive if the anomaly persists on post-biopsy imaging. The biopsy may have been benign if the tissue had been taken enough, but this sampling mistake explains why it was included in our dataset.

Conclusion:

The precision medicine programme encourages innovative methods and technologies to capitalise on diverse medical data. I think machine learning will be crucial in this space. Machine learning researchers require domain adaptation. New, difficult goals require new models and solutions. My precision medicine machine learning research is shown here. This article describes my work customising traditional machine learning approaches to fulfil tough clinical objectives by working closely with doctors and using their experience.

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