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INTELLIGENT SYMPTOMS CHECKER USING ARTIFICIAL INTELLIGENCE

Mohammed Najm Abed ALAAMERI

Master`s Thesis

Supervisor

Asst. Prof. Dr. Ayça Kurnaz TÜRKBEN

Istanbul, 2023

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The thesis titled INTELLIGENT SYMPTOMS CHECKER USING ARTIFICIAL INTELLIGENCE prepared by MOHAMMED NAJM ABED ALAAMERI and submitted on /2022 has been **accepted unanimously** for the degree of Master in Electrical and Computer Engineering.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Mohammed Najm Abed ALAAMERI

Signature

DEDICATION

I dedicate this work to the one who led that hearts and minds of mankind to safety, the first teacher of mankind, our Prophet and Messenger (Muhammad) upon him be the best of prayers and peace.

I dedicate my work and this thesis to my loving parents who have always encouraged me to complete my studies, perseverance, and success, and to my dear family, who is a took a lot of their time and provided me with amenities and a beautiful study atmosphere in order to continue and succeed until I completed the study period and the period of writing the thesis. I also dedicate this thesis to many of my friends who stood by me and gave advice and encouragement throughout my practical study period. Despite all circumstances, I will always appreciate everything they did for me to reach the end and complete the thesis in a better way. May Allah protect you all and I will never forget your kindness and help for me.

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I also extend my thanks to all the brothers whom has made obligated to help me and send them special scientific books to complete this thesis. A Message of thanks, appreciation and respect to everyone who helped and supported me, but I could not mention him.

ABSTRACT

INTELLIGENT SYMPTOMS CHECKER USING ARTIFICIAL INTELLIGENCE

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Globally, there is a substantial unmet need for reliable detection of a broad variety of diseases. When trying to establish an early diagnostic tool and a successful therapy, the complexity of the several disease processes and underlying symptoms reported by the patient group offers great difficulties. With the use of machine learning (ML), a subfield of artificial intelligence, researchers, clinicians, and patients can overcome some of these difficulties (AI). Based on recent research, this article discusses how machine learning (ML) is now being utilized to aid in the early detection of a variety of illnesses.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, CNN, SVM.

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ABBREVIATIONS

ANN	:	Artificial Neural Network
ML	:	Machine Learning
CNN:	:	Convolutional Neural Network
AI	:	Artificial Intelligence
DL	:	Deep Learning
SVM	:	Support Vector Machine

1. INTRODUCTION

1.1 BACKGROUND

It is difficult to provide a single and precise definition of what learning means, since there are theories that defend different positions, as well as the existence of different types of learning. However, whatever the process of acquiring knowledge or skills, if it is done by a machine, it is called machine learning. The main objective of machine learning is the creation of a system capable of giving a satisfactory response when information is entered into it. Depending on the feedback received by the system, several paradigms can be distinguished. This work is part of the field of supervised learning, which is characterized by knowing what the expected outputs are for a certain set of input data (labeled data). What is intended is that the system generalizes those associations to respond appropriately when it receives new inputs.

Other paradigms are semi-supervised, in which there is a part of the initial data whose expected output is unknown, and unsupervised, in which there is no a priori knowledge about the labeling of the initial data. The construction of the system usually comprises several stages that, broadly speaking, can be grouped into three: data pre-processing, training of one or more models and post-processing of the results. The data received by the system may be incomplete, contain redundant or irrelevant information, be disturbed by noise, or present in any other way that affects performance. For this reason, in the preprocessing stage all these inconveniences must be solved. In the training phase, the refined information is received, and the core of the system is built: a model. There are different types of models, but their essential function is to process an input and offer an answer in accordance with the knowledge extracted from the labeled data. In the post-processing phase, the suitability of the responses provided by the model(s) must be evaluated to determine their performance and choose the best one, if applicable. In addition, other actions can be carried out to facilitate the presentation of the outputs to the user of the system, including additional information if necessary.

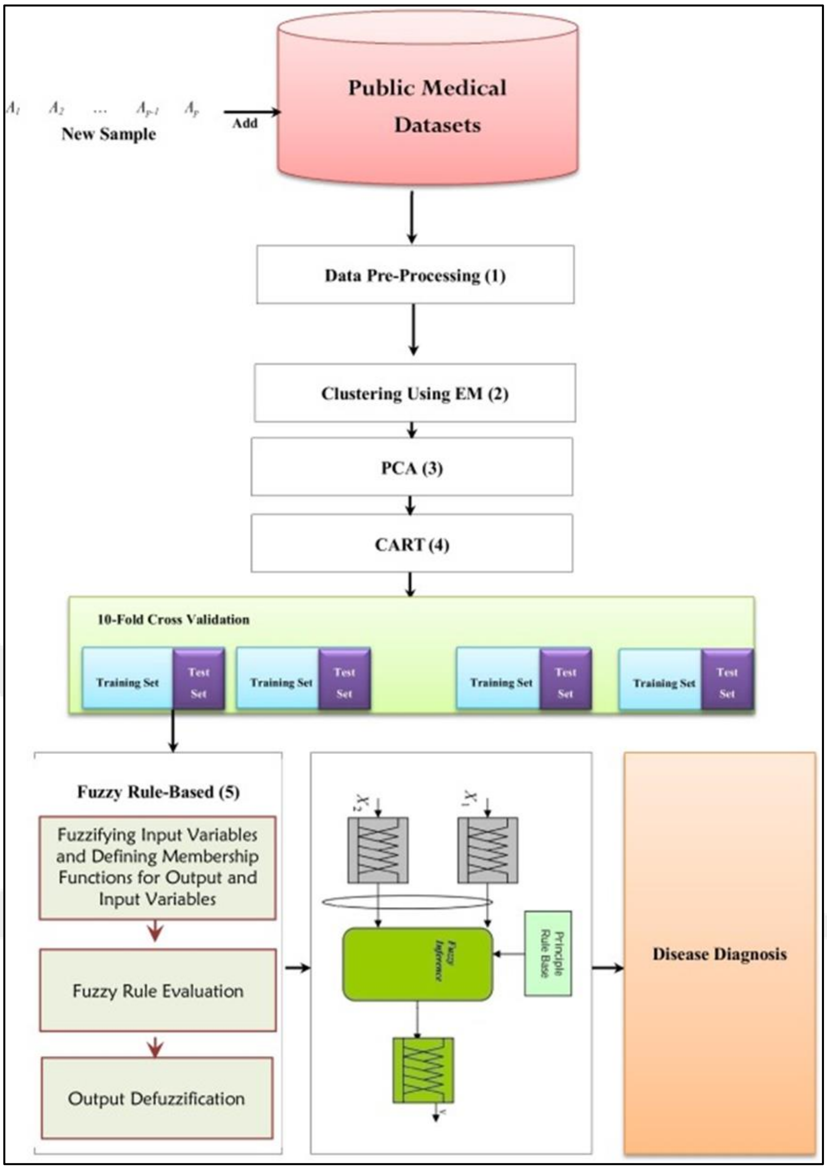

Figure 1.1: General Process of Disease Prediction.

1.2 PROBLEM STATEMENT AND CHALLENGES

In medicine, one of the main challenges is to take a sample or a vital signal from a patient via a specific sensor or by physico-chemical analysis to study and process it and extract relevant information to identify related diseases. Due to the very high cost of these treatments and the number of patients increasing day by day, the need to automate this treatment or behavior has become a necessity and a solution to this problem, and with the development of intelligence artificial in recent times years where we can replace the health professional with a machine where we can The latter make critical decisions and a very low error rate compared to the facilities provided by the inclusion of techniques of artificial intelligence, especially the speed of implementation, it is able to diagnose hundreds, but thousands of patients in a very short time compared to doctors. We can assume that the disease identification problem is seen as the pattern recognition problem, where the patterns represent a group of observations or patient samples. Currently, pattern recognition has been widely studied in recent years in the scientific literature. However, despite all the extensive research, the recognition techniques available in this field are still inferior to human visual abilities, since in the latter it is mathematical operations that contain an error rate, even if it is low. To enable pattern recognition, machine learning (ML) can learn to separate shapes from any of the other shapes where the data needs to be linear. This is why the so-called deep learning has emerged which is even capable of processing non-linear data, as many techniques have been developed to improve the performance of biomedical systems such as tumor recognition, medical image segmentation, cell classification and disease identification. Unfortunately, in the systems of the literature, we find effective techniques, but their implementation can be long or fast but do not give enough satisfactory results.

1.3 MOTIVATION

The growing computerization of the world allows the collection of large volumes of data and the need arises to exploit them effectively and efficiently. Therefore, machine learning is becoming increasingly important in various branches of science, technology or business. Specifically, this work focuses on the medical field, which is a field of interest for me, both professionally and personally. The first objective of the work is to carry out a review of machine learning applications in medicine. The characteristics of the most successful models are presented, highlighting their advantages and disadvantages. In addition, some techniques that help enhance the performance of the models or facilitate their use by medical specialists are analyzed in detail. The second objective consists of experimentally verifying some of the results established by the theory. The usual procedure of performing the first tests on very simple data sets and then on other more complex but well-known ones is followed. Finally, the techniques studied are applied to new real problems in the medical field and the results obtained are assessed.

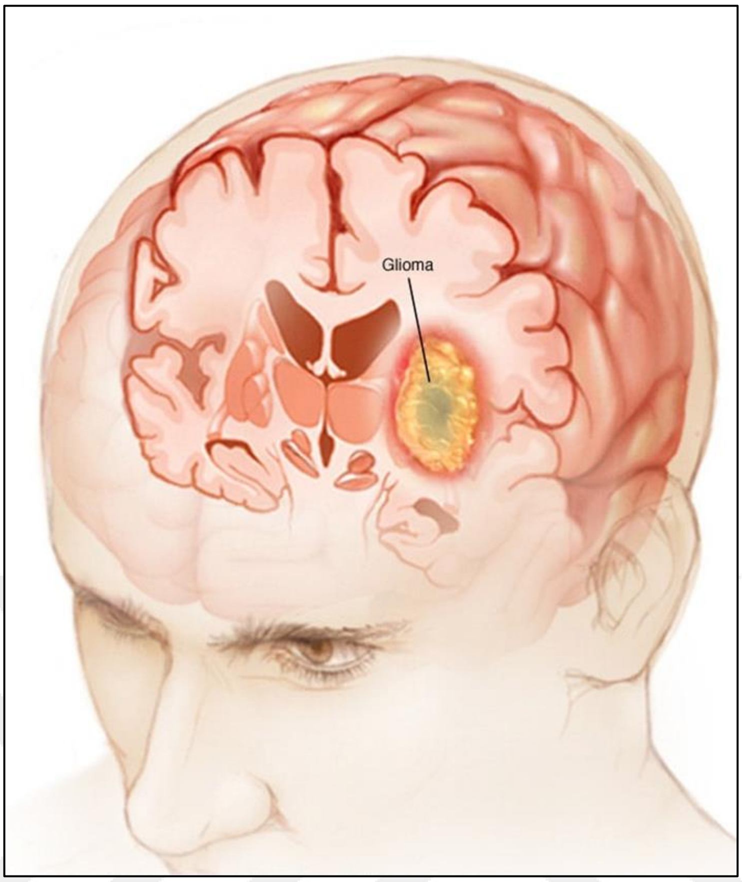

Figure 1.2: Brain Tumour Glioma**.**

1.4 CONTRIBUTION

In this thesis, we present a disease recognition system using a biomedical dataset for several different diseases (diabetes, Alzheimer's...) by including deep learning techniques where the difference between these techniques is highlighted based on ways of linking layers and methods of "neurons", there is also uncensored, supervised and enhanced learning in deep learning algorithms as they indicate how the algorithm is supplied with data by the researchers. Beyond that, convolutional neural networks (CNNs) are typical for recognizing image, video, and audio data, due to their ability to work with dense data. Recurrent Neural Networks (RNNs) are used to process natural languages while LSTMs are differences in RNNs that aim to retain structured information based on data

1.5 THESIS ORGANIZATION

To complete this work, our thesis is organized in three chapters as follows:

a. The first chapter gives a general overview of biomedicine and its relationship with machine learning.

b. In chapter two, we will highlight the most important differences between machine learning and deep learning, and then explain how deep learning techniques work.

c. The third chapter presents and discusses the results obtained with four different real databases and a comparison of the results to determine the technique that gives better performance than others.

2. LITERATURE REVIEW

2.1 CHAPTER OVERVIEW

Significant effort has been invested by medical institutions in the development of disease prediction systems. These systems use several machine learning algorithms. This chapter aims to explain some of the previous works done in classifying Diseases, looking for viable answers for the current scenario.

2.2 RELATED WORKS

Senthil Kumar Mohan et al. [1] claimed that hybrid machine learning approaches may be used to effectively forecast cardiac disease. The use of machine learning, which has been shown to improve the accuracy of cardiovascular disease prediction, is being used to identify significant inclusions. The expectation model is developed utilizing a combination of many well-known arrangement methods and a variety of highlight mix combinations. In terms of predicting cardiovascular illness, the hybrid random forest that integrates a linear model has an enhanced display level and an accuracy rate of 88.7 percent (HRFLM) In recent years, KNN, SVM, NN, and Vote are among the data mining methodologies and prediction algorithms that have acquired substantial momentum. These strategies and techniques are used to identify and predict cardiovascular disease.

According to an article by Sonam Nikhar and colleagues [2] it has been proposed that computer-based methods might be used to predict heart illness. This analysis will give an in-depth explanation of how Nave Bayes and decision tree classifiers are used in our research, especially with relation to the prediction of heart disease, via a wealth of detail. Research using the same data set demonstrates that the Decision Tree classification strategy outperforms the Bayesian classification method in terms of predictive power.

Prediction of Heart Disease, by Prof. Kailas Devadkar, Ph.D., Aditi Gavhane, Gouthami Kokkula, and Isha Pandya, was published in the Journal of the American College of Cardiology. This paper's datasets were trained and analyzed using the MLP (multi-layer perceptron) neural network technique. Utilizing Machine Learning, this assignment was accomplished. This method will use many levels, including an input layer, an output layer, and maybe other hidden layers in between. These hidden layers link every node in the input layer to every node in the output layer. This relationship has been accorded a heightened level of significance. The bias input, which has a weight of b, is applied to every node in the perceptron to ensure that it is distributed uniformly among the network's nodes. You have complete control over whether the nodes are connected through feedforward or feedback.

Abhay Kishore and his coworkers created a technique titled Heart Attack Prediction Using Deep Learning. This work employs deep learning algorithms and an explicitly recurrent neural system to establish a technique for forecasting a patient's chance of developing a heart-related infection. This is a way for forecasting the chance that a patient may get a heart-related infection. A recurrent neural network is a novel technique to character computing that employs deep learning in artificial neural networks. This study invests a great amount of effort to describing both the framework's essential features and its associated assumptions. This model does not create any errors since it employs both deep learning and data mining. This study provides a compass and a point of reference for the development of an alternative platform for the prediction of heart attacks. The first phase of the predictive process.

Lakshmi Rao and his colleagues authored and published Machine Learning Techniques for Heart Disease in [5]. Predictions on the factors that may increase an individual's risk of having heart disease and the causes of heart disease (circulatory strain, diabetes, current smoker, high cholesterol, etc..). As a direct result, cardiac disease may be challenging to appropriately identify. Utilizing a variety of data mining and neural system approaches, it is now feasible to estimate the severity of cardiac disease in individuals. The possibility that a person may get ill with coronary heart disease (CHD) is perplexing; hence, one must approach the subject with considerable caution. You run the risk of suffering a heart attack or abruptly dying away if you do not get treatment immediately. Data burrowing is a technique that allows the framework to benefit from prior information testing and model evaluations without being explicitly modified. This enables for the progress of medical research in the future. Data burrowing is used to uncover distinct metabolic machine learning types. Machine learning logic is generated from the study of previously gathered data.

Dr. Geetha S. and Mr. Santhana Krishnan J. created an algorithm based on machine learning for predicting cardiovascular disease. In this research, classification algorithms are utilized to accurately diagnose male patients with heart disease. This page includes a plethora of information about coronary heart disease, including its causes, its multiple classifications, and the risk factors for getting the condition. WEKA, which stands for "Waikato Environment for Knowledge Analysis," is a useful Data Mining Tool in the field of bioinformatics. This system employs all three of WEKA's interfaces, which correspond to the major data mining techniques known as Naive Bayes, Artificial Neural Networks, and Decision Trees, respectively. The methods of Naive Bayes and Decision Trees are used most often for predicting outcomes.

According to studies done by Avinash Golande et al. [7], experts may utilize data mining to aid authorities or physicians in discriminating between heart disease and other diseases. Decision trees, k-nearest neighbors, and the Naive Bayes algorithm are some of the most often used methods. In addition to the packing calculation, component thickness, sequential negligible streamlining and neural systems, straight Kernel self-organization guidance, and SVM, there are other characterization-based procedures that are unique (Bolster Vector Machine). It should come as no surprise that the research methodology will be discussed in the succeeding section.

VV Ramalingam and coworkers provided a method for predicting heart disease based on a large number of medical datasets, and they did it by using several machine learning approaches. In recent years, it has become increasingly common for academics to use machine learning methods, such as neural networks, to aid in the diagnosis of heart-related diseases. This corpus of work investigates and evaluates the efficacy of such algorithms and strategies. In academia, supervised learning algorithms like as SVMs, KNNs, Naive Bayes, Decision Trees, Random Forests, and Ensemble Models are highly regarded. These models all use supervised learning techniques. Using approaches validated on a variety of clinical data sets, it is possible to automate the examination of vast amounts of data. This may be achieved by using these strategies. When it comes to automating the examination of massive volumes of complex medical data, an increasing number of academics are turning to machine learning methods and methodologies. In recent years, a large number of researchers have resorted to machine learning approaches in order to aid in the detection of heart-related problems for the medical sector and medical professionals. The goal of this research is to analyze different algorithms and strategies in order to evaluate their performance in real-world scenarios. Researchers often use models that are based on supervised learning techniques. Support Vector Machines (SVM), KNearest Neighbour (KNN), Nave Bayes, Decision Trees (DT), Random Forest (RF), and ensemble models are examples of these types of models. Methods to enhance the financial condition of professionals in the mental health industry and heart disease analysis. In this study, a variety of models that rely on such calculations and methodologies are examined and evaluated. Due to directed learning, the academic community is familiar with computational approaches such as Support Vector Machines (SVM), Nave Bayes, Decision Trees (DT), Random Forest (RF), and group models.

MS Uzer and colleagues [11] developed a hybrid technique for breast cancer detection. In order to classify the data, artificial neural networks (ANNs) were deployed. When a person has cancer, their cells lose the ability to function normally and begin dividing and replicating uncontrolled, which may contribute to the development of the illness. Cancer is a disease that occurs when cells in the body cease performing their regular functions and begin proliferating uncontrollably. Cancer, especially cancer originating from malignant tumors, is the greatest cause of mortality on a global scale. For the hybrid function selection, the authors used sequential backward selection, sequential forward search, and principal component analysis (PCA). This was followed by a 10-fold cross-validation procedure that yielded 98.57 percent accurate findings.

Author [12] developed a local linear neural wavelet network to diagnose breast cancer using the Recursive Least Square (RLS) method, which improved the network's individual performance. Estimations and comparisons with the outcomes of prior experiments indicate that the suggested technique is fairly successful and gives a decent classification [21], [22]. In the study [13] conducted to predict medical problems, researchers modified the SVM classifier using RS. We integrated RS and SVM to reduce the quantity of duplicate information and segregate the data required for training and testing.

Three separate data sets were used to evaluate the approach, and the results show that it is more dependable than the options that came before it. In order to improve classification performance, the author [14] FDT has proposed a decision support system based on fuzzy logic and fuzzy decision trees (FDT) that is simple to use. When applied to both breast cancer datasets, the 70:30 split ratio produced error rates of 0.3661 and 0.1414, respectively. Utilizing Fuzzy Logic and Fuzzy Decision Trees enhanced the performance of the categorization of the decision support system. It was determined to use the FDT, a method that is not only simple but also important. The error rates for the two distinct breast cancer data sets were, respectively, 0.3661 and 0.1414. The data sets were divided 70:30 into two distinct groups. It is required to improve CAD-based approaches so that they can provide more accurate outcomes.

As shown in the work of author 1[5,] the challenge of properly describing breast cancer may be solved using an algorithm that incorporates the beneficial characteristics of a number of "boost" strategies. Using actual breast cancer patients as test subjects, researchers revealed that the hybrid boosting algorithm outperformed the other boosting algorithms by a 48 percent margin.

This study [16] discusses many methods that may be used to predict the risk of cardiovascular disease in Andhra Pradesh. In addition, IG, SU, and genetic search have been used to identify the exact traits that contribute most to the prediction of heart disease and, as a consequence, lower the number of illnesses found in the population. The author constructed the criteria for class associations by picking characteristics from a subset. Using these newly created criteria, it would be useful for clinicians to be able to estimate a patient's risk of heart disease. In addition, this strategy might be assessed using publicly accessible datasets and compared to other possible alternatives.

The author [17] examined three distinct algorithms and generated prediction models for the probability of getting type II diabetes. Inability of the pancreas to generate sufficient insulin for the body's demands results in an abnormally high blood sugar level. The three used approaches were artificial neural networks (ANN), Nave Bayes, and K-nearest neighbors (KNN). We noticed that the neural network produced more accurate predictions than both the Nave Bayes method (with a 95 percent accuracy rate) and the KNN algorithm (with a 91 percent accuracy rate). To simplify the process of cardiovascular disease diagnosis

T.Manju et al. 1[8] were the creators of genetic algorithms and multi-layer feed-forward neural networks (MLFFNs). The most common cause of mortality is a heart attack, which may be caused by a variety of illnesses, including diabetes, an unhealthy diet, hypertension, obesity, and smoking. In the United States, heart attacks are also the biggest cause of mortality. Using a neural network that combines the Genetic Algorithm (GA) with the Back Propagation Network, the occurrence of a heart attack may be predicted (BPN). When training the neural network, only six of the thirteen parameters included in the data set were used. The original objective of ANN was to assess the chance that a patient might have a heart attack.

Babak Sokouti and colleagues 1[9] predicted that an LM feedforward MLP neural network will be able to categorize cervical cell images from 100 distinct patients.

Image preprocessing and a feed forward MLP neural network are crucial components of the method for semi-automatic cervical cancer identification. Using the proposed procedure, images of cervical cells were able to be categorized -with a high degree of accuracy. With the suggested semi-automated method, it will be easier to detect precancerous and cancerous cells.

In order to accurately predict chronic kidney disease, Charleonnan and colleagues applied four distinct machine learning algorithms, including the k-nearest neighbors, support vector machine, logistic regression, and decision tree classifiers. [20] Numerous models' prognostic accuracy for chronic renal disease was studied and compared so that the appropriate classifier could be chosen. During the course of the experiments, the SVM classifier achieved its greatest level of accuracy, 98.3%. After training and testing using the provided approach, the SVM's sensitivity is at its maximum. As a result, the SVM classifier is acceptable for application in chronic renal disease predicting. This conclusion is deductible.

Asif Salekin and John Stankovic have developed and published a unique method for evaluating chronic kidney disease (CKD)[21] as part of their work. [Bibliography required] As classifiers, they employed k-nearest neighbors, random forests, and neural networks to arrive at an acceptable answer. The scientists used the wrapper method to determine which characteristics are the most dependable predictors of chronic renal disease (CKD). The objective of this research is to develop a CKD detection classifier that is both cost-effective and highly accurate while utilising just five parameters. This method, which has a detection accuracy of 0.993, yielded a root mean square error of 0.1084, which is rather excellent. Using the wrapper subset attribute evaluator and the best first search strategy, the classification model for CKD patients was developed. Using the same methods, the model for patients without CKD was created. When classifying CKD patients and non-CKD patients, the models performed much better.

Several distinct models were assessed and compared to one another [22]. The comparison indicates conclusively that classifiers performed far better on the smaller data set than on the larger one. Sahil Sharma, Vinod Sharma, and Atul Sharma [23] utilized a data set to evaluate and compare 12 different classification methods. Real-world medical outcomes of a patient were assessed alongside different therapy techniques in order to determine the effectiveness of various treatments. The authors assessed performance based on all of the following characteristics: predicted accuracy, sensitivity, precision, and specificity. Approximately 98 percent, 97 percent, 97 percent, 97 percent, and 97 percent of the time, the correctness of the decision trees was proved by the test outcomes.

The authors [24] recommended use a hybrid ensemble approach with two phases. Various methods are included into a two-stage hybrid ensemble classifier. The statistics suggest that the hybrid two-stage ensemble is an incredibly effective method for classifying individuals with chronic renal failure (CKD). After getting the results from this ensemble classifier, it was established that the proposed technique was effective in terms of a range of performance metrics, including 2-class accuracy, sensitivity (precision), and specificity (precision). A diagnostic tool with a graphical user interface that verifies the findings of physicians was also developed.

Researchers R Rao R Bharat et al. [25] developed a method that they refer to as lungCAD to help in computer-aided diagnostics (CAD). Using a classification technique, the system was able to detect pulmonary nodules in chest CT scans. Chest x-rays and computed tomography (CT) scans were used in order to accomplish the medical diagnosis. By using LungCAD, the physician's ability to deliver an accurate diagnosis was considerably enhanced. In 2006, the FDA awarded clearance for lung cancer adenocarcinoma.

Shivajirao M. Jadhav et al. [26] built an artificial neural network (ANN) multilayer perceptron (MLP) utilizing EKG data to detect athymias in the human heart (ECG). Based on their qualities, the suggested technique classed the patterns as either "normal" or "abnormal." This data set was also used for the training of a modular artificial neural network (ANN). The classification accuracy of the MLP was 93.11 percent, whereas the classification accuracy of the Modular ANN was 93.1 percent. The Modular ANN's sensitivity was 86.67 percent.

Random Forest (RF) ensemble classifiers were used by Akin [27] to increase the accuracy of the diagnosis of cardiac arrhythmias. It was established that random sampling was effective for training the RF ensemble classification algorithm, and testing proved that it was a successful technique with a 90 percent accuracy rate. Pinar Yildirim [18] studied the effect of class imbalance in training data on the development of a neural network classifier for medical choices about chronic kidney disease. Throughout the course of the research, the use of multilayer perceptrons with varied learning rates for predicting CKD utilizing neural networks was investigated. The findings of this research indicate that sampling methods may help improve the performance of classifiers beyond their prior levels. Moreover, it emphasizes the significance of the learning rate to the success of the multilayer perceptron.

The author of this work [29] developed a hybrid approach that combines the genetic algorithm and the random forest to predict lymphatic illness. This technique is known as the hybrid method. The lymphatic system is essential to the immune system and is responsible for fluid transport throughout the body. Lymphatic vessels, which are a part of the immune system, transport fluids to different sections of the body. In order to categorize the lymph disease dataset, we used the genetic algorithm and the random forest approach, both of which were previously employed to minimize the dataset's size. To test how efficiently our system performs, we compared its functionality to a number of different feature selection methodologies, such as principal component analysis (PCA) and radio frequency (RF). Based on the results of this investigation, it was established that GA-RF had a 92,2 percent success rate when trying to classify a particular object.

The approach developed by the authors [30] was meant to be used for remote monitoring of the health of heart failure patients. In addition, it provides abilities for data mining that may be used to the real-time monitoring of patients. It was suggested that data mining and CART classifiers be used in order to perform a "Heart Failure Severity Assessment." The system was evaluated, and the outcomes of the evaluation were positive. During the HF identification procedure, the percentages of precision and accuracy were 96.39 and 100.00, respectively. The proportions of patients with severe HF vs those with moderate HF were 79.31 and 82.35 percent, respectively.

3. MATERIALS AND METHODS

3.1 INTRODUCTION

In this chapter, the required and key ideas that were used in the construction of this work are described. The purpose of this work is to produce a categorization of the current malware in order to gain a better knowledge of the many behaviors that may be shown by malware. In English, the phrases "biomedicine" and "biomedical" have distinct beginnings and trajectories; in German, the terms are "Biomedizin" and in French, the terms are "biomedicine," although their meanings are fairly similar today. After making its debut in the writings of American and British authors in the 1920s, the term "biomedical" was not used again until 1940, 10 years after its predecessor. Clinical medicine that is "based on the concepts of physiology and biochemistry," according to the definition provided by the American Medical Dictionary (1923). Therefore, biomedicine and biomedical research were perceived, from the very beginning, to be a branch of medicine that had more to do with experiments and the laboratory than it did with what a doctor understands and what takes place in a clinical setting.

3.2 PUBLIC HEALTH SCREENING

Screening is a public health action a list of operations to be undertaken of a collective nature with a view to improving the health of a population. Screening for a disease has favourable repercussions in subjects correctly identified as positive or negative. For the true positives, the advantages can be better effectiveness of the intervention (treatment or preventive measure) instituted earlier, better chances of survival for the patients, or an improvement in the quality of life of the patients by reducing the treatments and savings in resources generated by a reduction in the total cost of treating the disease (less radical initial treatments and reduction in morbidity and mortality). For true negatives, the benefits may be a sense of tranquillity experienced by patients and a possible alleviation of monitoring measures. Moreover, screening can contribute to equity by allowing access to care for part of the screened population [1]. Apart from the importance of medical screening on human health, we can use new, more developed, and precise methods to improve the effectiveness and the result of our screening, such as digital screening, and this is what we will see in our memory.

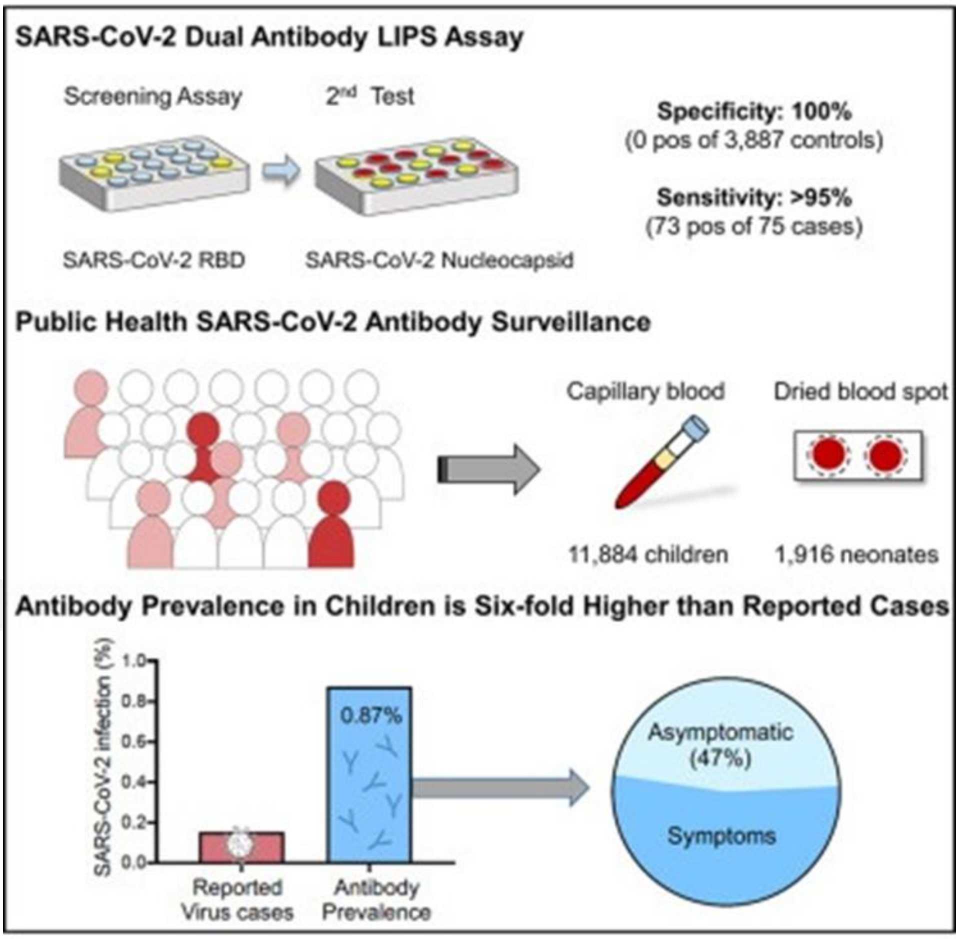

Figure 3.1: Public Health Screening**.**

3.3 BIOMEDICINE

Nowadays, the study of biomedical signals and the extraction of useful information in an intuitive way are very important and help doctors understand the behaviour of different cellular tissues to make a good diagnosis and build patient databases. In the following, we quote the used-most biomedical signals in the automatic treatment of patients using machine learning:

3.3.1 Electromyogram

An electromyography device, also known as an electromyography device, is used to record the electromyogram (EMG). This instrument monitors the electrical potential of the muscle. The activity of the muscle fibers, which in most cases results in movement, is controlled by the central nervous system, which is comprised of the brain, spinal cord, and peripheral nerves. Power derives from specialized cells that are controlled by neurons and have the ability to both expand and relax. Surface electromyography, in which electrodes are placed on the surface of the skin, is one of two ways to record an electromyogram. Intramuscular electromyography, in which a needle electrode is inserted into the skin, is the more common method, but surface electromyography is less invasive and therefore more widely used. When a single or several motor units are measured by a surface EMG, the resulting value is referred to as the motor unit action potential (PAUM). The true potential is around 100 mV, but the EMG is a complicated signal with a considerably lower amplitude because of the layers of connective tissue and the skin (around 5 mV)

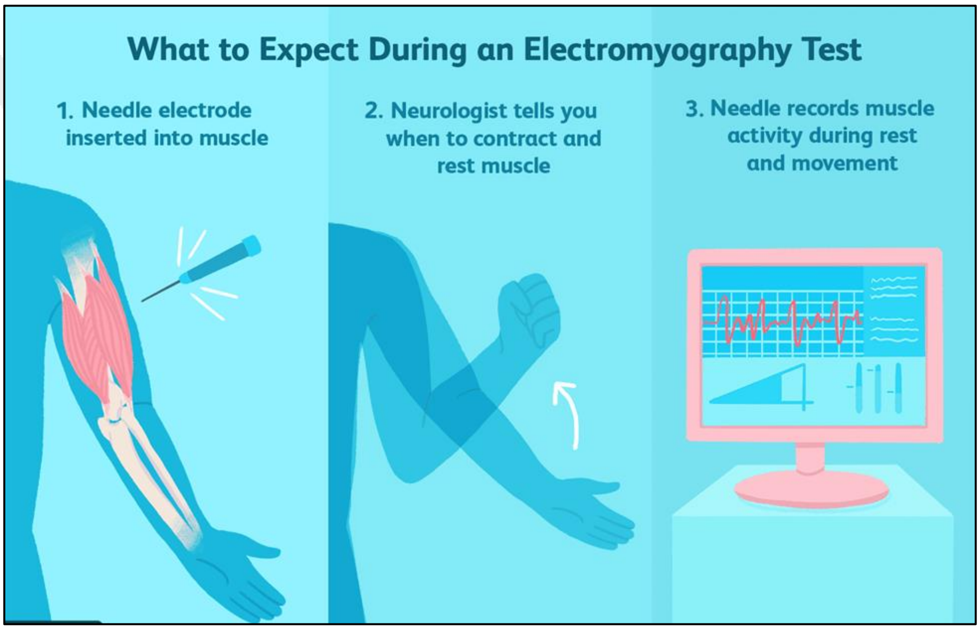

Figure 3.2: Recording Human Electromyogram (EMG).

3.3.2 Electrocardiogram

The electrocardiogram, often known as an ECG, is a depiction of the electrical activity of the heart. The sinus node, which is a pacemaker cell, is responsible for controlling the rhythm of the heartbeat (SA). An ECG cycle consists of the PQRST waves, as well as occasionally the U wave: the P wave is observed when the SA node triggers the impulse that propagates in the atria and creates the atrial contraction; the PQ interval (where isometric segment) is the duration of the impulse's propagation from the atrium to the ventricles, allowing blood flow to flow in the same direction; the QRS complex occurs when the impulse arrives at the ventricles and translates the Otherwise, the amplitude level and the slope of this segment are indicators of the ischemic state of the myocardium. Finally, the T wave which expresses the ventricular repolarization, it is the state of rest of the ventricles. The ST segment is the period of the depolarization of the ventricles, and in a normal case, it needs to be isoelectric (relaxation). Electrodes are attached to certain areas of the body in order to record electrical impulses using either a 12-lead or 12-channel electrocardiogram (used in hospitals) or a 3-channel electrocardiogram.

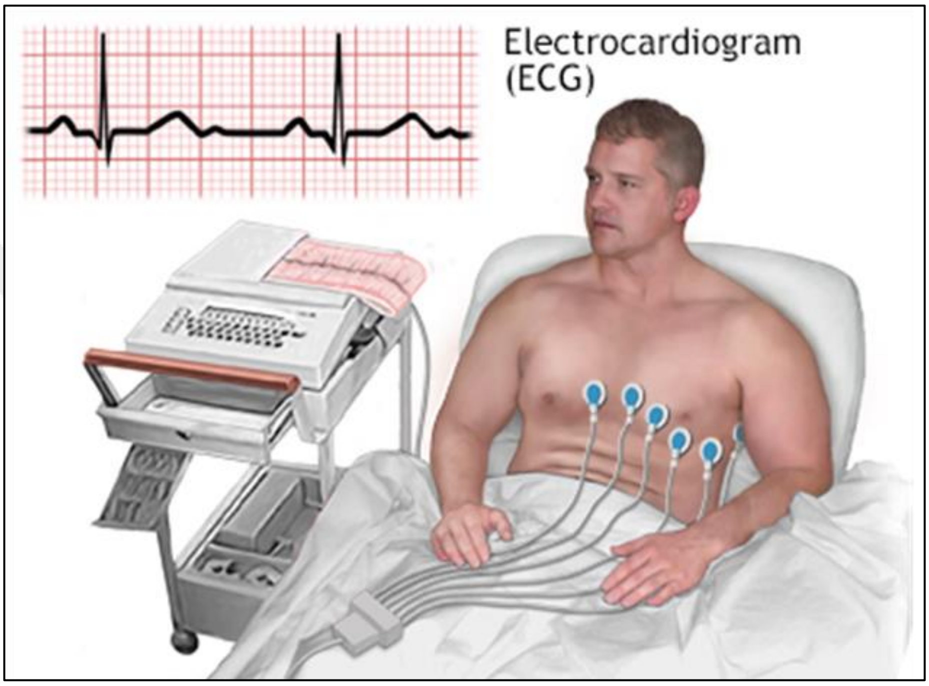

Figure 3.3: Electrical Impulses are Recorded Through Electrodes.

3.3.3 heart disease

People with heart disease are becoming an increasingly large percentage of the general populace. Numerous lives can be saved by early and accurate diagnosis and treatment. Older women in particular are at greater risk for heart disease, according to new findings from the National Heart, Lung, and Blood Institute (NHLBI). Researchers have found that if recognized early, heart disease may be successfully managed. However, it is difficult to accurately diagnose cardiac disease because of its numerous intricate variables. Even while heart illness can manifest itself in a variety of ways, there are many other human organs connected with varied clinical symptoms. Because of this, it is necessary to automate the process of medical diagnosis in order to assist clinicians in the diagnostic process.

3.3.4 Alzheimer's Disease

900,000 people are affected by Alzheimer's disease in France each year [23] . memory loss, difficulty in finding one's bearings in time and space, progressive loss of language and autonomy…are some of the characteristic symptoms of generative neurodiseases such as Alzheimer's disease. In our brain, neurons are organized in networks. these cells transmit nerve impulses and information. In Alzheimer's disease, this brain tissue is damaged. In the brain of patients, three things are observed characteristic of the disease:

a. A loss of neurons

b. The formation of so-called amyloid plaques

due to the accumulation of certain proteins (Tau proteins) which make up the internal structure of neurons. All of these lesion’s progress in the brain year after year. They begin by affecting the innermost structures of the brain, including the hippocampus, which is dedicated to memory. This is the reason why the disease usually manifests itself at the beginning by memory disorders. Then, the lesions reach the posterior and external areas of the brain which process more global information, related to gestures and language. Hence language disorders (called aphasia). Patients can no longer name objects (this is agnosia), they no longer recognize things, have difficulty coordinating their gestures and performing concrete gestures (what is called apraxia) Eventually, the patient's brain ends up completely atrophying. When the first signs of Alzheimer's disease appear, the process has already been at work for several years. These signs often include impaired memory, thinking, judgment, unreasoning, language and behavioral disorders (agitation, aggressiveness, insomnia, depression, anxiety, paranoia, visual hallucinations). At a more advanced stage, the person becomes dependent, no longer recognizes his relatives and runs the risk of falls and accidents. Diagnosis is primarily based on observation of the signs and discussion with the family. A neurological examination and tests evaluating memory as well as the ability to cope with daily activities are also carried out. dementia. Advancement to detect Alzheimer's disease, we use neuropsychological tests, medical imaging to visualize the area responsible for memory in the brain, or even lumbar puncture to detect biological markers of the disease [2].

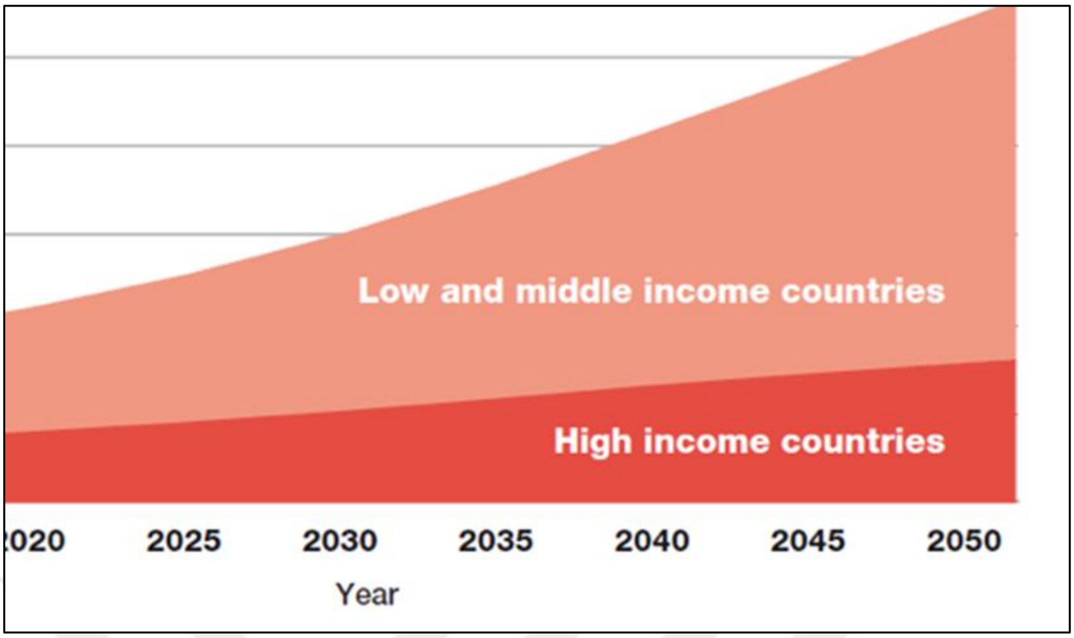

Figure 3.4: Distribution of Alzheimer's by 2025**.**

3.3.5 Diabetes

The Diabetes level is used to define this term. The long-term effects of a rise in Diabetes can harm a variety of organs. For example, the eyes, kidneys, nerves, and blood arteries all fall under this category. Nearly 90% of diabetics live for years without knowing it since diabetes is triggered when fasting blood sugar is more than 1.20g/l. Two blood glucose tests are recommended [3].

3.3.6 Screening for Cancer

Screening consists of a series of medical examinations, repeated at regular intervals, which make it possible to discover the possible presence of a disease long before it begins to cause noticeable abnormalities (symptoms). Only certain cancers are currently covered by screening. Screening makes it possible to detect certain cancers (or certain pre-cancerous abnormalities) long before the appearance of the first symptoms. Its objective is clear:

a. to prevent cancer by treating precancerous lesions.
b. increase the chances of recovery (or allow a much less aggressive treatment) thanks to early management of the disease. Screening is currently only possible for a limited list

of cancers. Other screenings are not subject to scientific consensus, even if some patients resort to it after discussion with their attending physician.

3.4 ARTIFICIAL INTELLIGENCE

a. Knowledge and reasoning are processed in order to allow a computer to do tasks traditionally associated with human beings. This is known as artificial intelligence. For "intelligent" activities, artificial intelligence tries to imitate human cognitive processes. Like "the development of computer systems that execute tasks better than humans because they demand high-level brain functions example:

b. learning Perceptual.

c. Critical reasoning and Memory organization.

This standard defines artificial intelligence as the "capacity of a functional unit to execute activities commonly associated with human intelligence, such as thinking and learning." Qualified as the next computer revolution, artificial intelligence is at the heart of all current affairs, it seems essential to define this breakthrough technology and to clarify its legal regime, but also to identify the applications in progress or in development in companies and the profits they derive from them.

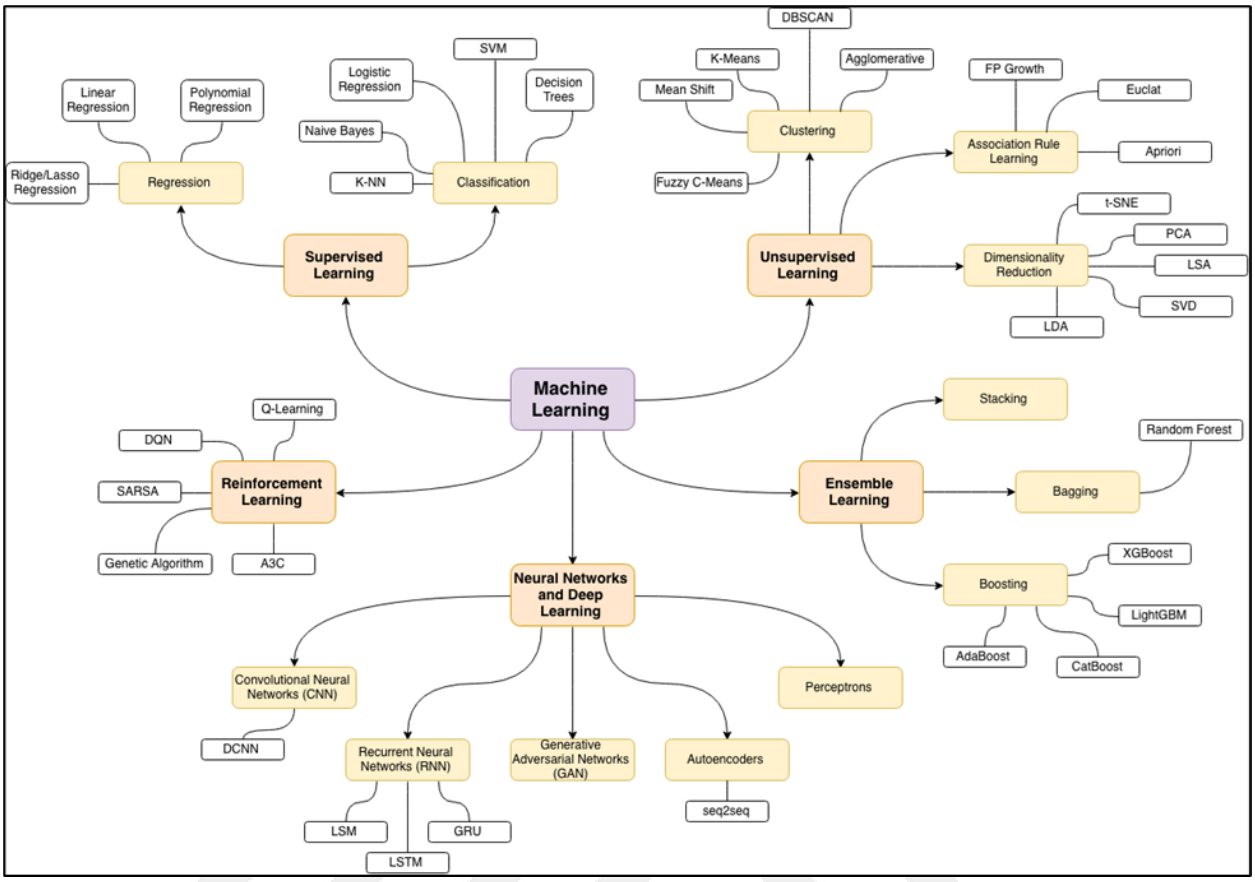

Figure 3.5: Fields of Application of AI**.**

3.4.1 History of AI

It is interesting to return to the origins and history of artificial intelligence in order to fully understand its first orientations and its prospects for the future:

a. 1950: Alan M. Turing, mathematician and theorist who was a precursor of I' computing, launches the concept of artificial intelligence.

b. Allen Newell, John C. Shaw, and Herbert A. Simon, a logic theorist, are credited with launching the first artificial intelligence program during the years 1955 and 1956.

c. Modeling of chess games began in 1957.

d. In 1958, John McCarthy came up with the idea for the interactive programming language known as Lisp (list processing) (development at MIT).

e. Construction of the first neural network, the Perceptron, by Frank Rosenbaltt in 1958. This "connectionist machine" was the first neural network ever built.

f. The first general problem solver, or GPS, was developed in 1959, marking the end of the first epoch in the history of artificial intelligence.

g. 1970: Neo connectionism.

h. 1989: Deep Thought, IBM's supercomputer, two million strokes per second.

i. 1990–1997: Development of Deep Blue, later renamed Deeper Blue; creation of a system consisting of 256 processors that can work in parallel and calculate about three million strokes per second individually.

j. 2009 saw the beginning of an initiative at MIT to reevaluate existing artificial intelligence research.

k. In 2011, IBM's Watson, a supercomputer, competed on the game show Jeopardy and won two out of the show's three rounds. For this artificial intelligence, the performance consisted of providing answers to queries pertaining to general culture.

l. 2013: The Year of the Human Brain Project On the facilities of NASA, Google has established a new research center.

m. 2014: Deep Knowledge Ventures appoints VITAL, an algorithm that is able to figure out its conclusions by examining the financial sheets of potentially intriguing firms, clinical trials, intellectual property, and past investments, to its board of directors.

n. Research in Artificial Intelligence (AI) at Facebook in 2015 (FAIR). TensorFlow, an artificial intelligence system developed by Google, is going to be made available to the general public. A growing concern that, at some point in the future, the performance of artificial intelligence will exceed that of human intellect.

o. Amelia, a virtual agent working for IP Soft in the year 2016. In addition, AlphaGo prevailed over Lee Se-Dol, the reigning world go champion, three times in a row in five sets.

Multiple applications of artificial intelligence Artificial intelligence has already found multiple uses within society:

i. Search engines: All search engines (including travel agencies) are based on intelligent systems for extracting, analyzing and classifying data to produce a result relevant to the user's request as quickly as possible. RankBrain9 is the name given by Google to the system that it put into place for its search engine in October 2015 to make use of machine learning methods. This technology turns enormous volumes of text into mathematical vectors in order to assist the system in determining the meaning of words or phrases that it is unfamiliar with. This allows the system to process the 15 percent of never-before-seen inquiries that it gets on a daily basis.

ii. Recommendation engines: Based on data from a user's browsing and purchases, sites such as Amazon or Netflix are able to offer him other similar products that might interest him. These predictive technologies are also used for online advertising platforms (Google, Criteo) to provide visitors with content from advertisers related to the pages they have visited.

iii. Machine translation: This is based on natural language statistical modeling algorithms. They integrate the construction rules of each language.

iv. Personal assistants (Siri, Cortana, Google Now, etc.): They are deployed on Smartphones which rely on several technological bricks: voice recognition to convert sound into text, natural language to understand the meaning of words, a search engine to find the answer to the question and the voice synthesis to communicate the answer to the user, planning for event management, etc.

v. Chatbots: They are used in the fields of customer support and telemarketing and consist of chat windows that open by themselves on a website, or voice servers that answer questions 24 hours a day. They use natural language and their access to vast databases allows them to answer the simplest questions.

vi. Autonomous vehicles: While some prototypes are already driving on the roads in contact with other vehicles, cars that park by themselves or brake in anticipation are already a reality. The autonomous piloting of airplanes, the trajectory management of space spacecraft, or the flight paths of unmanned aerial vehicles are all examples of applications of artificial intelligence.

vii. GPS navigation systems: Developed in 1968 by the Stanford Research Institute, this algorithm makes it possible to optimize the path between several points in a network based on the cost of the trip or the distance traveled.

viii. Finances: They are controlled by intelligent systems that not only arrange their operations, manage their assets, and invest in the stock market, but also monitor for transactions that are not typical of the company and alert the appropriate personnel. Additionally, in relation to the provision of loans, financial institutions have specialist risk assessment systems (credit-scoring).

ix. Cyber security: Machine learning methods have been employed by players in the field of cyber security in order to detect aberrant behavior in information systems and to detect persistent threats in order to prevent engaging in espionage or data extraction operations 10. When developing the behavioral analysis model, over three hundred factors, such as the timings and IP addresses of connections and computers, as well as downloads, are taken into consideration. The initial learning phase of the model takes around seven days to complete. Mention should be made of Sentry, a relatively new company with headquarters in Lyon that incorporates machine learning algorithms to safeguard vital industrial facilities.

x. Video games: They use artificial intelligence techniques to bring non-player characters to life or to create entire universes from algorithms. In 1997, IBM's supercomputer DeepBlue beat Garry Kasparov, reigning world chess champion. In 2016, it was DeepMind, Google's artificial intelligence program, which announced the victory of its AlphaGo program against the reigning European go champion, Fan Hui13. This result is based on neural network technology, which we describe previously. Deepmind had already developed an artificial intelligence system capable of determining the most sensible action to beat the man in about twenty arcade games.

xi. Medicine: IBM's Watson computer aims to compile the largest database dedicated to health in the world, covering 300 million patients. IBM's health branch has acquired four medical companies since its creation: Phytel (health & population), Explorys (clinical health files), Merge Healthcare (medical imaging) and Truven (medical analytics). This supercomputer has proven itself in particular in an oncology department for personalized services: analyzing DNA, patient records and other publications and clinical trials. The computer proposes a protocol adapted to the patient. The American company Enlitic offers artificial intelligence technologies to analyze medical imaging, which would make it possible to detect fractures more efficiently than radiologists according to the statements of the company.

3.4.2 Future of Artificial Intelligence

We have just seen that artificial intelligence is already a reality for multiple applications. But in view of the research being carried out around the world, it still has a bright future ahead of it. The applications of artificial intelligence for the future can go even further, particularly in the field of: autonomous cars, robotics, connected buildings and medicine.

3.5 MACHINE LEARNING

Machine learning is a discipline of AI that offers computers the ability to learn from a set of observations called a training set [4]. Each observation, such as "I ate such and such foods at such and such a time of day during such a period, which caused such and such a disease" is described by means of two types of variables:

a. The first are called predictive variables (or attributes or characteristics), in our example my age, my medical file, my medical history. These are the variables from which we hope to be able to make predictions. The n predictor variables associated with an observation will be denoted as a vector x= (x1...xn) with n components. A set of M observations will consist of M such vectors x (1) ... x (M)[4].

b. A target variable whose value we want to predict for events not yet observed. In our example, this would be the disease contracted. this target variable will be denoted y [4]. In summary, the value of the variable y depends on:

c. A function F(x) determined by the predictor variables.

d. A noise ε(x) which is the result of a number of parameters which cannot be taken into account. Both F and ε will never be known, but the goal of an ML model is to get the best possible approximation of F from the available observations. This approximation will be denoted f, it is called the prediction function [4]. Here are some examples of using ML [4]:

   i. Computer vision

   ii. Fraud detection

   iii. Classification (image, text, video, sound ...)

   iv. Targeted advertisements

   v. Medical diagnosis

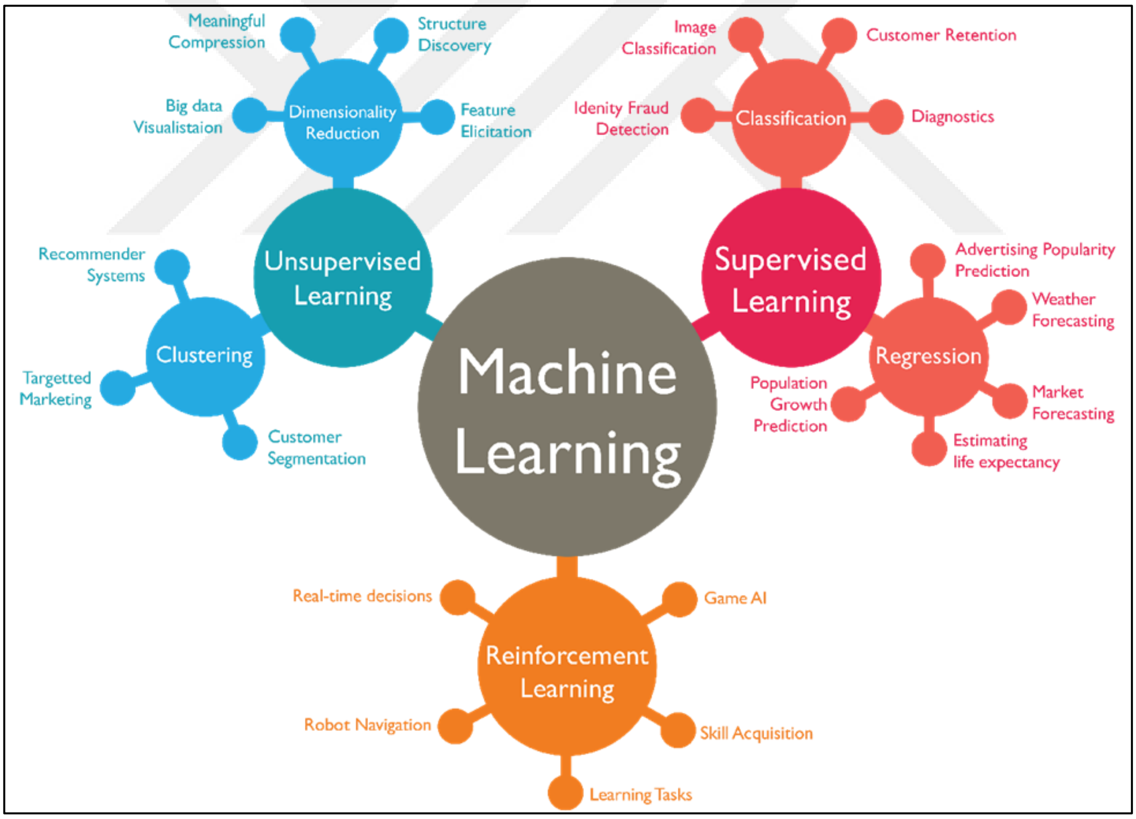

Figure 3.6: Machine Learning Operations**.**

3.5.1 Learning in ML

Learning is the mechanism by which the nervous system adapts to the outside world. The precise mechanisms of learning by the brain remain largely misunderstood and involve both genomic modifications partly under the control of OTX2 (methylations of citosines, retrotransposons), neuronal modifications (increase in the exchange surface of synapses, the number of post-synaptic receptors or the number of pre-synaptic neuromediators) but also the microenvironment where the astrocytic feet also play a key role. Machine learning is most likely fundamentally different from brain learning. In effect, today the main learning techniques are said to be supervised, namely that we provide the algorithm with ground truths. Our brain seems to it to learn in a largely unsupervised way. One of Tom Michels' historical definitions of machine learning said that a system was intelligent if for a task T measured by a performance P, P improves at task T with experience E. Recent advances in parallel computing have made it possible in many visual applications to equal or even exceed human capacities for the task assigned to them. Nevertheless, the current challenge is the transferability of this knowledge and moving from so-called discriminative networks to generative networks by integrating them into larger representations than simple tasks. Machine learning is essentially done by successive iterations seeking to minimize the overall error of a model measured by its cost function. This type of problem refers to all the techniques of optimization and more particularly of minimization. One of the minimization techniques used in machine learning in our work is CNN Convolutional Neural Networks.

3.5.2 Machine Learning and its Applications to Biomedical Researchers

in artificial intelligence always aim to program machines capable of performing tasks that require intelligence. However, programming machines capable of adapting to all situations and possibly evolving according to new constraints is difficult. The challenge is to circumvent this difficulty by providing the machine with learning capabilities allowing it to take advantage of its experience. This is why, in parallel with research on automatic reasoning, research on learning by machines in English “machine learning” has developed. The purpose of this study is to automatically find solutions to difficult issues by arriving at conclusions after basing those conclusions on observations of the difficulties. There has been a notable uptick in the number of biomedical applications that make use of machine learning. This rekindled curiosity may be traced back to a few different sources. On the one hand, the successful application of machine learning techniques in different fields on the other hand, the most recent development is the advent of electronic medical records.

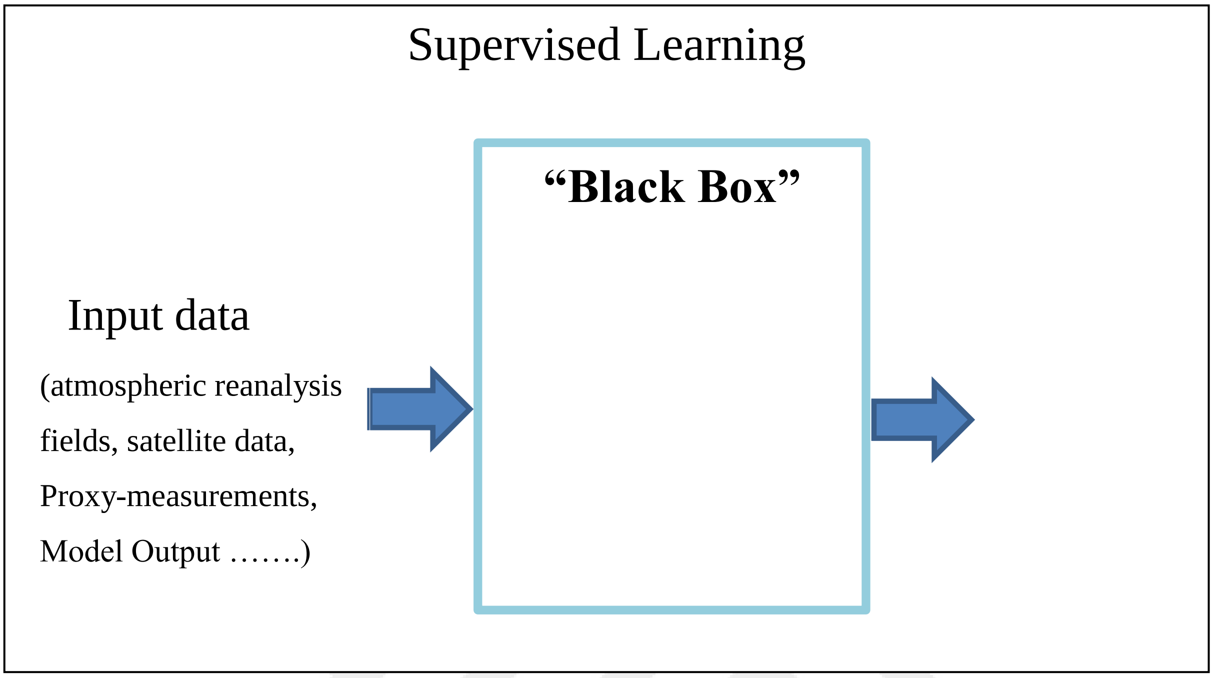

Figure 3.7: Machine Learning for Biomedical Applications**.**

3.6 MACHINE LEARNING ALGORITHMS

3.6.1 Support Vector Machines (SVMs)

Support Vector Machines, sometimes known as SVMs, are a type of nonlinear binary classification technique that is extremely strong. Building a nonlinear separation band with the widest possible width that can differentiate between two different sets of data and then utilizing that band to produce predictions is the core idea behind support vector machines (SVMs). Using a nonlinear transformation, Support Vector Machines (SVMs) are able to accomplish this by moving the points x (1),..., x(M) from the original n-dimensional space (where n is the number of predicative variables) to new points (x(1)),..., (x(M)) in a space of dimension greater than n, where they will be easier to distinguish from one another. Classifiers known as SVMs are based on two primary concepts, which are as follows: The first step is to choose a linear separator that has the greatest possible width, denoted by the notation c', which stands for "maximum margin." The margin is the distance that separates the separation border from the samples that are physically closest to it. Support vectors are another name for them. The challenge is to identify this most effective border for dividing. If the issue can be broken up into linearly distinct parts, then the choice of the hyperplane that separates them may not be clear. In point of fact, there is an infinite number of separating hyperplanes, each of which has performances in the learning phase that are similar to one another, but which might have quite different performances in the test phase. It has been demonstrated that there is a single ideal hyperplane, which can be thought of as the hyperplane that maximizes the margin between the samples and the separating hyperplane. This has enabled researchers to devise a solution to the issue. There are conceptual justifications for this decision. Vapnik demonstrated that an increase in the margin of classes of separating hyperplanes results in a decrease in the capacity of such classes. The second fundamental concept behind support vector machines (SVMs) is to transform the representation space of the input data into a higher-dimensional space, in which it is likely that there is a linear separation. This is done in order for SVMs to be able to deal with situations in which the data cannot be linearly separated. This is made possible by a kernel function, which satisfies the requirements of Mercer's theorem and has the benefit of not necessitating the explicit knowledge of the transformation that has to be done in order to modify the space. This is made possible owing to the kernel function. Kernel functions make it possible to transform an expensive dot product in a high-dimensional space into a straightforward point evaluation of a function. This transformation is made possible by the fact that the dot product can be transformed. The kernel trick is the name given to this particular method. The polynomial kernel and the Gaussian kernel are the two types of kernel functions that are utilized the most frequently. The support vector machine (SVM) makes it feasible to cope with difficult nonlinear classification issues. They also provide an alternative to neural networks since they are quicker to train, however SVMs are frequently less effective than random drills [4].

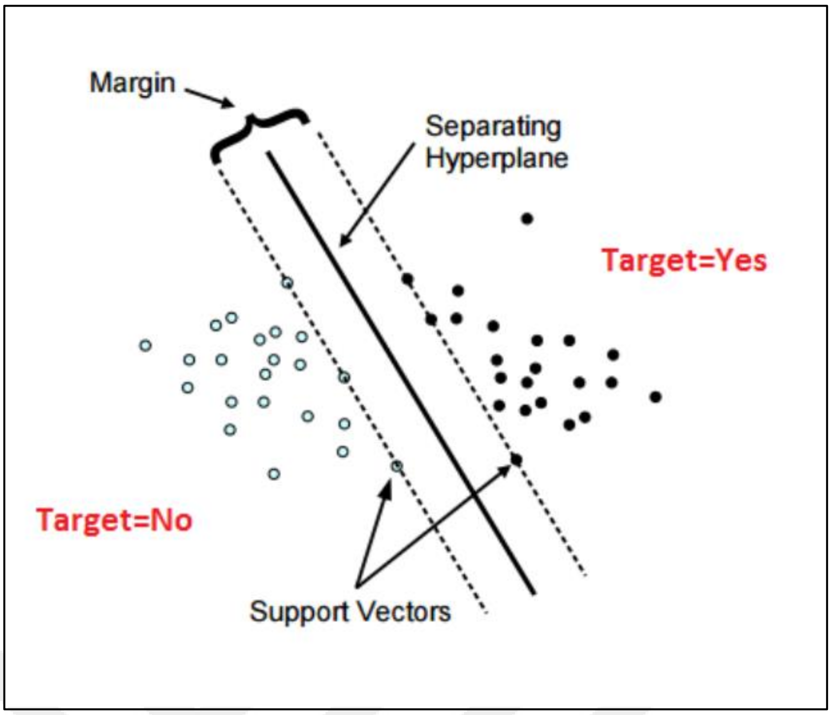

Figure 3.8: Workflow of SVMs.

3.6.2 Neural Networks

Neural networks offer a simulation of the functioning of the nerve cell using an automaton. Neural networks are made up of a set of neurons (nodes) connected to each other by links that allow signals to be propagated from neuron to neuron. Thanks to their learning capacity, neural networks make it possible to discover complex non-linear relationships between a large number of variables, without external intervention. As a result, they are widely used in many problems of classification (marketing targeting, pattern recognition, signal processing, etc.), estimation (modeling of complex phenomena, etc.) and forecasting (stock market, sales, etc.). There is a trade-off between model clarity and predictive power.

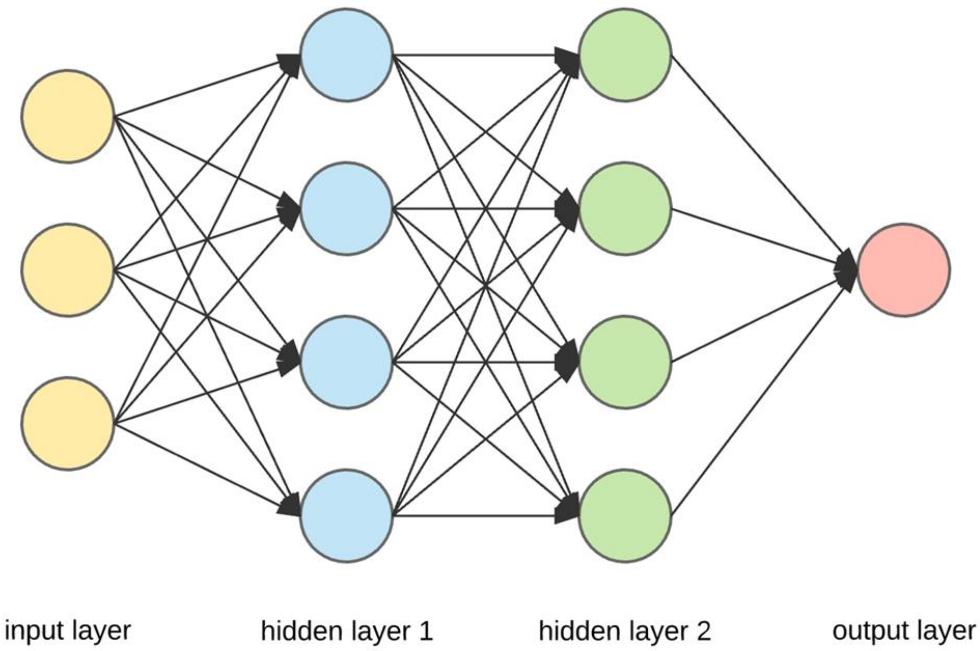

Figure 3.9: Structure of ANN.

The simpler a model, the easier it will be to understand, but the less it will be able to take into account too varied dependencies.

Presentation of some Types of neural networks: There are many types of neural networks, each type being developed for a particular purpose [5].

a. Formal Neuron: A biological neuron is analogous to a formal neuron, which is a mathematical and computational model of a biological neuron. In most cases, the formal neuron will have several inputs, but only one output. These inputs and outputs will correspond, respectively, to the dendrites and the emergence cone of the biological neuron (the point where the axon would begin). [5] The majority of the time, the excitatory and inhibitory actions of synapses are represented by numerical coefficients (synaptic weights) that are related with the inputs [5]. During the learning phase, the numerical values of these coefficients will be modified as necessary. A formal neuron, in its most basic form, computes the weighted sum of the inputs that it has received, and then applies an activation function, which is often a nonlinear function, to this number [5]. The output of the neuron, which can be written as [5] is the value that is obtained in the end. The formal neuron is the fundamental building block of artificial neural networks, in which it collaborates with its neighbors to compute arbitrarily complicated functions [5]. These networks have a wide range of applications in the field of artificial intelligence.

b. Multilayer neurons: The multilayer perceptron, also known as an MLP multilayer perceptron, is a linear classifier of the formal neural network type that is organized in several layers (Figure 3.10) Within each layer, information flows from the input layer to the output layer in a one-to-one fashion; as a result, this type of network is known as a feedforward type network. The number of neurons that make up each layer can vary, but the neurons that make up the output layer are guaranteed to always correspond to the system's outputs [5].

c. Recurrent Neurons: Recurrent Neural Networks (RNNs) make it possible to analyze vector sequences just like hidden Markov models. hidden ticks) calculated at time t are re-injected at the input of the network and/or at the input of the hidden layer [5].

d. Hopfield networks: A discrete-time recurrent neural network model known as the Hopfield neural network has a connection matrix that is symmetric and has a zero in the diagonal position. Additionally, the dynamics in this model are asynchronous (a single neuron is updated at each unit of time). In 1982, physicist John Hopfield was the one who made the discovery. His finding contributed to the resurgence of interest in neural networks, which had waned in the 1970s when a paper written by Marvin Minsky and Seymour Papert [5] failed to pique people's curiosity about the subject. A Hopfield network is a memory that may be addressed based on its content. A remembered form can be obtained by stabilizing the network, provided that it has been stimulated by an acceptable part of the form [5].

e. Convolutional Neural Networks: In the machine learning field, a convolutional neural network (also known as a CNN or ConvNet) is a specific kind of acyclic artificial neural network in which the connection structure between neurons is modeled after the visual brain of animals. When the visual field is tiled, the neurons in this part of the brain are organized in such a way that they correspond to sections that overlap one another. Their mode of functioning is modeled after biological processes; they are made up of a multilayer stack of perceptron’s; and their primary function is to do pre-processing3 on very tiny quantities of input [5]. Image and video vector recognition (single, double, and three-dimensional), recommender systems, and natural language processing are just few of the areas where convolutional neural networks find widespread use. As a result of these qualities, it is one of the methods whose application might be particularly ideal for the categorization of biological data.

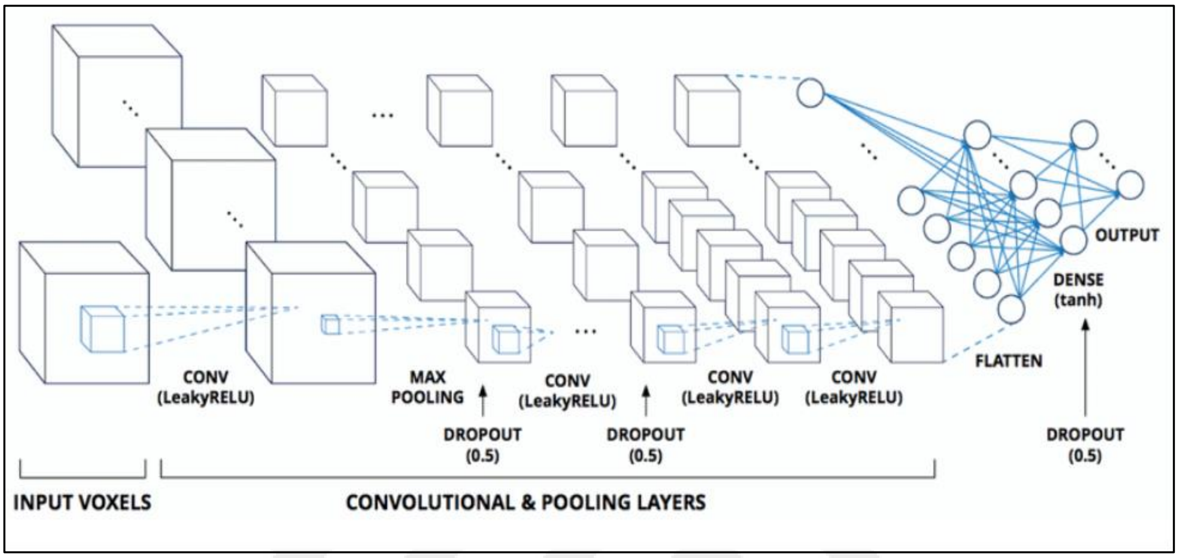

Figure 3.10: Layers of CNN Algorithm.

Types of problems that can be solved by neural networks Neural networks can be used to solve two main types of problems:

f. Classification problems: where we seek to predict a class, a category. A distinction is made between binary classifications (two classes to be predicted) and "multi-class" classifications where several classes are to be predicted [6]. This distinction is important because for each type of problem, the evaluation of the performance of this network will be done in a different way. This performance measure, also called the "cost-function", reflects how much the neural network errs for the task assigned to it. For example, in the context of classification problems, log-loss 1.3 or cross-entropy is conventionally used J is the cost function, M represents the number of classes to predict, yo, c, a binary indicator equal to 0 or 1 depending on whether the class c is correctly predicted for the observation o etpo, c the predicted probability for each of the classes of observation o. This kind of cost function therefore particularly penalizes the results which are wrong and are sure of themselves [6].

3.6.3 Gaussian Model

Modeling with the Gaussian mixture A Gaussian mixture model, often known as a GMM, is a type of probabilistic model that asserts that all data points created are drawn from a mixture of finite Gaussian distributions but does not provide any parameters for any of the distributions. Using either an iterative anticipation-maximization approach or a maximum a posteriori estimate generated from a well-trained prior model, the parameters of the Gaussian mixture models may be calculated. When it comes to modeling data, especially data from various groups, Gaussian mixture models are incredibly important tools to have. In biometric systems, where the parametric model assists in better understanding characteristics or measurements linked with features such as spectral properties of the vocal tract, the usage of Gaussian mixture models is commonplace. It is claimed that Gaussian mixture models are the most statistically mature technique to classify objects. These models may also be used to estimate densities of items.

3.6.4 Hidden Markov Chains

Hidden Markov models MMCs are statistical models, rich and widely used in signal processing. They are developed by Andrew Markov (a student of Chebyshev), and they are primarily oriented to linguistic goals in works of Russian literature. These are effective tools for modeling sequential data or 'time-series Data'. Later used in speech recognition problems by Baker, their basic theory was introduced by Baum and his colleagues in the late sixties. Currently, these models are increasingly adopted in automatic speech recognition, for the analysis of DNA sequences, and in problems related to writing and word processing. Also, their use in vision is vast. They are implemented in image segmentation, face recognition, gesture interpretation, as well as background modeling and recently in video processing

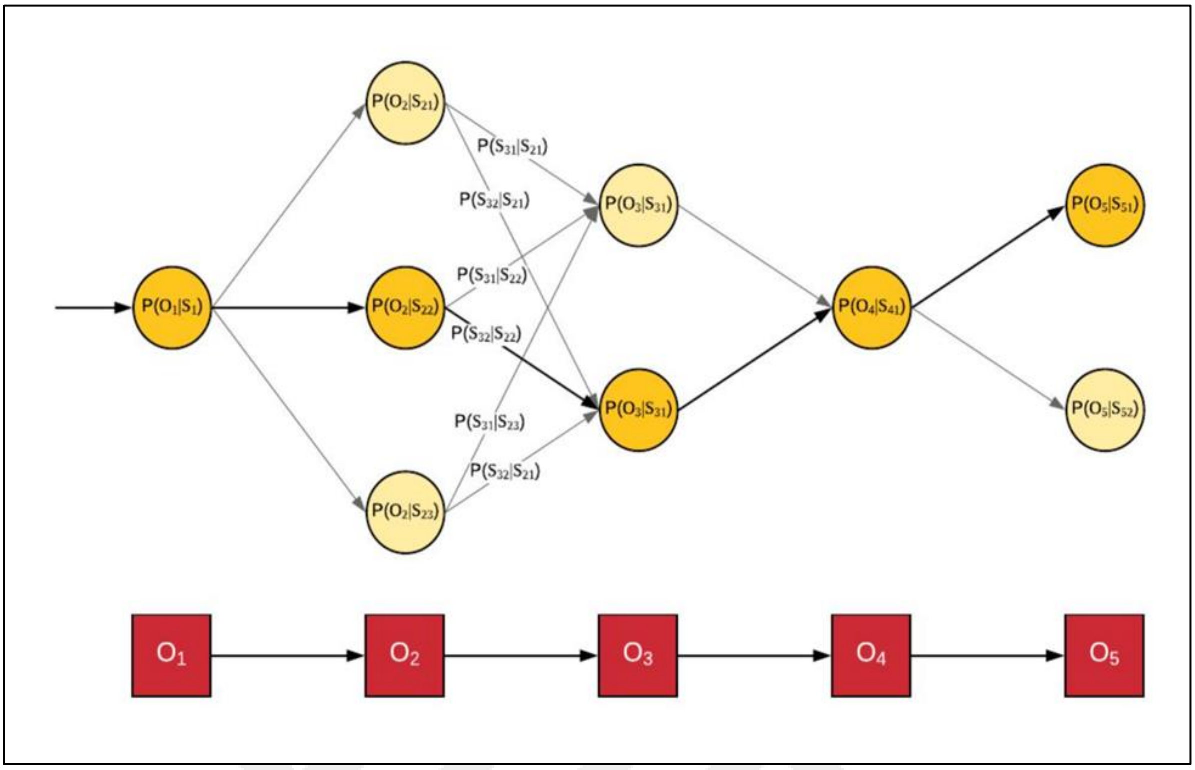

Figure 3.11: Hidden Markov Models MMCs**.**

3.7 CLASSIFICATION AND LEARNING

a. Supervised methods: In the case of supervised learning, we make use of a collection of labeled data, which refers to samples that have been assigned to a category by a trainer, an instructor, or another knowledgeable individual. The learning foundation is comprised of this collection of illustrative examples [5]. The general goal of constructing from the learning base, or classification functions, is what supervised learning techniques set for themselves as their own general target. A function such as this one makes it possible to recognize a certain property of an item based just on the description of that object, [5]. In [3], Inductive inference is defined as a process that, beginning with specific knowledge observed on specific objects and an initial inductive hypothesis, allows one to obtain an inductive assertion implying or accounting for observations strongly or weakly. This definition of inductive inference is based on the fact that one can obtain an inductive assertion by beginning with specific knowledge observed on specific objects and an initial inductive hypothesis. Specific knowledge is represented by a collection of objects that are classified into predetermined categories in the context of supervised inductive learning, which is a subfield of inductive inference. The inductive assertion is communicated through the use of a categorization rule that places each item into the appropriate class. If the rule can properly classify all of the existing objects, then the strong implication has been met. [5].

b. Unsupervised methods: Unsupervised learning, also known as learning from observations or discovery, is the process of obtaining a "sense" categorization from a series of objects or given situations (unlabeled instances) [5]. This process is also known as learning from discovery. We have a large amount of data that is not distinguished, and we need to determine whether or not it has any group structure. The purpose of this is to determine whether or not there is a propensity for the data to be sorted into classes. The fields of automated categorization and digital taxonomy both make use of this sort of learning, which is sometimes referred to as ING Cluster or Analytical Cluster. This particular method of organization has been around for an untold amount of time. It focuses mostly on the natural sciences (Fig. 3.11), a system developed over many centuries by philosophers to classify papers and books and to organize scientific fields [4]. Researchers are looking for ways to automate classification. In order to construct object classes, a metric of object similarity is utilized as a foundation. Intra-class similarity is prioritized above inter-class similarity in the design of the classes or ideas. When a set of predetermined ideas can be used to characterize a class of objects, unsupervised learning is equivalent to conceptual categorization [5].

c. Hierarchical methods: In ascending hierarchical classification. The process consists of grouping the individual observations into classes by part of the same class. The methods are distinguished by the choice of the distance between the observations and the definition of the aggregation strategy. In the basic algorithm, the calculation of the distance (it is more exactly a question of a quantity criterion which one calls distance by misuse of language) is done by recurrence from the matrix of the distances between observations.

d. Non-hierarchical methods: The result of a non-hierarchical classification or partitioning is the breakdown of the set of all persons into m distinct sets or equivalence classes, where the number m of classes remains constant. The end result is a partition of the set of persons, which may be thought of as a collection of sections or classes of the set I of individuals, and it is obtained in such a way that:

a. Any class is non-empty.

b. ·Two distinct classes are disjoint.

c. ·Every individual belongs to a class.

This algorithm is called "aggregation around variable centers". A slightly different version, known as "dynamic clusters", consists of representing each group not by its center, but by a set of randomly chosen points (core) inside each group. We then calculate an "average" distance between each observation and these nuclei, and we proceed to the assignment.

e. Non-parametric methods: A classified is said to be non-parametric if no parametric statistical distribution is used, only the spectral distance will then be taken into account. This category includes in particular methods based on distance minimization (hyper box or parallelepiped, minimum distance and Mahalanobis distance, K nearest neighbours, K-means, ISODATA, etc.), new methods that have recently appeared are added to this category such as neural networks and Support Vector Machines (SVM)[5]. Parametric methods: A classifier is said to be parametric if it associates with the spectral signature (or profile) a known statistical distribution, most frequently for image processing, the normal or multi-normal law. This association offers the possibility of assign to each pixel a probability of belonging to a given class [5]. Structural methods: This type of method exploits structural and contextual information of an object, they analyze the object in terms of its components (primitives) and their properties, one finds for example the syntactic analysis of a form or a object from a grammar, tree distance, graph distance (isomorphisms of graphs, of sub-graphs, with error correction, etc.). In the structural method the class mainly comes in the form of small round regions [5].

Table 3.1: Non-Parametric Methods of Machine Learning

Data Analysis Approaches	Scenarios for Common Use	Advantages	Disadvantages
Non-Parametric Methods also known as • Data-Driven Methods. • Direct Signal Analysis. • Model-free Methods. • Non-Physics-Based Methods.	• Structure may not be a critical structure. • Structural prediction is not critical. • Many structures need to be monitored. • There is time for training the system.	• No need for models, therefore no modeling costs. • May detect and localize changes/damage. • Many options for signal analysis. • Incremental training can track damage accumulation. • Good for long-term use on structures for early detection of situations requiring model-based interpretation.	• Physical interpretation of the signal may be difficult. • Weak support for decisions on rehabilitation and repair. • Indirect guidance for structural management activities such as inspection and further measurement. • Cannot be used to justify replacement avoidance.
Parametric Methods also known as • Structural Methods. • Model-based Methods. • Physics-Based Methods.	• Design model is not accurate. • Structure has strategic importance. • Damage is suspected. • There are structural management challenges.	• Interpretation is easy when links between measurements and potential causes are explicit. • The effects of changes in loading and use can be predicted. • Guidance for further inspection and measurement. • Consequences of future damage can be estimated. • Support for planning rehabilitation and repair. • May help justify replacement avoidance.	• Modeling is expensive and time consuming. • Errors in models and in measurement can lead to identification of the wrong model. • Large numbers of candidate models are hard to manage. • Identification of the right model could require several interpretations–measurement cycles. • Complex structures with many elements have combinatorial challenges.

f. Reinforcement methods: The input data is the same as for supervised learning, however learning is guided by the environment in the form of rewards or penalties given depending on the error made during learning [5]. Semi-supervised method: The input data consists of labeled and unlabeled examples. This can be very useful when we have two types of data, because it allows not to leave out and to use all the information [5].

3.8 CONCLUSION

In this chapter, we have presented the relation of our work with medical screening and its importance on human health, we even have notions on biomedical and its relationship with learning machines. We have seen what a learning machine (ML) and we is have shown its relationship with the improvement of treatments and medical decisions (digital screening) by health professionals. We have thus presented the different categories of learning machines and also the different types of learning. In the next chapter, we will see the principle of deep learning (Deep learning) and convolutional neural networks (CNNs)

4. PROPOSED METHOD

4.1 SYSTEM OUTLINE

The primary focus of artificial intelligence (AI) research in the field of medicine is on creating the algorithms and methods that can evaluate whether or not the behavior of a system represents an accurate illness diagnosis. A medical diagnosis is the process of determining which disease or disorders are responsible for a patient's symptoms and indicators. In most cases, diagnostic information is gleaned from the patient's medical history as well as the results of a physical examination [1]. It is usually challenging due to the fact that many signs and symptoms are unclear, and a diagnosis can typically only be made by highly qualified medical professionals. Therefore, it is difficult for nations like Bangladesh and India, who are still building their healthcare systems and do not have an adequate number of medical experts to care for their people, to provide appropriate diagnostic procedures to the greatest number of patients possible [2]. In moreover, many diagnostic treatments need expensive and time-consuming medical testing that many low-income individuals cannot afford.

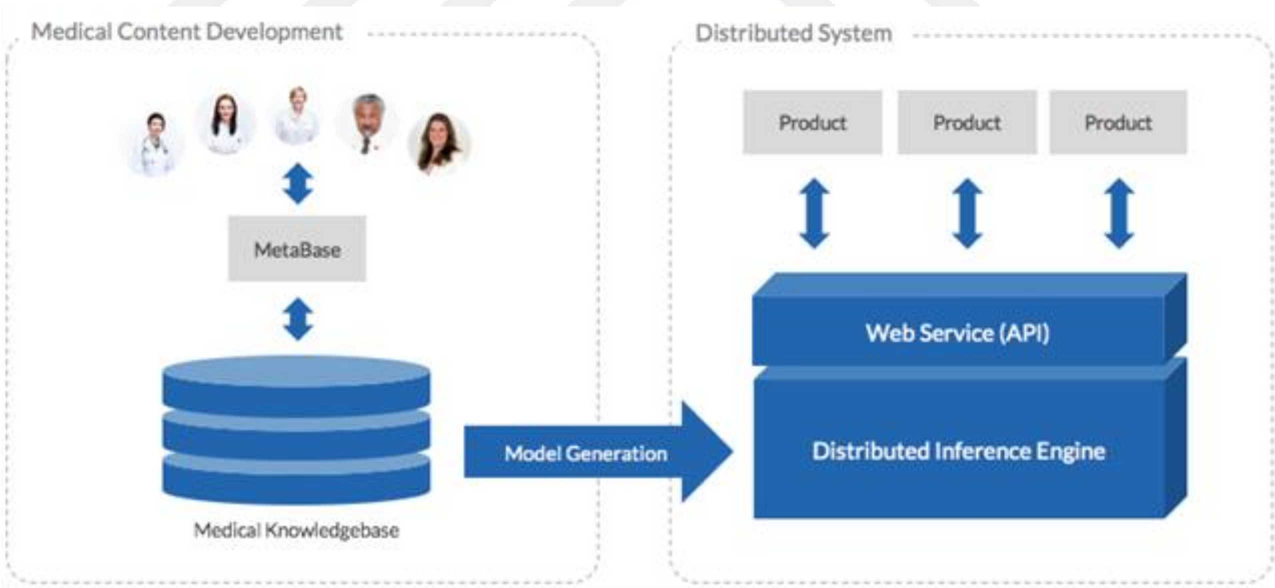

Figure 4.1: AI Based Symptoms Checker.

Due to the fact that a disease predictor may detect a person's condition without the need for direct physical contact, it may be advantageous in instances where the virus is spreading, such as with COVID-19 and EBOLA. They do exist, but they lack the required level of precision since they do not take into account every factor. As a direct result, a multitude of models were created in an attempt to determine which one was the most realistic portrayal of the real thing. Even though the scope and degree of complexity of ML projects may vary considerably, their fundamental structure remains constant. Various rule-based machine learning methods were used to remember the construction and deployment of the prediction model. The raw data was collected using a variety of machine learning (ML) methods, and it was then categorized based on gender, age, and symptoms. Various machine learning models, including Fine, Medium, and Coarse Decision Trees, Gaussian Naive Bayes, and Kernel Naive Bayes, Fine and Coarse KNN, Weighted KNN, Subspace KNN, and RUSBoosted trees, were used to analyze the data. The accuracy of the ML models was observed to vary. To determine whether or not a patient has influenza, Monto et al. [6] developed a statistical model. There were a total of 3,744 influenza patients that participated in this study. All of these patients, who varied in age from adults to adolescents, experienced a fever in addition to at least two additional disease-related symptoms. The laboratory verified that 2,470 of the 3,744 individuals tested positive for influenza. Karayilan and coworkers [10] developed the backpropagation technique for artificial neural networks. Backpropagation was utilized to train the neural network, which was subsequently used to produce 95 percent accurate predictions on the presence or absence of heart disease based on a set of 13 clinical criteria. Chen et al. [11] enhanced the efficacy of a variety of machine learning techniques to more precisely predict the onset of an epidemic of a chronic disease. There was a glaring lack of completeness in the data gathered for training purposes. In order to solve this problem, a model with latent components was used. CNN-MDRP is a novel multimodal disease risk prediction model that is based on convolutional neural networks (CNNs). The computer program was able to achieve a 94.8 percent accuracy rate. Four distinct deep learning models were utilized by Chae et al. [12] to monitor eighty infectious diseases in six groups: DNN, LSTM, OLS, and an autoregressive integrated moving average. These models were used for disease surveillance (ARIMA). The top performing models included the DNN and the LSTM. On average, the DNN model performed better than the LSTM model. The LSTM model was able to generate accurate predictions when there were several events, but the DNN model performed better overall. The database employed by Haq et al. [13] to get their results include information on individuals with any kind of cardiac disease. The following techniques were used to extract features: relief, minimal redundancy and maximum relevance (mRMR), and least absolute shrinkage and selection operator. For cross-verification of the results, the K-fold technique was used. The retrieved characteristics were identified depending on whether or not they indicated the existence of cardiac disease using six unique machine learning techniques. [4] Mohan and his coworkers developed a successful approach for the early identification of cardiovascular diseases. The accuracy of the model for predicting heart disease, which was a combination of a random forest and a linear model, was 86.4%. (HRFLM). Maniruzzaman et al. categorized the different kinds of diabetes using ML algorithms. Using logistic regression, the variables that raise a person's likelihood of acquiring diabetes were identified (LR). The overall accuracy of the system based on machine learning was 90.62 %.

4.2 METHODS OF DISEASE CLASSIFICATION

4.2.1 SVM

The support vector machine (SVM) is an example of supervised machine learning since it can be used to generate models for both classification and regression. Another example of this type of machine learning is deep learning. Classification models often use SVM approaches, which represent each dataset record as an independent point in an N-dimensional space and then generate a hyperplane to separate two or more datasets. In recent years, these algorithms have become more popular. Support vectors are the physical locations nearest to the hyperplane or separator, which help to sustain the separating plane. The objective of algorithm development is to generate hyperplanes with a maximum distance between classes or datasets and a small number of misclassifications. When data points cannot be separated linearly in an SVM analysis, the kernel function is used.

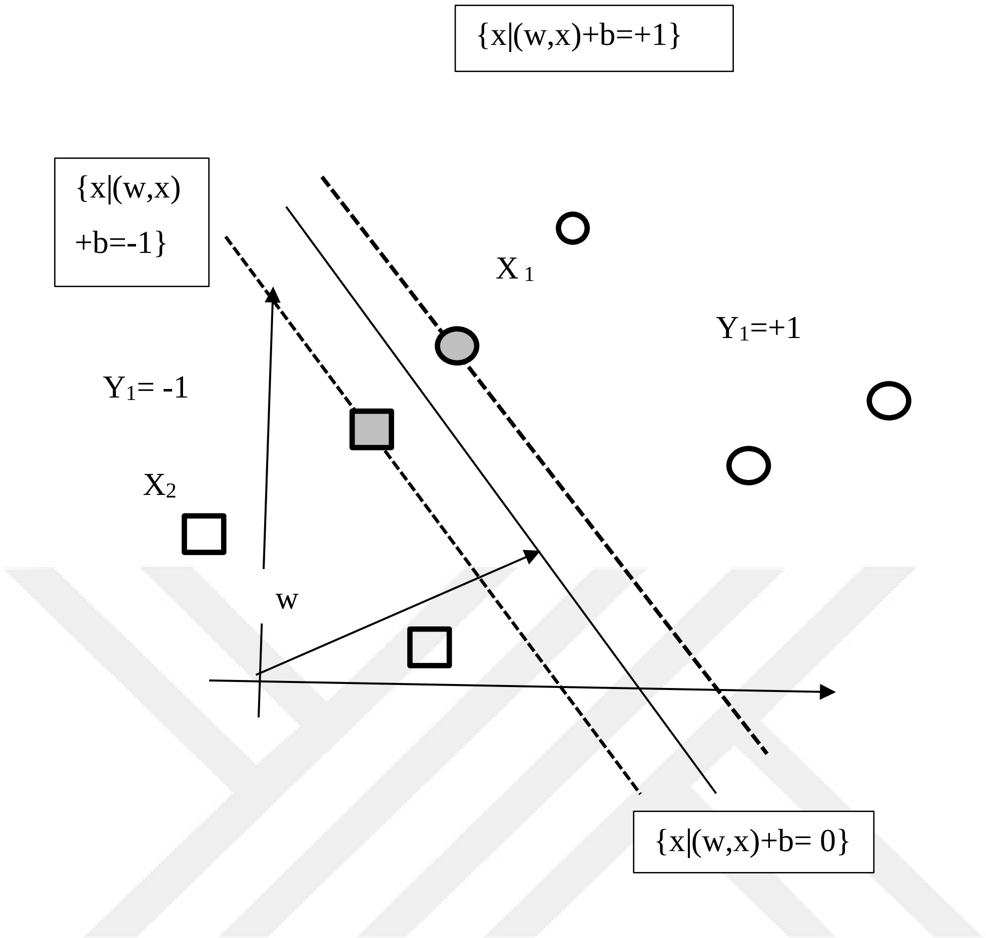

Figure 4.2: SVM Classification Procedure**.**

4.2.2 KNN

It is a technique to supervised machine learning that does not depend on parameters and whose theoretical and practical applications are clear. kNNs decide the query class based on the majority vote of the class members. This is performed by collecting the query record data points that are most comparable to those in a previously identified data collection. The input characteristics of the dataset are used to compute the degree of similarity between the records. k is the number of data points that are considered for the vote for deciding the result of the prediction. kNNs have a number of benefits, including the fact that they are not susceptible to overfitting, their ease of implementation, and the speed with which they can learn new information. The algorithm also has the drawbacks of being sensitive to noise and requiring a tremendous amount of storage space.

4.2.3 ANN

ANN algorithms are meant to work in a way that is akin to the structure of the human nervous system, which is made up of a huge number of neurons that are linked to one another in a layered fashion. Analytical neural networks, also known as ANNs, are formed of three layers: an input layer, a hidden layer, and an output layer, which is responsible for giving the results. The nodes in the network stand in for the variables, and the edges demonstrate how the nodes are related to one another. ANN is able to identify non-linear correlations between variables and generate predictions by employing nodes and edge weights as its major tools. ANNs offer a variety of strengths, including a tolerance for background noise, the capacity to learn from complicated data sets, and the power to categorize circumstances into more than one output. When dealing with massive neural networks, you face the danger of facing both issues in the interpretation of the algorithm and delays in the processing time.

4.3 PROPOSED METHOD

Listed below are the stages involved in our suggested procedure: there are a few tasks on my to-do list that must be accomplished before I can begin assessing the data. In the second phase, i will gather information linking symptoms to specific illnesses in order to provide a more complete picture. I will next use the patient's symptoms as input for the multilinear regression analysis i will do on the data. After assessing the acquired symptoms, the next step is to utilize multilinear regression to identify which illnesses are most likely to be the cause. As a result, the system will produce a diagnostic based on the maximum and minimum number of illnesses conceivable. The technique is shown in the flowchart that follows:

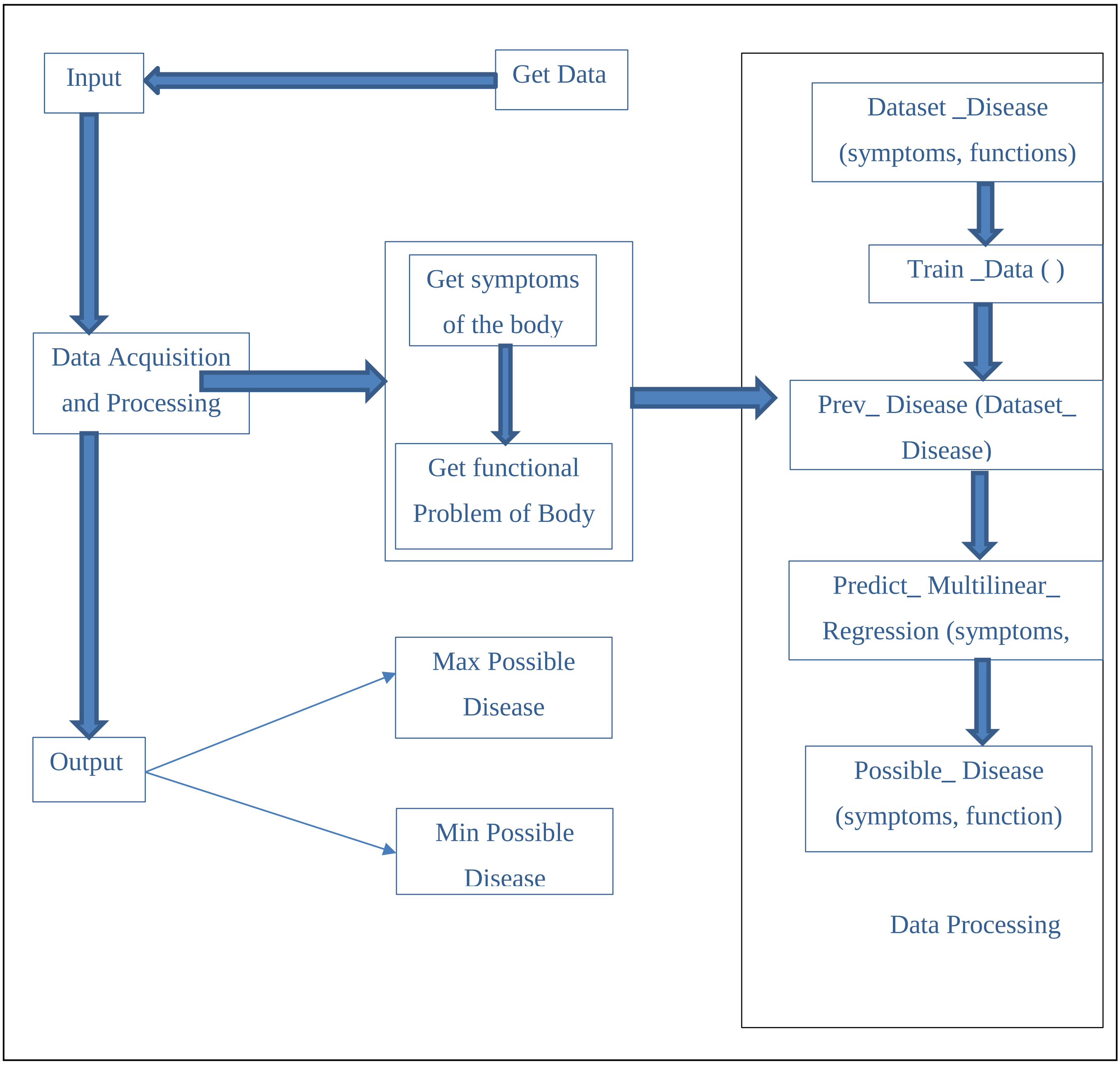

Figure 4.3: Proposed Method**.**

Within the scope of our illness prediction system, we use a Support Vector Machine (SVM) to categorize data and Multilinear Regression to forecast outcomes (MLR). It is a kind of regression technique that employs multiple independent values, which means that predictions are made using two or more variables. In linear regression, there is just one independent or predictor (X) variable, and that variable is used to model the response variable (Y). When the response variable is impacted by many forecaster variables, the MLR method is used.

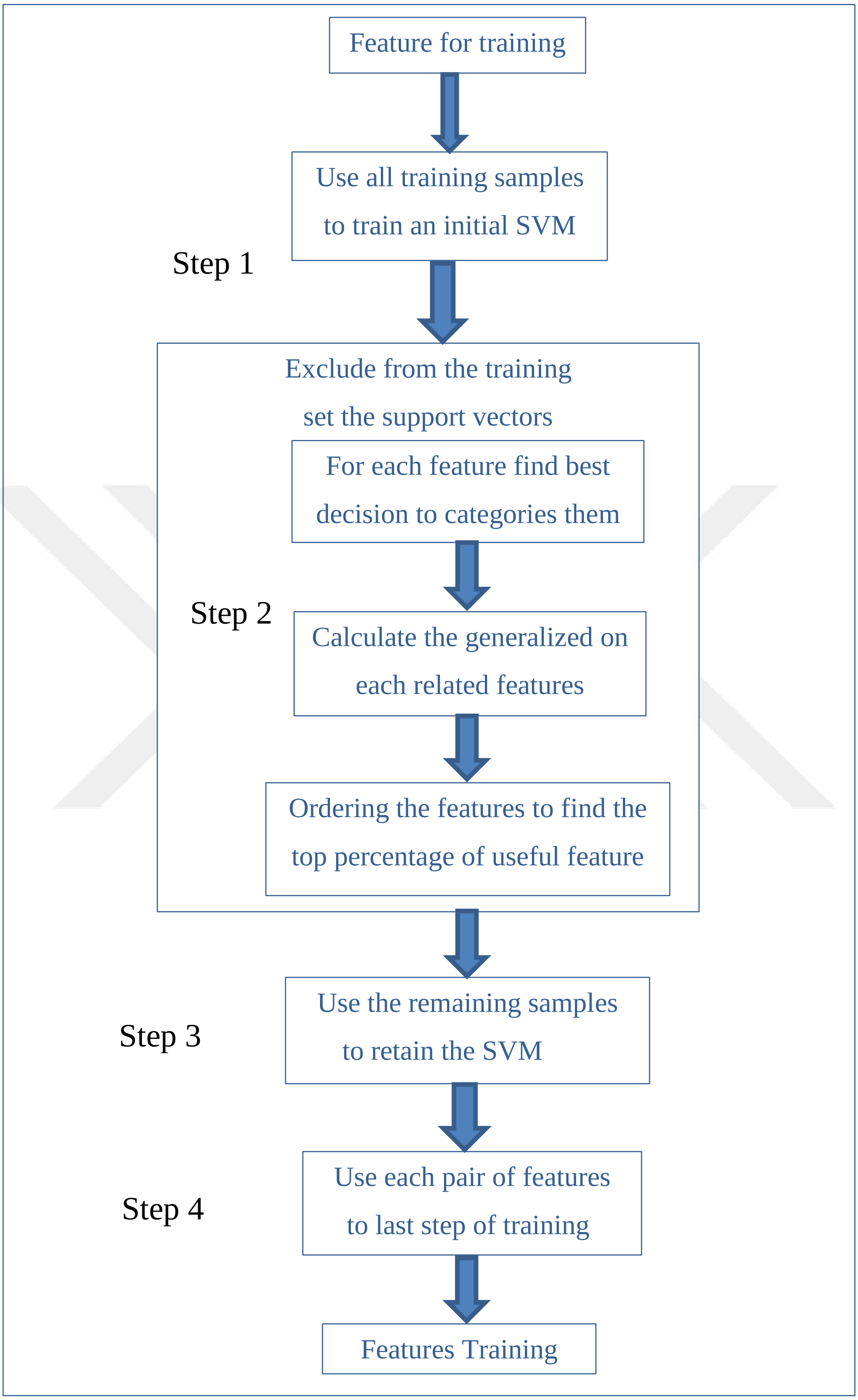

Figure 4.4: Feature Training in SVM.

These circumstances are typical. The DPS architecture consists of a variety of fields: Input The user employing the illness prediction system will provide a list of symptoms, and we will use this information. Provide Symptoms In this field, symptom information should be supplied. Information gathering and doing analyses This site is responsible for data processing. The first step of the process of collecting and processing data is the gathering of data, which is followed by the analysis of that data and the derivation of information from it. Observe the Signals Your Body Is Sending You This discipline involves the recording and study of diverse physical symptoms. In order for the computer to use this information to make predictions about potential illnesses, they must be inputted. Taking Care of the Functional Needs of the Body The functional difficulties of the body that are related with symptoms are listed in this section. In this method, it will be able to identify the presence or absence of disease.

4.4 RESULTS DISCUSSION

Using the provided data as input, a variety of machine learning models were assessed to see how well they predicted illness. Eleven distinct machine learning models were used to get the forecast. In six of the eleven models, we were able to achieve at least fifty percent accuracy. The Weighted KNN model obtains the maximum degree of accuracy, which is 93.5 percent, as shown in Figure 4.5.

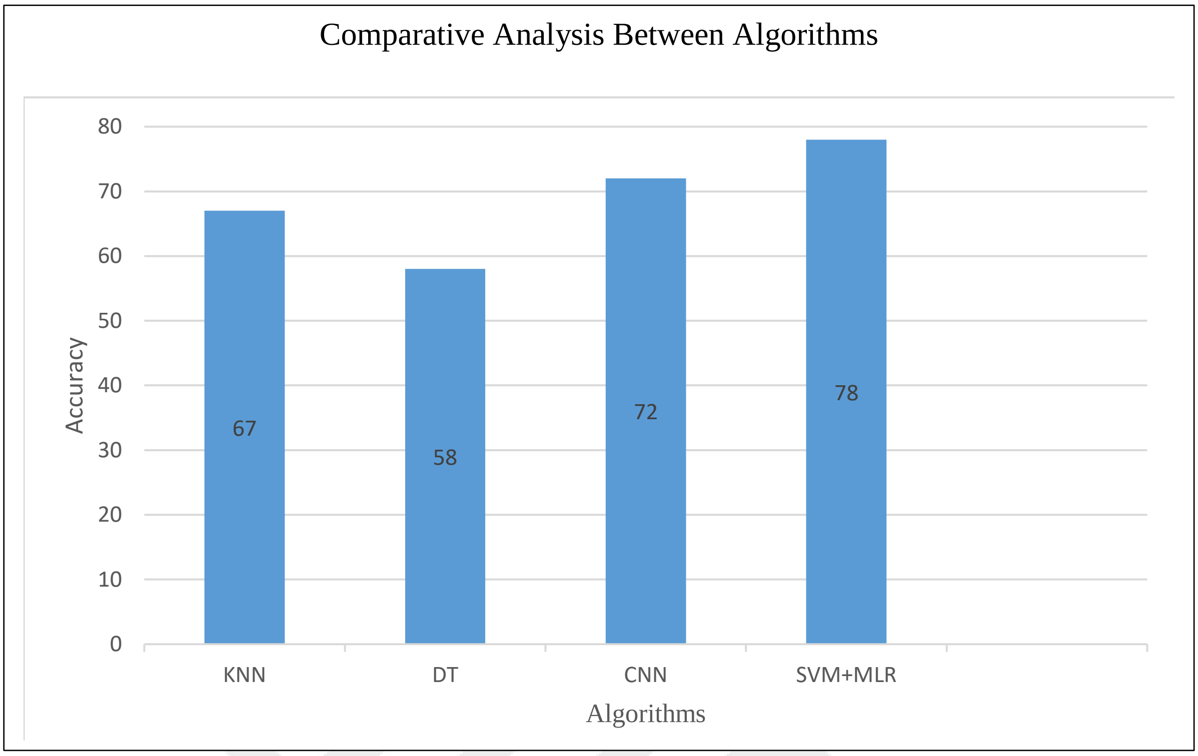

Figure 4.5: Accuracy Comparison for Different Algorithms**.**

Due to the fact that the value of K fluctuated during the life of this model, the weighted KNN was

rather accurate. This number changed greatly based on the size of our practice set, which went from very little to enormous. Due to this variation, it was determined that the machine learning method created the most accurate model compared to the others. We were able to classify individuals into several groups by examining their gender, age range, and symptoms. Only 5.3% of the time did coarse KNN correctly predict the outcome. Subspace KNN generated correct results 73.2% of the time.

4.5 CHAPTER CONCLUSION

In the chapter, the symptoms, age, and gender of a specific patient were considered in order to predict the disease. The aforementioned criteria, when implemented within the framework of the Weighted KNN model, yielded an accuracy rating of 93.5 %. The majority of ML models generated accurate results. A number of models were dependent on factors, however their accuracy percentages when trying to predict diseases were poor. If the disease could be foreseen, it would be relatively simple to organize the many medication resources needed for therapy. This strategy would reduce the total cost of treating the illness while accelerating the healing time.

5. COCNLUSION

This Thesis a variety of machine learning algorithms for predicting cardiovascular disease. To choose the optimal algorithm for machine learning, we analyzed its constituent parts and assessed a large number of alternatives. Under the various test conditions, each algorithm created its own unique set of results. As a direct result of this, more complex models are required to accurately forecast early cardiac disease in order to boost the predictive potential of already used models. In the future, technologies will be introduced for the early identification of heart illness that are accurate, inexpensive, and simple. It is hard to overstate the importance of receiving a timely and accurate diagnosis for any health issue. In cases when a disease presents a threat to the patient's life, the conventional method of diagnosis may not be enough. In the future, it is likely that doctors may be able to make more accurate diagnosis by using machine learning (ML) algorithms to make disease predictions. This is in contrast to the diagnostic processes now used. The development of a system for illness forecasting has included the use of several machine learning techniques. The information may be used to treat over 230 different ailments. Throughout the diagnostic procedure, an individual's age, gender, and symptoms are considered in order to determine the type of any sickness they may be suffering. Compared to the other techniques, the weighted KNN approach yielded the best results in terms of performance. The weighted KNN algorithm contributed to the accuracy of the projection, which surpassed expectations at 93.5 percent. Our model may serve as a physician in the sense that it may detect diseases early on so that treatment can be commenced, and lives can be saved. Frequently, the focus of present machine learning models for medical research is confined to a single illness or condition. Such as one analysis for the diabetes analysis, another analysis for the cancer analysis, etc. On the basis of a single piece of study, there is no tried-and-true procedure for generating a large number of hypotheses for a particular disease. This article utilizes the Flask API to create predictions about a variety of diseases. Diabetes, diabetic retinopathy, cardiovascular disease, and breast cancer are a few of the many health issues covered on this website. It is feasible that more disorders, such as those that damage the skin, those that can be identified with a test for fever, and many others, may be included in the future. Several evaluations of the illness were conducted using machine learning techniques.

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