International Journal of Trend in Innovative Research (IJTIIR)
Available Online @ www.ijtiir.com | ISSN: 2582-0354

Techniques for Machine Learning: Identifying Heart Disease within E-Healthcare through Implementation: Logistic Regression Model

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Abstract-- Machine learning is a field of study that developed from the search for artificial intelligence. Some academics were intrigued by the idea of letting computers learn from data in the early stages of AI as an academic field. They made an effort to tackle the issue using a variety of symbolic techniques as well as what were at the time referred to as "neural networks," which were primarily perceptrons and other models that were subsequently discovered to be reimagining's of the generalized linear models of statistics. Moreover, probabilistic reasoning was used, particularly for automated medical diagnosis. A computer programme is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, increases with experience E," wrote Tom M. Mitchell in a more formal definition that is frequently cited. Instead of describing the discipline in terms of cognition, this characterization of the tasks in which machine learning is concerned offers a fundamentally operational definition. In his essay "Computing Machines and Intelligence," Alan Turing made the suggestion that the question of "Do computers think?" be changed to "Can machines perform what we (as thinking creatures) can do?" Artificial intelligence has a subfield called machine learning. Its main goal is to create systems that can learn from their experiences and make predictions as a result. It builds a model using algorithms that have been trained on training data to improve prediction and accuracy. The model forecasts heart disease using the new input data. The models by utilising machine learning to find hidden patterns in the input dataset. It provides precise forecasts for fresh datasets. The dataset and fill in the missing values before can use a machine learning algorithm. The model forecasts heart disease using the new input data, and its precision is subsequently evaluated.

Key words: *Techniques for machine learning: Identifying Heart disease within E-Healthcare through Implementation: logistic regression model*

I. INTRODUCTION

Data mining employs a variety of machine learning techniques, albeit with distinct purposes. Much of the misunderstanding between these two research communities—which frequently have separate conferences and journals, with ECML PKDD being a notable exception—results from the fundamental presumptions they operate under. For example, performance in machine learning is typically measured in terms of its capacity to replicate existing knowledge, whereas in knowledge discovery and data mining (KDD), the main objective is the discovery of previously undiscovered knowledge. While supervised methods cannot be employed in a typical KDD job due to the lack of training data, uninformed (unsupervised) methods will readily beat other supervised methods when evaluated with respect to known knowledge.

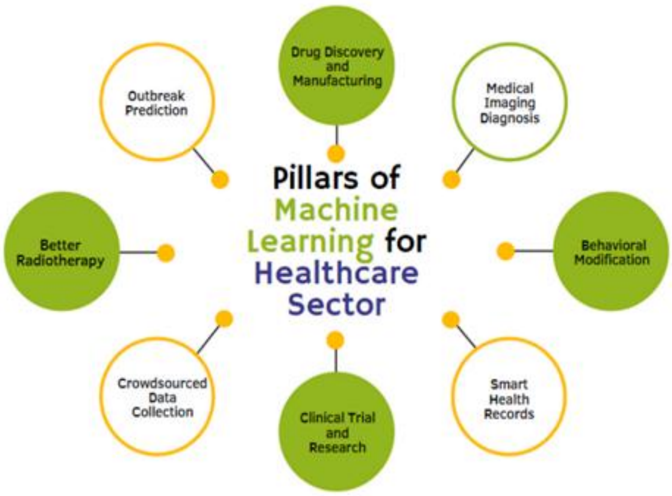

Figure:1 Pillars of machine learning for healthcare services.

Contemporary machine learning has two purposes: the first is to classify data using established models, and the second is to forecast future results using these models. Computer vision of moles combined with supervised learning may be used to train a hypothetical algorithm tailored to data classification to identify malignant moles. While a stock trading machine learning algorithm may alert the trader to potential future projections.

II. MACHINE LEARNING AS AN AI SUBFIELD:

While research on symbolic/knowledge-based learning within AI did continue, leading to inductive logic programming, the more statistical line of enquiry was being conducted in pattern recognition and information retrieval outside of the purview of AI. Around the same time, both AI and computer science gave up on research into neural networks. Researchers from other fields, such as Hopfield, Rumelhart, and Hinton, continued this line of enquiry as "connectionism" outside of the AI/CS field.

The reintroduction of backpropagation in the middle of the 1980s was the key to their main success.

In the 1990s, machine learning (ML), which had been reorganized as a distinct field, began to thrive. The field's focus shifted from developing artificial intelligence to solving practical problems that can be solved. It started focusing on techniques and models taken from statistics and probability theory rather than the symbolic approaches it had received from AI.

Many sources still claim that machine learning is still a branch of artificial intelligence as of 2020. The main point of contention is whether or not all machine learning (ML) constitutes AI, as doing so would allow anyone using ML to claim they are doing so. Others believe that only a small portion of machine learning—those considered to be "intelligent"—comprises AI.

Judea Pearl provides an explanation of the distinction between ML and AI in The Book of Why. As a result, while AI assumes an agent interacting with the environment to learn and take actions that maximise its chance of successfully attaining its goals, ML learns and predicts based on passive observations.

Machine learning concentrates on prediction, based on known qualities:

While machine learning concentrates on prediction, based on known qualities learnt from the training data, and data mining concentrates on the finding of (previously) unknown properties in the data, both techniques frequently use the same methodologies and have significant overlap (this is the analysis step of knowledge discovery in databases). In contrast, machine learning also uses data mining techniques as "unsupervised learning" or as a pre-processing step to increase learner accuracy.

Optimization

Moreover, optimization and machine learning are closely related since many learning problems are phrased as the minimization of a loss function on a training set of samples. The gap between the model's predictions and the actual problem occurrences is expressed by loss functions (for example, in classification, one wants to assign a label to instances, and models are trained to correctly predict the pre-assigned labels of a set of examples).

Generalization

The distinction between machine learning and optimization stems from the generalization objective: although optimization methods can reduce loss on a training set, machine learning is focused on reducing loss on untried samples. Research on characterizing the generalization of different learning methods is ongoing, particularly for deep learning algorithms.

Statistics application in ML:

Although their main objectives are dissimilar, machine learning and statistics are closely connected areas in terms of methodologies. Machine learning seeks generalizable predictive patterns while statistics draws population inferences from a sample. Michael I. Jordan asserts that statistics has a rich history that predates machine learning, from methodological principles to theoretical tools. In addition, he proposed the phrase "data science" as a working title for the entire field.

Data model and algorithmic model are the two statistical modelling paradigms that Leo Breiman defined, with "algorithmic model" generally referring to machine learning methods like Random forest.

Some statisticians have incorporated machine learning techniques:

To generalize from experience is one of a learner's main goals. In this application, generalization refers to a learning machine's capacity to execute tasks or instances accurately after being exposed to a learning data collection. The learning algorithm must develop a comprehensive model of the space of occurrences that will allow it to make sufficiently accurate predictions in new situations. The training examples come from some generally unknown probability distribution (considered representative of the space of occurrences).

Computational learning theory is a subfield of theoretical computer science concerned with the computational study of machine learning algorithms and their performance. Learning theory typically does not provide assurances of algorithm performance due to the finite nature of training sets and the unpredictability of the future. Instead, probabilistic performance constraints are frequently used. One method for calculating generalization error is the bias-variance decomposition.

The complexity of the hypothesis should be equal to the complexity of the function underpinning the data for the optimum generalization performance. The model has under fitted the data if the hypothesis is simpler than the function. The training error lowers as a result of increasing the model's complexity. The model is vulnerable to overfitting if the hypothesis is too complex, and generalization will suffer as a result.

Learning theorists also look at the temporal complexity and viability of learning in addition to performance constraints. A computation is deemed feasible in the computational learning theory if it can be completed in polynomial time. Time complexity outcomes come in two different varieties. Positive results demonstrate the polynomial-time polynomial-class learning of a particular class of functions. Negative findings indicate that some classes cannot be taught in a polynomial amount of time.

Approaches and learning algorithms types:

The methods used by various machine learning algorithms, the kinds of data they input and output, and the kinds of tasks or issues they aim to resolve are all different.

A supervised learning model called a support vector machine separates the data into areas with linear boundaries. The white circles and the black circles are separated here by a linear barrier.

A mathematical model of a set of data that includes the intended inputs and outputs is created by supervised learning techniques. The information is a collection of training examples and is referred to as training data. A supervisory signal, also known as the intended output, is present in each training example along with one or more inputs. Each training example is represented in the mathematical model by an array or vector, sometimes referred to as a feature vector, while the training data is represented by a matrix. Supervised learning techniques develop a function that can be used to anticipate the output connected to fresh inputs through repeated optimization of an objective function. The algorithm will be able to accurately predict the result for inputs that weren't included in the training data thanks to an optimal function. An algorithm is considered to have learned to do a task when, over time, the accuracy of its outputs or predictions increases.

Regression, classification, and active learning are supervised learning algorithm types. Regression techniques are used when the outputs can have any numerical value within a range, while classification methods are used when the outputs are constrained to a small set of values. An email would be the input for a classification system that filters emails, for instance, and the output would be the name of the folder to put the email in.

Although the goal of similarity learning, a subfield of supervised machine learning that is closely related to regression and classification, is to learn from examples using a similarity function that gauges how similar or related two objects are, is not to be confused with these two other subfields. It can be used for speaker verification, visual identification tracking, rating, recommendation systems, and face and voice recognition.

Unsupervised learning algorithms analyse a collection of input-only data to identify patterns, such as grouping or clustering of data points. So, test data that hasn't been labelled, classified, or categorised is used to train the algorithms. Unsupervised learning algorithms locate commonalities in the data and act based on the existence or absence of such commonalities in each new piece of data, as opposed to reacting to feedback. Unsupervised learning is widely used in the area of density estimation in statistics, which includes determining the probability density function. Unsupervised learning, however, also applies to fields that summaries and describe data features.

While performing a cluster analysis, a set of observations is divided into smaller groups, or "clusters," where observations from the same cluster are similar based on one or more predetermined criteria, while observations from other clusters are not. Different clustering methods base their assumptions on different aspects of the data's structure, which is frequently determined by some kind of similarity metric and assessed, for instance, by internal compactness, or the similarity between cluster members, and separation, or the distance between clusters. Other approaches rely on graph connectedness and estimated densities.

Between supervised learning (with labelled training data) and unsupervised learning is semi-supervised learning (with completely labelled training data). Many machine learning researchers have discovered that unlabelled data, when utilised in conjunction with a little amount of labelled data, can generate a significant gain in learning accuracy even though some of the training examples lack training labels.

Although the training labels in weakly supervised learning are generally noisy, constrained, or imprecise, they are frequently less expensive to collect, leading to larger useful training sets.

A subfield of machine learning called reinforcement learning looks at how software agents should behave in a given environment to maximise a theoretical total reward. Owing to its generality, the area is explored in many different academic fields, including statistics, genetic algorithms, multi-agent systems, game theory, control theory, operations research, and information theory. Often, a Markov decision process is used to represent the environment in machine learning (MDP). Dynamic programming approaches are used in many reinforcement learning systems. Since precise models are impractical, reinforcement learning methods are applied. These techniques do not need knowledge of an accurate mathematical model of the MDP. In autonomous vehicles or while learning to play a game against a human opponent, reinforcement learning algorithms are used.

In 1982, the concept of self-learning as a paradigm for machine learning was developed, coupled with the crossbar adaptive array neural network (CAA). It is a learning experience without outside rewards or teacher counsel. The CAA self-learning algorithm computes both decisions for actions and emotions (feelings) regarding consequence scenarios in a crossbar approach. The connection between intellect and emotion powers the system.

It is a system having a single action (or behaviour) an as its sole output and a single situation (s) as its sole input. Neither a distinct reinforcement input nor a recommendation input from the environment exist. The sentiment towards the consequence circumstance serves as the back propagated value (secondary reinforcement). The CAA exists in two environments: the behavioural world in which it acts, and the genetic environment from which it learns initial emotions about circumstances that it will face in the behavioural environment for the first time and only once. The CAA develops a goal-seeking behaviour in an environment with both desirable and unwanted situations after getting the genome (species) vector from the genetic environment.

Principal component analysis and cluster analysis:

As a pre-processing phase before performing classification or predictions, feature learning algorithms, also known as representation learning algorithms, frequently make an effort to maintain the information in their input while simultaneously transforming it in a usable way. While not always being loyal to configurations that are improbable under that distribution, this technique allows reconstruction of the inputs originating from the unknown data-generating distribution. This eliminates the need for manual feature engineering and enables a machine to learn the features and apply them to a particular task.

Either supervised or unsupervised feature learning is possible. Using labelled input data, features are learned in supervised feature learning. Examples include supervised dictionary learning, multilayer perceptrons, and artificial neural networks. Unlabeled input data is used to train features in unsupervised feature learning. Dictionary learning, independent component analysis, auto encoders, matrix factorization, and other clustering techniques are among examples.

The learning representation must be low-dimensional in order for manifold learning algorithms to succeed. Sparse coding techniques make an effort to do this while being constrained by the fact that the learned representation is sparse, i.e., the mathematical model contains a lot of zeros. Without transforming them into higher-dimensional vectors, multilinear subspace learning techniques seek to learn low-dimensional representations for multidimensional data directly from tensor representations. Deep learning algorithms identify a hierarchy of features or many levels of representation, with higher-level, more abstract features defined in terms of (or produced by) lower-level features. A machine is said to be intelligent if it learns a representation that separates the underlying sources of variation from the seen data.

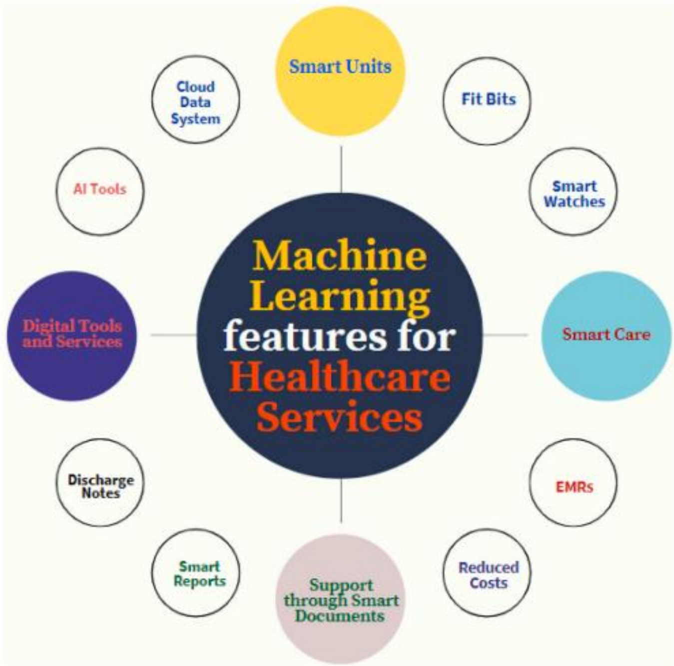

Figure 2: Smart features of machine learning for healthcare domain

Applications of machine learning (ML) are significantly changing the healthcare industry. The goal of machine learning (ML), a branch of artificial intelligence (AI), is to increase the efficiency and precision of medical work. AI offers great hope for countries now struggling with overcrowded healthcare systems and a physician shortage. The best trial sample can be found using the healthcare data, which can also be used to increase the number of data points collected, evaluate trial participants' ongoing data, and correct data-based errors. ML-based methods aid in spotting the first signs of an epidemic or pandemic. In order to assess whether the illness would spiral out of control, this system looks at satellite data, news and social media reports, and even video sources. Using ML in the healthcare industry has the potential to revolutionize this industry. It gives healthcare professionals more time to devote to patient care rather than information entry or search.

Logistic Regression Models in Predicting Heart Disease

This study predicts the risk of suffering from heart disease among the elderly by exploring the feasibility of using logistic regression models. Through the technology of data mining, the main pathogenic factors of heart disease were found, and the incidence of heart disease was predicted by using the regression model. The accuracy of logistic regression model was compared with other explored algorithms, and I found that the logistic regression model was worthy of research in the field of heart disease prediction.

The forecast of cardiovascular disease, one of the most common heart diseases, is considered to be one of the most significant topics in the analysis of clinical data.

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) kills about 31% of the world's population each year, with older people at greater risk than other age groups.

Through applying the technology of data mining, a new idea is provided for the prediction of heart disease, extracting clinical attributes and pathological data from large medical data sets, and generating biological hypotheses. At present, some studies have applied data mining technology to the prediction of heart disease, but there are limited studies on the important features of cardiovascular disease, while logistic regression can extract the risk factors of disease and predict the incidence probability of patients in real time.

Presently, the major challenge of the medical industry is to predict the cardio vascular disease with less expensive and more reliable method to avoid the compounding effect of the disease in low income or developing countries. The early detection not only reduce the cost but also improves the quality of life.

Implementation: logistic regression model

Dataset

The data from UCI machine learning repository was collected. The dataset contains 303 records, and 14 attributes. Thirteen parameters were used as the eigenvalues for the forecast of heart disease and one of the parameters is the output value or the forecast value of the patients with heart disease. ('num' means Numeric, and 'nom' means Nominal)

Attributes from UCI Dataset1

Attribute		Description	Type
①	Age	Age in years	**num**
②	Sex	Sex (1 = male; 0 = female)	**nom**
③	Cp	chest pain type -- Value 1: typical angina -- Value 2: atypical angina -- Value 3: non-anginal pain -- Value 4: asymptomatic	**nom**
④	Trestbps	Resting blood pressure	**num**
⑤	Chol	Serum cholestoral in mg/dl	**num**
⑥	Fbs	Fasting blood sugar > 120 mg/dl	**nom**
⑦	Restecg	Resting electrocardiographicresults -- Value 0: normal -- Value 1: having ST-T waveabnormality -- Value 2: showing probable ordefinite leftventricular hypertrophy by Estes' criteria	**nom**
⑧	Thalach	Maximum heart rate achieved	**num**
⑨	Exang	Exercise induced angina	**nom**
⑩	**Oldpeak**	**ST depression induced by exercise relative to rest**	**num**

Attributes from UCI Dataset2

11	Slope	The slope of the peak exerciseST segment Nominal -- Value 1: upsloping -- Value 2: flat -- Value 3: downsloping	nom
12	Ca	Number of major vessels (0–3) coloured by fluoroscopy	num
13	Thal	3 = normal; 6 = fixed defect; 7 =reversable defect	nom
14	Num	Diagnosis of heart disease(angiographic disease status) -- Value 0: no heart disease -- Value 1-4: presence of heartdisease	nom

UCI ML repository's Cleveland heart disease dataset—feature subset

Attribute name	Attribute description
Age	Age in years
Sex	1 denotes male and 0 denotes female
CP	Chest pain type 1, typical angina; type 2, atypical angina; type 3, nonanginal pain; and type 4, asymptomatic
trestbps	Resting blood pressure (in mmHg at entry to the health center)
chol	Serum lipid level in mg/dL
fbs	1 denotes true, i.e., the fasting blood sugar level > 120 mg/dL; 0 denotes false
restecg	Resting ECG results: null, normal; 1, ST-T wave abnormality; and 2, probable or definite left ventricular hypertrophy
thalach	Maximum heart rate achieved
exang	Exercise induced angina (1 = yes; null = no)
oldpeak	ST depression induced by exercise relative to rest
slope	The slope of the peak exercise ST segment (1, 2, and 3): 1, upsloping; 2, flat; and 3, downslopingca Number of major vessels (0-3) colored by fluoroscopy
thal	Thalassemia: 3 = normal, 6 = fixed defect, and 7 = reversible defect

Table 1: Statistical outline of subset attributes

Attributes	Age	Sex	CP	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
mean	54.44	0.68	3.16	131.69	246.69	0.15	0.99	149.61	0.33	1.04	1.60
std	9.04	0.47	0.96	17.60	51.78	0.36	0.99	22.88	0.47	1.16	0.62
min	29	0	1	94	126	0	0	71	0	0	1
25%	48	0	3	120	211	0	0	133.5	0	0	1
50%	56	1	3	130	241	0	1	153	0	0.8	2
75%	61	1	4	140	275	0	2	166	1	1.6	2
max	77	1	4	200	564	1	2	202	1	6.2	3

Table 2: Feature selection using correlation.

Features	Correlation
Exang	0.436757
Cp	0.433798
Oldpeak	0.430696
Thalach	0.421741
Ca	0.391724
Slope	0.344029

One of the most life-threatening disease is cardiovascular disease. Its high mortality rate contributes to nearly 17 million deaths all over the world. Early diagnosis helps to treat the disease in timely manner to prevent mortality. There are several machine and deep learning techniques available to classify the presence and absence of the disease. In this research, Logistic Regression (LR) techniques is applied to UCI dataset to classify the cardiac disease. To improve the performance of the model, pre-processing of data by Cleaning the dataset, finding the missing values are done and features selection were performed by correlation with the target value for all the feature. The highly positive correlated features were selected. Then classification is performed by dividing the dataset into training. testing in the ratio of 90:10, 80:20, 70:30, 40:60 and 50:50. The splitting ratio of 90:10 gives best accuracy as listed below. The LR model obtained 87.10% accuracy.

Boost the precision of the outcomes:

• Because to technological advancements and powerful ML and AI applications that greatly increase the accuracy of outcomes, electronic medical gadgets are becoming more familiar.

• Examples of medical gadgets include diagnostic tools like computerized tomography scanners, ventilators, pacemakers, heart-lung machines, diabetes monitoring equipment, or infant incubators. Medical personnel must rely on precise operation and measurement of these devices since they provide crucial information about the patient's state.

• The time it takes for humans to advance to the next stage of evolution is being significantly sped up by ML. The healthcare practitioner may talk about how cancer has been treated or a terrible pandemic avoided thanks to a straightforward smartphone app in the coming years as more use cases, tests, and apps are created.

A wide spectrum of enterprises and industries currently employ ML as a result of its recent substantial advancements. No exception, the healthcare sector is already gaining from ML. This technology has the potential to enhance patient care and quality of life in a variety of contexts, from drug discovery to diagnostics. Essential healthcare problems are already being resolved by ML. Massive amounts of data are now available as a result of the increased reliance, and their processing requires machine learning automation.

Medical professionals have access to a multitude of data that can help them make informed decisions, including health records, clinical trials, claims processing, billing records, and other data. In healthcare delivery systems, ML has a significant impact on patient care strategies. The most popular deep learning approaches for healthcare include computer vision, reinforcement learning, and natural language processing. Automated diagnostic recommendations are created using deep learning algorithms, which are precise and effective. This can lower healthcare expenses, lessen the administrative burden on medical staff, free them up to concentrate on more sophisticated diagnostic procedures, and avoid delays in the reporting of urgent situations. Using diagnostic data and auditing, prescriptions aid in reducing errors and speeding up the diagnostic process.

Healthcare personnel can work together to enhance clinical results and the hospital experience by being aware of ML potential. By identifying patterns in unstructured data and turning them into structured data, this technique automates computer systems' processes. By giving practitioners access to real-time data, this will help them make important judgements.

Hospitals and doctors will be impacted by ML since it is crucial to medical decision support, enabling earlier illness documentation and customized treatment regimens for the best results. Moreover, AI may show patients important outcomes and disease pathways for various types of treatment and educate them about them. By boosting productivity and reducing expenses of care, it can enhance hospital administration and health care systems. Computed tomography and magnetic resonance imaging both use object identification and picture recognition to identify and predict disease. Using imaging data, deep learning models can produce useful interpretations such tissue form, size, and volume. The invention of novel medical procedures, improved management of chronic diseases, and improved handling of patient data and records are all products of ML breakthroughs. The amount of data available has drastically expanded in recent years. As ML develops, it will become more integrated with data and analytics, affecting how data is shared, used, and stored across numerous healthcare applications. Yet, for AI and ML to be effective, hospitals need to have good, trustworthy, and timely data.

The ML system, which is built on vast databases of unprocessed images of these disorders, is often more accurate than detecting them. The primary/tertiary patient care and public healthcare systems should increase the quality of automation and intelligent decision-making; this could be the most significant effect of AI tools because it enhances the quality of life for billions of people worldwide.

There are many obstacles preventing widespread ML adoption in healthcare now. Getting patient data sets with the quantity and quality of samples needed to train cutting-edge ML models is one of the trickiest difficulties. Patient data is protected by stringent privacy and security regulations, making it difficult to access, transmit, and disseminate. Moreover, cleaning and preparing the data for ML analysis requires a significant amount of work due to difficulties with data structure and quality.

To increase patient survival rates, accurate cardiac illness prediction and early detection are crucial. The increased gathering of medical data has given practitioners a fantastic opportunity to advance healthcare diagnostics. Text detection and recognition early prediction, power quality disturbance detection, truck traffic categorization, and agricultural are just a few of the applications where machine learning (ML) is crucial. To help with patient diagnostics, ML has now established itself as a crucial tool in the healthcare industry. The majority of the time, practitioners' assessments of a patient's medical history, symptoms, and reports from physical examinations are used in the current approaches for predicting and diagnosing cardiac disease.

In databases used in the healthcare industry today, information about patients including clinical reports is freely available and is growing quickly every day. The dataset from the UCI ML repository was used to create the prediction model for heart disease in this research. Based on the features that are already present in the dataset, the computer is trained to learn patterns. A successful machine learning strategy for prediction is classification. Classification is a powerful supervised ML technique for diagnosing disease when properly trained with sufficient data.

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