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Original Article

Principles and Perspectives in Medical Diagnostic Systems Employing Artificial Intelligence (AI) Algorithms

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Abstract: *The process of identifying a health problem, illness, disorder, or other condition is known as disease diagnosis. Diagnosing certain diseases may be quite simple at times, but there may be more difficult cases. Large data sets are accessible, however the number of instruments that can reliably, Identify the trends and formulate hypotheses. Traditional disease diagnosis techniques involve physical labor and are prone to inaccuracy. When artificial intelligence (AI) predictive approaches are used instead of solely relying on human expertise, auto diagnosis is made possible and detection mistakes are decreased. We have examined the last ten years' worth of literature in this study, from January 2009 to December 2019. Eight of the most popular databases were examined for the study, and 105 publications in all were reviewed. A thorough examination of such publications was carried out to categorize the most popular AI methods for medical diagnostic systems. We also go over a number of illnesses and the relevant Artificial Intelligence (AI) methods, such as machine learning, fuzzy logic, and deep understanding. The purpose of this study paper is to shed light on several significant aspects of the various AI methods that are being and have been utilized in the medical profession to forecast heart disease, brain disease, prostate, liver disease, and renal disease. Finally, based on a list of unresolved issues and obstacles, the study offers several directions for future research on AI-based diagnostics systems.*

Keywords*: Artificial intelligence, Deep learning, Machine learning, Big data analytics, Chronic disease, Diagnosis, Soft computing, Healthcare prediction.*

I. INTRODUCTION

The study of disease diagnosis is essential to the healthcare industry. A disease is any condition or set of conditions that results in discomfort, illness, malfunction, or ultimately, death in a person. Illnesses can have an impact on an individual's bodily and mental well-being, significantly altering their way of life. The term "pathological process" refers to the study of disease causation [1]. A disease is resulting from indications or symptoms that medical professionals interpret [2]–[4]. The process of determining a disease's pathophysiology through the identification of its signs and symptoms is known as diagnosis. As seen in Fig. 1, diagnosis is also the process of determining which disease a person has based on their symptoms and indicators [5]. The knowledge needed for a diagnosis is derived from the physical examination and medical history of the patient with the illness. Frequently, during this treatment, at least one diagnostic procedure such as a medical test is performed. An authentic diagnosis is formed by a medical professional through a procedure that includes a number of processes, enabling them to gather as much data as feasible [6]. A medical care professional's ability to diagnose a condition is crucial to their care, making it the most difficult task to complete. The diagnosis procedure may be quite laborious and intricate. Medical professionals gather empirical evidence to determine a patient's illness to reduce uncertainty in medical diagnosis. If the diagnosis procedure is flawed, the patient may not receive the proper therapy or it may be postponed if they have major health problems. Sadly, not every medical professional is a specialist in every area of practice. Therefore, an automatic diagnostic system was required. It benefits from computer accuracy as well as human knowledge [7]. To obtain precise diagnosis results at a lower cost, an appropriate decision support system is required. For humans, classifying diseases based on different criteria is a difficult undertaking. Specialists, but AI would assist in identifying and managing these kinds of situations. Currently, the medical industry uses a variety of AI algorithms to effectively diagnose illnesses. AI is a crucial component of computer science that gives computers intelligence. Learning is a fundamental requirement for every intelligent system. Deep learning, machine learning, and other learning-based AI techniques are only a few examples. A rule-based intelligent system, which is one particular type of AI technique that is important in the medical industry, offers a collection of if-then rules for healthcare and functions as a decision support system. Artificial Intelligence (AI) based automated methods are gradually replacing intelligent systems in the medical profession when human participation is minimal [8], [9]. The artificial neural network (ANN), often known as a neural network, is a vast array of neural units created from biological neurons that are connected in the brain. It is a human simulation, the brain and functions are precisely the same. Every neuronal unit is connected to a large number of other neurons in a manner akin to the bipartite graph [10]. These systems automatically pick up new skills and become trained. It is laborious work for physicians and surgical specialists to determine the possibilities and predictions surrounding health conditions. In certain instances, artificial neural networks (ANN) make fast healthcare decisions by gathering, interpreting, and identifying data points that are critical to prediction [11], [12]. In the medical area, deep learning—a subset of machine learning that is likewise algorithm-based is utilized to support experts in the evaluation of any ailment making better medical decisions as a result. Numerous domains, including medication development, medical imaging genome analysis, and Alzheimer's disease detection, can benefit from deep learning [13]. This paper mainly focuses on the three primary areas of artificial intelligence: Deep learning, machine learning, and fuzzy logic. The main use of deep learning in medicine is the early detection of breast cancer. According to a recent study by a cancer institute, automatic breast cancer detection has an accuracy level that is either higher or equal to that of human radiologists. Additionally, AI is more likely to generate results that are more accurate than before because it has been continuously training itself. The Internet of Medical Things, which facilitates the use of IOT devices to gather healthcare data, is another important application of AI. Artificial intelligence (AI) software senses the symptoms of the disease even before it manifests. In less time than a skilled radiologist, neural networks can be trained to detect lung cancer, breast cancer, and strokes. A range of AI algorithms assists physicians in the analysis of medical pictures, including CT, MRI, and X-ray images, enabling them to identify some diseases. Physicians can more effectively diagnose patients and recommend the best course of action by using medical expert systems. Doctors can categorize the various deadly diseases using AI tools in addition to being able to identify the sickness itself. Currently, available AI algorithms assist physicians in organizing a thorough strategy for disease. Additionally, they are frequently employed to enhance surgical robots that carry out extremely complicated procedures. This study offers three distinct contributions. We start by outlining the current components that influence the early stages of disease identification.

- Afterwards, we go into how AI methods have been modified for early illness diagnosis.
- We offer a comprehensive examination of medical diagnostic systems via a methodical study. We apply the widely recognized PRISMA methodology.
- Next, we give an overview of each of the chosen articles, including the diseases they addressed, the AI methods they employed, and the objectives and conclusions of their respective studies.

We also provide a comprehensive analysis of the articles that were examined, followed by suggestions for further research. This is how the remainder of the paper is structured. In part II, we provide the relevant papers on AI-applied techniques for medical diagnostic systems. Sections IV and V introduce machine learning-based diagnostic systems, while Section III discusses fuzzy logic-based medical diagnostics and algorithms for deep learning, respectively, We use the Prisma approach to convey the review guidelines in Section VI. Section VII summarizes the research findings, discussion, and directions for future research, while the last Section wraps up this review.

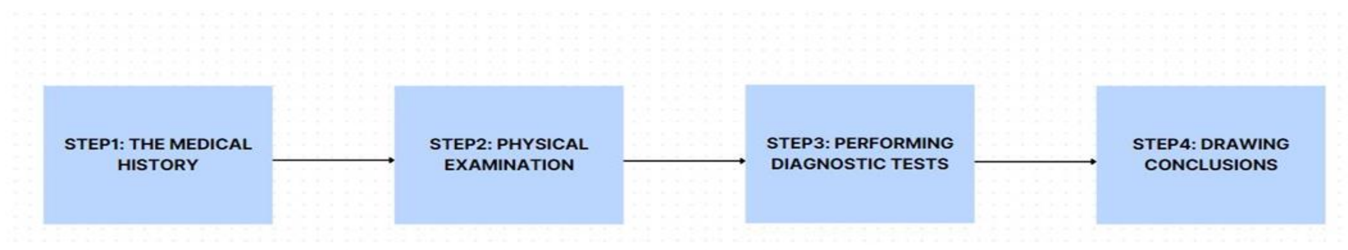


Figure 1: Block diagram of the diagnosis process

II. RELATED WORKS

This part covers our contribution to the present body of work, pertinent survey studies on the diagnostic process, and the state-of-the-art applied AI approaches utilized for disease diagnosis. An automated surveillance study on healthcare-associated infections was conducted by Van Mourik et al. [14]. The writers of this article have explained how, in comparison to manual surveillance techniques, autonomous surveillance systems built on machine learning algorithms offer improved performance and dependability. The utilization of regression models can enhance the effectiveness and sensitivity of monitoring operations, according to another review conclusion. A number of issues, including post-discharge surveillance, case-mix modification, and quantification of device usage, must be resolved soon. A frequent lung infection in younger children and newborns is called BRONCHIOLITIS.

This illness and Respiratory Syncytial Virus (RSV), which can be a primary cause of bronchiolitis, were reviewed by Luo et al [15]. The systematic study offers some new perspectives on predictive modeling and details how machine learning might help overcome some of its drawbacks. The potentially fatal illness known as sepsis is brought on by your body's reaction to an infection which results in inflammation and the simultaneous failure of several organs. A comprehensive review was conducted by Bhattacharjee et al. [16] to look into the patterns of sepsis diagnosis in hospitals today. The advantages and disadvantages of several sepsis detection screening methods and scoring systems have been examined by authors in general hospital wards. Ultimately, they discovered that biomarkers and electronic health records can significantly impact the prediction of sepsis. Sinha et al. conducted one more investigation on sepsis [17]. They mentioned a few problems with regular blood culture testing for the diagnosis of sepsis. In order to examine appropriate automated sepsis detection techniques, seven molecular technologies utilizing blood samples were examined. They have covered several current and upcoming trends in this analysis. They have also examined the effects of machine learning algorithms on the identification of sepsis using electronic medical data. They conclude that combining several technologies can enhance detection and reduce danger. As far as is known, this is the first attempt to offer a thorough survey for illness prediction utilizing fuzzy logic, machine learning, and profound comprehension. Additionally, this work has concentrated on a specific spectrum of illnesses, such as heart disease brain disease, prostate, liver disease, and renal disease, in contrast to previous survey papers that are available in the literature.

III. FUZZY LOGIC AND DISEASE DIAGNOSIS

This section begins with a summary of recent fuzzy logic-based related research. Later on, we will go over the fuzzy logic method for diagnosing illnesses.

A) Existing Works Using Fuzzy Methods

Fuzzy logic offers flexible solutions for challenging issues. For systems that make decisions, like expert systems or pattern categorization systems, fuzzy logic is thought to be a reliable technique [18]–[21]. Because it produces an accurate examination report, fuzzy logic is essential to the medical evaluation process. These kinds of frameworks offer a quick and easy method for clinical evaluation. In the absence of an expert or clinical specialist, they are also helpful. These frameworks produce results based on the body of knowledge that is integrated into them from specialists or experts in the topic.

Numerous clinical diagnosis systems that have been developed and used in the medical industry rely on the fuzzy set model [22]. Anything unclear is referred to as fuzzy. Fuzzy logic can be used to provide reasoning for situations like the one shown in Figure 2 when we are unsure of the validity of the state. It is an approach based on rules. A common method in the medical field that derives from Fuzzy Inference Systems (FIS) is the Fuzzy Rule-Based System (FRBS). FRBS uses IF-THEN rules to represent information [23]. In addition, classification and clustering methods are applied in the medical field. Additionally, it is found that FIS and FDSS are the most widely used methods in the medical field [24]. Fuzzy logic's primary characteristic is its ability to reduce uncertainty and inaccuracy in any given circumstance. A fuzzy logic system has intermediate values that are partially true and partially false, but there is no rationale for absolute acceptable and invalid values. To demonstrate how fuzzy logic functions, let's look at the following example. Over the last few years, the use of fuzzy logic in disease diagnosis based on various parameters has steadily increased.

For example, coronary illness is a type of disease that results from injury or blockage of heart veins, reducing the amount of oxygen reaching the heart's organs. Heart failure, arterial blockage, heart attack, stroke, and other cardiac conditions are common [25]. With the aid of expanding new artificial intelligence approaches, fuzzy logic is constantly evolving to discriminate cardiac patients globally. Numerous publications have been published using fuzzy logic to identify coronary disease. The results of Sari and Gupta's [26] study on the identification of coronary disease using a neuron-fuzzy integrated system were comparable to the views of medical professionals in cases of high or low cardiac risk. A cardiovascular arrhythmia grouping system was presented by Junior et al. [27] that uses fuzzy classifiers to identify a certain electroencephalogram point using network fuzzy rules. With this technique, a series of samples are used to shorten the overall processing time of the ECG signal without sacrificing any crucial information. The ECG signals are inserted into the cleaning framework, which then makes use of a clustering algorithm fiction as well as association. Their research revealed that their technology is capable of detecting common cardiac conditions such as angina, myocardial infarction, and arterial coronaria with ease. In comparison to other documented approaches, their approach offered superior disease diagnosis for Pulse Pressure Variation, based on the results collected. The deadly viral disease known as "Ebola hemorrhagic fever" is caused by the Ebola virus.

Therefore, research has been done on a secure diagnosis approach. According to Oluwagbemi et al. [28], the Ebola fuzzy informatics system was created with EVD diagnosis in mind. They employed a set of rules and fuzzy logic as their inference engine. A database was established to aid in the diagnosis of Ebola Virus Disease (EVD). Root Sum Square was the fuzzy inference technique employed. We may conclude that their method is a useful addition to the battle against Ebola based on its performance. A person with a brain disease or abnormality may have personality changes, twitching, small seizures, loss of memory, and an inability to think. The brain is the body's primary control center. The effects of brain disorders can be disastrous. Vision loss, weakness, paralysis, and other issues can be brought on by brain disorders such as stroke, brain tumors, and Alzheimer's disease [29]. For treatment to begin, these issues must be identified early on for both the patient and the physician. In [30], Gopal and Karnan proposed a brain tumor diagnosis technique. a system that uses MRI pictures and the Fuzzy C Means clustering algorithm to diagnose brain cancers. Particle Swarm Optimization and Genetic Algorithm are the tools utilized in conjunction with Fuzzy C Means methods. The two algorithms GA and PSO are used to break up the suspicious block. The brain tumor is subsequently verified and correlated in the diagnosis process using a computer-aided system. Brain tumor fragmentation adaptive threshold was found with the aid of Fuzzy C Means. The outcomes of current methods were compared with those of earlier methods. According to their findings, it can identify the best remedy and enhance the fragmentation's overall performance. Chen et al. [31] provided another representation in an effort to develop a useful brain problem-detecting system by the diagnosis of Parkinson's disease using fuzzy k-closest neighbor, or SVM. A comparison between FKNN and SVM was conducted. The experimental results demonstrated that the FKNN method outperformed the SVM classifier in terms of performance. 96.07 is the accuracy that the FKNN achieved, higher than that of the SVM approach. Several ANN processes were also used to diagnose a variety of ailments, including thyroid disorders, asthma, diabetes, cancer, heart disease, and neurological disorders. Patra and Thakur [32] have presented the neuro-fuzzy model as a means of accurately diagnosing adult asthma. The collection of the dataset came from several hospitals. To achieve accurate findings, three learning algorithms were used: ANN with the Backpropagation Algorithm, ANN with Learning Vector Quantization (LVQ), and ANN with Self Organizing Maps (SOM) in conjunction with the NF tool. After that, data was classified using fuzzy inference to help with disease diagnosis. Additionally, fuzzy logic has the ability to identify serious illnesses like cancer, particularly breast cancer. Breast cancer is a type of illness brought on by lumps in the breast tissue that surround the cells. Uncontrollably growing cells give rise to cancer. Working together, Miranda and Felipe [33] developed the Fuzzy Omega algorithm, an automated breast lesion detection method. The user provided features such as size, density, and contour, and the algorithm recommended the BI-RADS classification. For nodules, their method's accuracy was 76.6%, and for calcifications, it was 83.34%. Nilashi [34] offered an alternative strategy for an early diagnosis to combat the illness. Using clustering and classification techniques, the authors created an information-based architecture for the disease classification of breast cancer. They grouped the data using Expectation-Maximization. The classification of breast cancer disease was done using fuzzy rules that were taken from Classification and Regression Trees. Their approach can be applied as a disease diagnosis decision support system. Another type of hepatic illness that causes the liver to partially or totally stop functioning is liver disease. The majority of liver disease-causing factors are genetic or related to alcoholism. Fatty liver is the most well-known type of liver disease. Satarkar S.L. and Ali M.S. collaborated to create an expert system that could diagnose a liver ailment. with hazy reasoning. The authors claim that the Mamdani technique for identifying risk factors delivered the representation. Their approach has the potential to predict cirrhosis and obviate the requirement for a liver biopsy [35]. One type of illness that is brought on by the body's elevated blood glucose levels is diabetes. Aside from that, this illness causes type 1, type 2, or gestational diabetes by lowering the amount of insulin in body cells. An overabundance of sugar in the body can lead to many problems, such as damage to the kidneys and nerves. The goal of Kalpana and Kumar's study [36] was to create a model that would use a fuzzy determination method to examine diabetes. The author employed the fuzzy determination system to assess rules using the fuzzy operator in their study and depict knowledge with descriptions to determine whether or not a person has the potential to be diabetic. Using a fuzzy hierarchical model, Lukmanto [37] proposed an intelligence system capable of performing an early diagnosis of diabetes. After being applied to 311 pertinent data points, the suggested model achieved an accuracy of 8746.46%, which is comparable to a medical professional's declaration. Another suggestion for diagnosing diabetes using an associative classification approach based on fuzzy logic to address the issue of boundary value confusion while partitioning risks was made by Rajeswari et al. [38]. The word "dental diseases" refers to a group of conditions that affect teeth, including dental plaque, gingivitis, periodontal disease, and tooth decay. Based on periodontal dental disease, Allahverdi and Akcan examined around 164 fuzzy rules that were obtained with some inputs.

Reducing the time needed for early oral disease identification was the main objective of their investigation [39]. A method called the Dental Diagnosis method was created by Son et al. [40] to identify dental issues that rely on a hybrid approach of classification, fragmentation, and decision-making. The results of their investigation showed that the DDS has an approximate accuracy of 92% in detecting dental problems, which is higher than any other system, including the fuzzy inference system (89%), fuzzy k-nearest neighbor (80%), prim spanning tree (58%), and Kruskal spanning tree (58%). Cholera and other bacterial illnesses are caused by consuming contaminated or contaminated water. If this type of illness is not treated in a timely manner, it can cause diarrhea, drying out, and even death. A Mamdani fuzzy approach-based system was proposed by Uduak and Mfon. In MATLAB simulation, the centriod approach outperformed other defuzzers [41]. Okpor M.D. provided another representation; they used fuzzy classification to categorize their cholera inquiry. When compared to earlier uses, the outcomes for treating cholera were satisfactory [42].

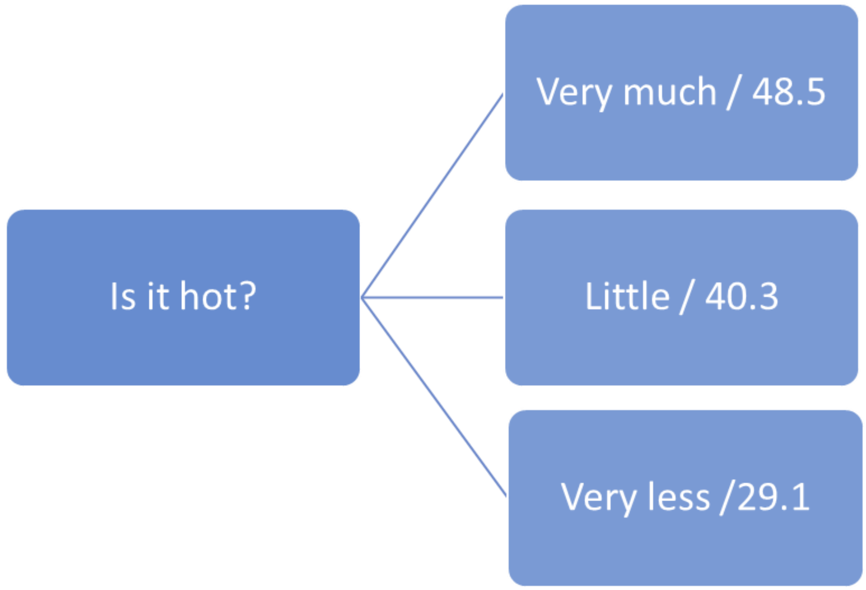


Figure 2: Process of Fuzzy logic

B) Medical Diagnosis Process Using Fuzzy Logic

Fuzzy logic is capable of representing data and results as semantic articulation. Since the majority of diagnosis procedures have been carried out based on the likelihood of medical findings, it is often helpful [43]. The authority to improve the diagnosis process, a clinical proof-based theory of human thought and decision-making ability is developed [44]. Owing to the proven effectiveness of using fuzzy approaches in the healthcare industry to represent uncertainty, they have been applied in the discovery process with different applications depending on the type of disease and the researchers' goals [45]. The two primary components of this medical science framework's basic rule are the usage of symptoms as input and the disease as output. The steps listed below typically comprise the fuzzy logic procedure for disease diagnosis shown in Fig.3:

Fuzzifier A fuzzifier is one who performs the fuzzification process. It involves converting a clear input value to a fuzzy set. Fuzzifier is thus employed as a mapping from an input that is observed to a fuzzy value.

Inference engine: Following the fuzzification process, the fuzzy value is processed by the inference engine according to a series of rules that serve as a guide for the knowledge base.

Knowledgebase: This is the fuzzy logic system's key element. The knowledge base is the foundation of the entire fuzzy system. It is also known as the database and is composed primarily of rules and both structured and unstructured data.

Defuzzifier: the procedure that transforms the inference engine's output into clear reasoning. The defuzzification process uses fuzzy value as an input, which transfers fuzzy value to crisp value.

One of the methods for artificial intelligence (AI) is fuzzy logic, which achieves intelligent behavior by building fuzzy classes with certain criteria.

Humans can understand the criteria and guidelines. The fuzzy classes and these rules are primarily defined by domain experts. Therefore, fuzzy logic requires a significant amount of human interaction. In essence, the data processing procedure presents the information using fuzzy logic. In the medical field, machine learning can be used to create one of these representations even more effectively than fuzzy logic. The estimation's statistical model is unable to yield findings with good performance. Large data values, missing values, and categorical data are not detected by statistical models [46]. Every single ML is crucial to many different applications including picture identification, disease diagnosis, information mining, and natural language processing. Throughout all within the aforementioned categories, machine learning offers suitable solutions based on the issue. As a result, Machine Learning (ML) also makes sophisticated diagnosis and treatment systems in healthcare possible. We go over how ML was applied to illness diagnosis systems in the part that follows [47].

IV. MACHINE LEARNING AND DISEASE DIAGNOSIS

This section begins by introducing the most recent machine learning-based related research. Next, we go over how machine learning is used to diagnose diseases.

A) Existing Works Using Fuzzy Ml

Machine learning is a field within the broader field of AI, where machines learn and perform tasks on their own through training. Machine learning includes supervised learning (under the control and“guidance” of a human expert), which initially recognizes both the inputs and outputs, and unsupervised learning (which requires very little There is an algorithm. Human intervention or subject matter expert services) results are unknown.The machine is trained to learn concepts by providing examples and creating sample models designed to distinguish between two or more objects.In the medical field, machine learning helps experts process large and complex medical data and also helps study the results. The output of this process can be used for further research. Therefore, when machine learning is applied in healthcare, it increases the patient confidence level in medicine to predict diseases through the implementation of machine learning algorithms. Diseases may not be detected early by human experts. In these cases, machine learning can be used to detect the early stages of a disease before it occurs or becomes dangerous to someone. This way, you can prevent future problems because "prevention is better than cure." The popularity of machine learning in various fields led to the birth of his machine learning algorithm, which requires less processing of raw data and produces correct results compared to traditional models. A variety of machine learning algorithms are used to identify different diseases, including ensemble classifier techniques, Bayes classifiers, Decision trees, Support vector machines, Multilayer perception, K-Nearest neighbor and others. Machine learning algorithms can be used to quickly predict diseases with great precision. Observations or information, such as examples, firsthand experience, or teaching, are the first steps in the learning process. Specifically, the algorithms seek out trends in the data and make more informed choices. The main objective is to let the machines learn on their own, devoid of human intervention, and modify the response as necessary [48]. The goal of AI's contribution to medical science is to create tools that assist medical professionals in making more precise and expert diagnoses. Disease prognosis is a key component of machine learning. Different A popular term used to describe a variety of disorders affecting the structure and function of the kidney is KIDNEY DISEASE. Kidney damage is the main factor used to define chronic kidney disease. or diminished renal function for a minimum of three months. One of the most dangerous consequences of long-term renal illness, the main cause being problems from reduced renal function [49]. A decision support framework was presented by Sinha and Sinha [50] for the diagnosis of kidney disease. The effectiveness of two classifiers—SVM and KNN—was examined. The algorithms' accuracy, precision, and execution time were the basis for comparison. They found that KNN performs better than SVM through their analysis. In a different study, Charleonnan et al. [51] categorised their findings based on four machine learning techniques: KNN. To select the greatest approach, they evaluated each other's performances. It was found that the SVM approach outperforms the other others and yields a 98.3% maximum accuracy. The most frequent cancer and the main cause of mortality for women is BREAST CANCER, a chronic illness. Machine learning has been a useful tool in the identification of breast cancer in recent years. Zheng et al.'s [52] main goal was to create a model that would use the properties of the retrieved tumour to identify breast cancer. The hidden designs of benign and malignant tumours were found using the K-means algorithm, which was then utilised to extract relevant information and diagnose the tumour. SVM was then applied to enable the classifier to distinguish between the incoming tumours. Their method increases accuracy by about 97%. Asri et al. [53] used various machine learning techniques to categorise their analysis of breast cancer in a distinct study. Using the Breast cancer dataset, the authors conducted a comparative performance-based examination of many machine learning techniques, including SVM, k Nearest Neighbours, and Decision Trees. The main goal was to assess each algorithm's accuracy in terms of correctness, precision, and sensitivity when categorising data. The results of those algorithms demonstrated that SVM offered the best accuracy. Arthritis is the term used to describe pain and stiffness in one or more joints that might develop with age. There are several types of arthritis, including rheumatoid arthritis and osteoarthritis. Every kind is treated differently. An individual's quality of life is diminished by arthritis. Therefore, it's imperative to detect arthritis early, and ML can help with that [54]. A method for categorising patients with arthritis using a dataset derived from Koch was described by Neeraj et al. [55]. Their method used the CART algorithm to classify the data based on attributes including age, gender, identity, and treatment to determine true or false rates. A chronic condition known as diabetes arises when the pancreas is unable to produce enough insulin. Nahla and Bradley [56] focused on diagnosis by applying SVM classification to determine diabetic disease by classifying based on a blood test. 94% SVM prediction accuracy, 93% sensitivity, and 94% specificity were attained. In order to categorise patients exhibiting diabetes symptoms, Kandhasamy and Balamurali [57] conducted a comparison of machine learning classifiers, including Random Forest, K-Nearest Neighbours, J48 Decision Tree, and SVM. The UCI data repository provided the data used to evaluate these methods. The specificity, sensitivity, and accuracy of the algorithms' output have been compared using datasets with and without noisy data. The methods have also been evaluated with noisy data. According to their investigation, the decision tree J48 classifier outperformed the other three classifiers in terms of efficiency. The ailment known as Parkinson's disease is the cause of the neurological system's malfunction in both progression and movement. Slowly, symptoms could initially start with a tremor in just one hand. In Sriram et al.'s system [58], Orange and Weka tools were utilised for evaluation and classification during experimentation analysis. The Voice dataset for Parkinson's disease was released by the UCI Machine Learning Repository. An algorithm for classification. The least accurate model is Naïve Bayes. (69.23). A machine learning system that was utilised to diagnose Parkinson's disease and progressive supranuclear palsy in patients was overseen by Salvatore [59] in 2014. They grabbed A classifier based on Support Vector Machines (SVM) that was applied to 28 MRI image records of individuals with Parkinson's Disease (PD) and PSP. Individual patients might be distinguished from PSP patients by the algorithm. Influenza is the term for a viral infection that affects the respiratory system, including the nose, throat, and lungs. Pineda et al. [60] examined seven distinct machine-learning classifiers for influenza detection and contrasted their output with an existing influenza Bayesian classifier. Their research proved that Machine Learning (ML) could diagnose illnesses that were too strong to resist. Concerning the occurrence of cancer in liver cells, Sandeep et al. [61] proposed a model for Lung images which can be classified into normal or dangerous categories. The authors claim that results might be obtained with great precision by using this mechanism. By means of using electronic data, machine learning can forecast a range of illnesses.

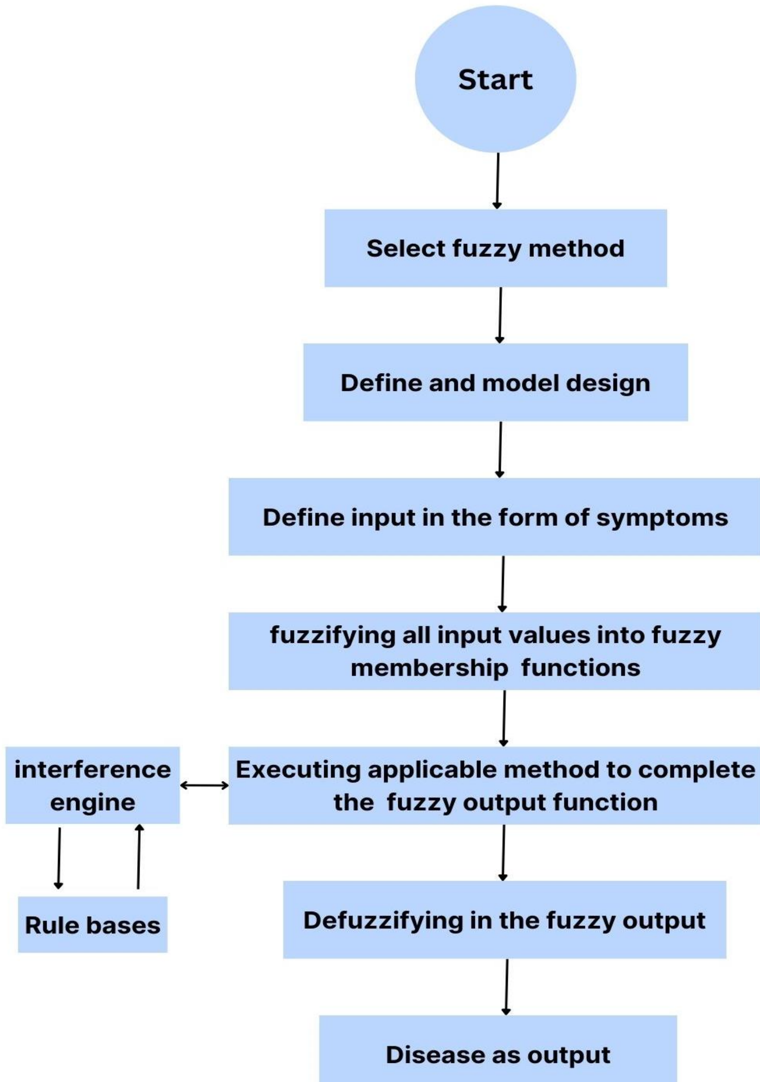


Figure 3: Flow chart of the fuzzy logic process

B) Medical Diagnosis Process Using Ml

Computer systems now possess new capabilities that were previously unimaginable thanks to machine learning. Machine learning is an area of artificial intelligence (AI) that enables machines to learn from examples [62] to assess how various models function in machine learning (ML) without the need for human judgement. As seen in Fig. 4, the step-by-step explanation of ML's operation is provided in [63].

Data Collection: Gathering data is the first thing to do. This is a crucial stage because quantity and quality have an impact on the system's overall performance. Basically, it's a method of collecting information on certain variables. 2) Data Preparation: Data preparation comes next after data collecting. It is a procedure for converting unusable data into information that can be used to make decisions. Another name for this procedure is data cleaning. 3) Select a Model: To include preprocessed data into a model, the task at hand dictates which approach is best. 4) Put the Model to Work: In machine learning, supervised learning is used to train a model that improves prediction or decision-making accuracy. 5) Assess the Model: A number of parameters are required to assess the model. The established objectives serve as the basis for the parameters. It's also necessary to record the model's performance in comparison to the prior one. 6) Parameter tuning: This stage could involve distribution, performance, learning rate, initialization settings, and training step numbering, among other things. 7) Make Predictions: Predicting some event on the test dataset is essential to assessing the produced model in the real world. The model can be used to make more predictions if the result agrees with domain experts or opinions that are closer to it. The following are the basic methods for utilising machine learning to diagnose diseases [62], [64].

1) Gather test results and patient information.
2) The process of feature extraction selects traits that are helpful in the prediction of disease
3) Following that, choose and handle the dataset after choosing the attributes.
4) The preprocess dataset can be subjected to a variety of classification techniques as indicated in the figure to assess the precision of the illness prediction.
5) The evaluation of several classifiers against one another to determine which performs best and has the highest accuracy.

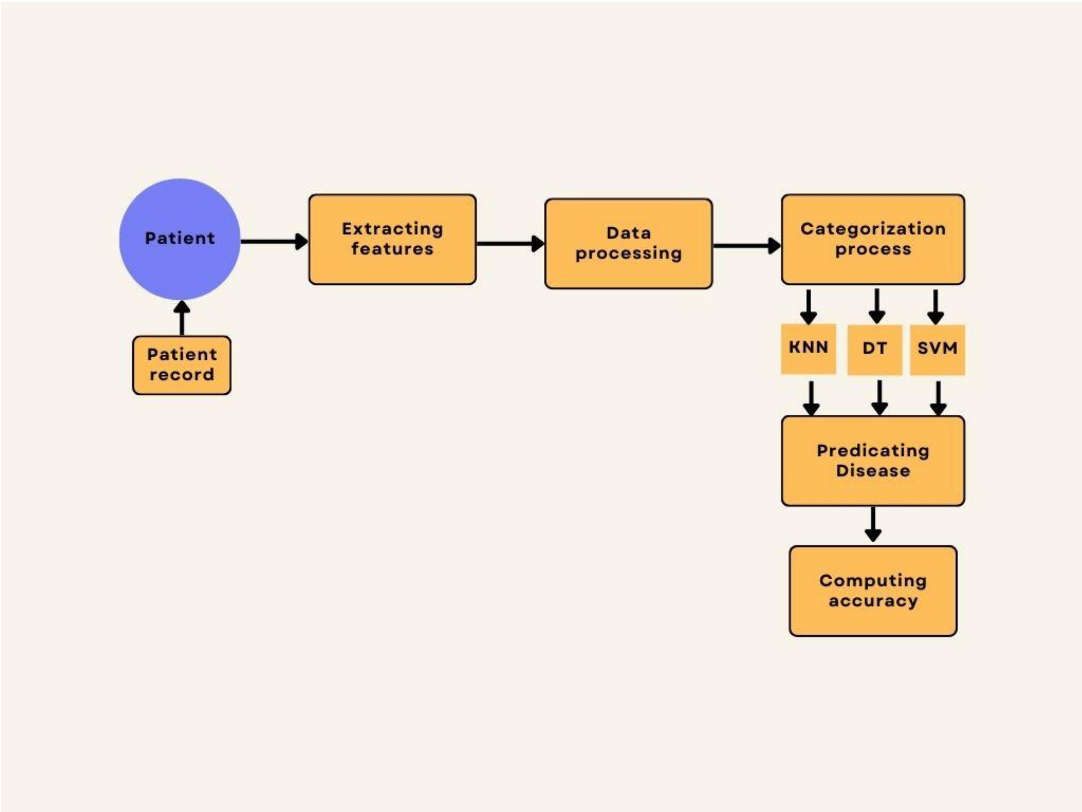


Figure 4: Machine Learning System

In machine learning, all features are extracted by domain experts to minimize the complexity of the data and develop patterns in a way that makes it easy for ML algorithms to see. However, deep learning-based techniques allow manual feature extraction without human intervention. The only condition is to make accurate decisions when the test data is likely to be correct. This technique eliminates the requirement of domain experts for feature extraction. The next section describes how deep learning is used in disease diagnosis systems.

V. DEEP LEARNING AND DISEASE DIAGNOSIS

This section begins by introducing the most recent deep learning-based related research. We go on to discuss the application of deep learning to illness-diagnosing procedures.

A) Existing Works Using Deep Learning

Deep Learning is an artificial intelligence method that simulates how the human brain functions and generates patterns for decision-making. The goal of the Deep Learning approach is to solve the problem from beginning to end, in contrast to machine learning approaches which need to divide a problem statement into separate sections first, with their results being combined at the end. Deep learning outperforms typical machine learning models in the field of medicine. [65]. There is a lot of interest in deep learning across all domains, but particularly in medical picture processing. The use of deep neural network models is referred to as "deep learning." The neurons that make up the neural network's primary component are simulations of the human brain. It operates based on a scenario where various signals are used as input, linked using weights, and then passed through to generate output [66]. Artificial neural networks, or AANs, and deep learning can be distinguished from one another based on the number of hidden layers, their interconnectivity, and how well they process input data to provide an output that is appropriate. The ANNs are typically made up of three layers and are programmed to extract structured data that might be appropriate. Conversely, however, the physical and clinical evaluation of the patient is based on the disease's nature in deep learning. Even with the wide range of instruments and methods available for disease diagnosis, there is still some degree of error and uncertainty in the diagnosis process. Numerous analytics surveys make it clear that applying machine learning techniques has certain drawbacks. Furthermore, the current diagnosis approach just uses characteristics to identify diseases. Sometimes the traditional method of choosing characteristics for illness prediction produces inaccurate results. Deep learning, as opposed to machine learning, may choose the most pertinent characteristics from the database, which ultimately results in highly accurate disease prediction [68]. The literature has a sizable number of deep learning-based diagnosis systems. Skin disorders can damage a person's skin, and because they typically affect the skin's layers, they appear to be exterior diseases. However, on occasion, it provides crucial hints for identifying the underlying causes of inside illnesses. Numerous skin conditions exist, such as rashes, acne, and skin cancer. To avoid more skin issues down the road, early identification of skin illness is crucial. Liao [69] presented a deep convolutional neural network-based method for the classification of various skin conditions. The CNN model was trained and evaluated by the suggested system using 2300 skin disease photos from the Dermnet and OLE datasets. Their system was able to reach 73.1% Top-1 accuracy. Shoieb et al. [70] provided a different categorization for the diagnosis of skin cancer. Their model identified the afflicted area of skin, and CNN is utilized for the purpose of feature extraction. Their model trained on skin image data using CNN and employed SVM as a classifier. When compared to earlier skin diagnosis results, theirs showed a notable improvement in accuracy. When deep learning is used to detect chronic diseases like breast cancer, the accuracy is higher than with previous methods. A deep belief network was used to represent the system CAD approach to breast cancer diagnosis that Zaher and Eldeib [71] proposed. Weights started using the deep network path in their technique, which involved an unsupervised path followed by a back-propagation supervised path with "Liebenberg Marquardt's learning function." When their function was tested using data on breast cancer, the accuracy of the results was up to 99% higher than with earlier methods. CNN was utilized by Charan et al. [72] to diagnose breast cancer. Out of the 322 mammography records that were taken for testing, 189 were usable, yielding negative results, and 133 had abnormal breast records. Their findings demonstrated the efficacy of deep learning in the diagnosis of breast cancer using mammography images. Diabetes is a metabolic disease that affects many populations globally. Its frequency rates are steadily and alarmingly rising. With the use of a deep learning system, Goutham et al. [73] developed a model for the classification of normal and diabetic heart rate signals. HRV data was used as the input, and CNN was used to extract features. SVM was used for feature classification. It is anticipated that their suggested system will assist medical professionals in accurately diagnosing diabetes utilizing ECG signals. Sisodia and Sisodia [74] provided another illustration of the early identification of diabetes. Their primary goal was to create a system that could most accurately forecast the likelihood of having diabetes. Thus, to identify diabetes early on, three machine learning algorithms—SVM, Naive Bayes, and Decision Tree—were employed. To conduct trials, the Pima Indians Diabetes Database was consulted. These algorithms' results were evaluated using a variety of metrics, including F-Measure, Accuracy, and Precision. Their findings showed that Naive Bayes outperformed earlier models, with a maximum accuracy of 0.76. Rubin et al. [75] classified heart illness and used an automated cardiac auscultation technique to identify heart sound variabilities. Their technique used a deep convolutional neural network to classify the time-frequency rate of cardiac sounds that it had recorded. Their goal was to identify cardiac sounds that were normal and pathological. Out of all the entries, the writers' specificity score was the highest. An improved deep neural network (DNN) for the diagnosis of heart disease was created by Miao and Miao [76]. A deeper multilayer perceptron architecture served as the foundation for the developed deep neural network model. Their model used the training set to determine how to classify the data. A total of 303 test results from patients with coronary disease were collected to examine the effectiveness of this approach. Their model succeeded. Regarding Liver sun et al. [77] created three deep learning algorithms with the use of stacked denoising autoencoders, deep belief networks, and convolutional neural networks to make a diagnosis of lung cancer. They evaluated each of the three algorithms' performance using 28 different lung dataset picture characteristics. SVM classification was employed. Accuracy values from CNN, DBNs, and SDAE were 0.7976, 0.8119, and 0.7929, respectively. An infectious virus causes COVID-19 (coronavirus) illness. When an infected individual coughs or sneezes, his droplets are disseminated to other people, which is how it spreads. The majority of COVID-19 infections result in fever, coughing, and breathing difficulties. Millions of individuals have died as a result of COVID-19 worldwide. The growing number of cases and limited supply of test kits make it more challenging to identify COVID-19. This is where the demand for additional options, like X-rays, has emerged. Researchers can more easily discover COVID-19 when they combine X-RAYS with AI methods. These days, a deep learning-supported model consists of four stages: preprocessing, stage I, stage II deep network model designing, and data augmentation. A total of 1215 X-RAY photos have been used to apply the model. First, with 93.01% accuracy, the stage 1 model distinguishes between bacterial pneumonia, induced pneumonia, and normal/healthy individuals. Images showing viral pneumonia are then forwarded to stage 2, where a 97.22% accuracy rate in COVID-19 detection is achieved. Overall, this model produces rapid, precise, and consistent results. Doctors sometimes mix COVID-19 illness with lung infection with this condition, making diagnosis challenging. This calls for a prompt diagnosis, which is achievable with various deep models. By employing chest X-ray pictures, we discovered a unique Convolutional CapsNet technology. With 97.24% accuracy in binary classification and 84.22% accuracy in multi-class classification, the model yields reliable results. A pre-trained deep neural network was employed in the study to identify COVID-19 on chest CT scans. Brain hemorrhage is the term for internal bleeding in the brain, which can be caused by a clot, brain tumor, or high blood pressure. When there is a hemorrhage, oxygen cannot get to the brain cells, which leads to the eventual quick death of the brain cells. Additionally, a novel convolutional neural network built on top of ResNet is created to identify and forecast the kind of brain hemorrhage. For this study, 752,803 DICOM files have been gathered. The accuracy of the model was 93.3%.

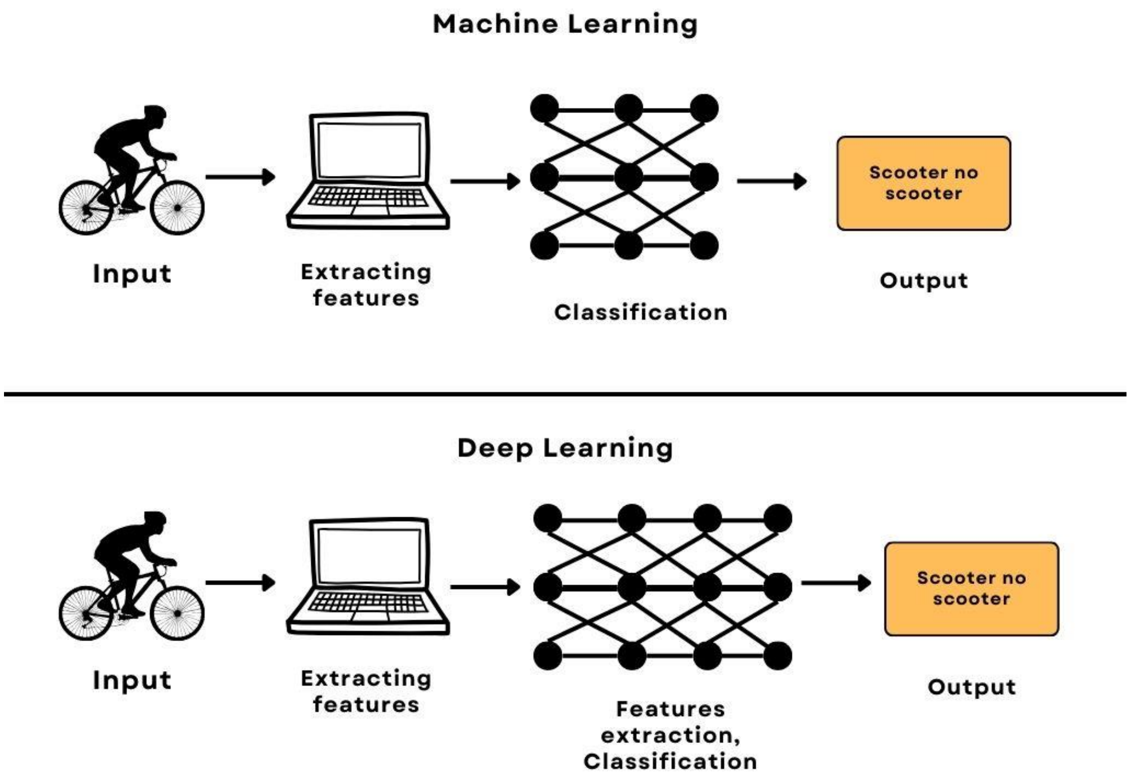


Figure 5: Difference between machine learning and Deep learning

B) Medical Diagnosis Using Deep Learning

As was previously indicated, a machine-learning algorithm was utilized in the traditional automated diagnostic approach, where a clinical expert manually extracted features from diagnosis reports. However, there were instances where it was challenging to extract features from a big dataset [47], [48]. As a result, as seen in Fig. 5, such methods struggled with accuracy and efficiency. One major challenge for deep learning models is the lack of relevant data. Electronic health records are currently used in medical research, however, there is currently no standardized method for assessing this information, which suggests that the accuracy of automated systems for diagnosis may be compromised. It is difficult to display an accurate prediction if the system is unable to gather exact data, which prevents the model from accurately diagnosing a disease. The authors in [64], and [65] created an efficient deep-learning model for the early and accurate diagnosis of a variety of diseases in order to address this kind of issue. A Deep CNN model is employed in the traditional method to identify illnesses. The neural system then makes use of methods for expanding data. Each layer in CNN applies a filter to the image's raw data to extract a particular pattern. The first few layers identify a broad feature set, such as diagonal lines, and the subsequent layers are utilized to extract more information and arrange it into more intricate features. The network fully connects when the last layer functions as a regular neural network [66], [67]. Then, it combined extremely specific features, such as different disease symptoms, and performed the disease prediction. The authors in [64], and [78] updated the methodology to address the problem of incomplete or missing data.

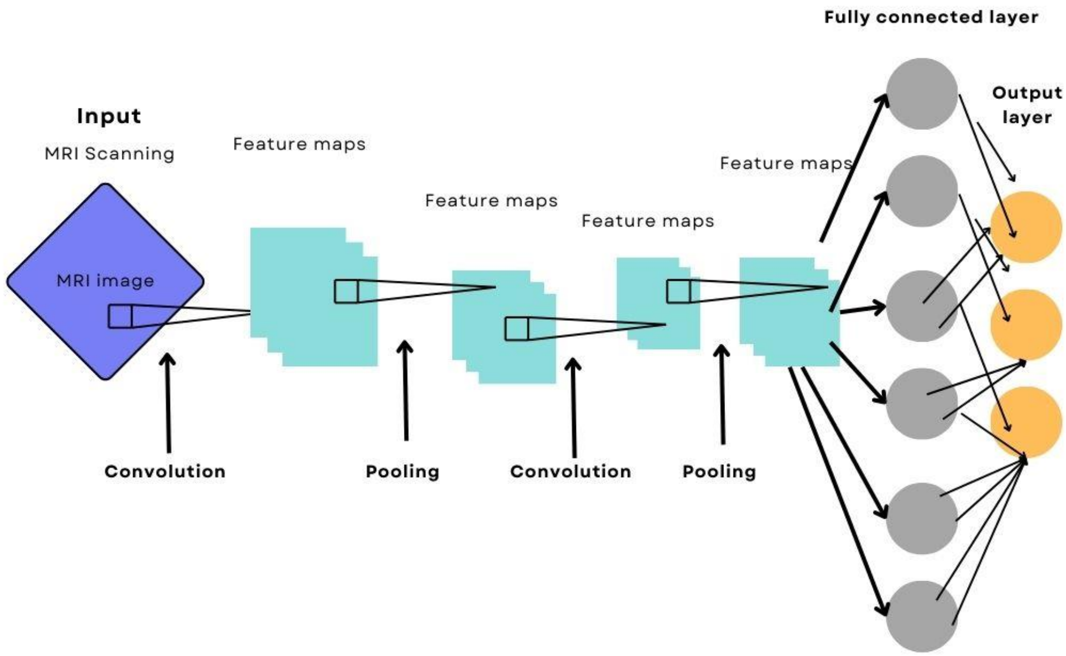


Figure 6: Deep process to diagnosis a disease

VI. RESEARCH METHODOLOGY

Systematic Review PRISMA (Preferred Reporting Items) & Meta-Analysis) approach was employed to conduct a systematic review. Moher et al. created this technique [79], [80]. In this approach, a survey is conducted using a predetermined question as the foundation for gathering data from the studies that are included in the survey. The findings are then methodically and critically assessed. Meta-analysis is a formal, statistical, quantitative research design technique that integrates and evaluates the results of previous studies and included studies in a systematic manner to draw conclusions. A crucial component of research to compile data on the effectiveness and safety of medical care interventions is accuracy and certainty. Both systematic reviews and meta-analyses play this role of elements supported by data and meta-analyses that use a structured strategy based on preset queries that can be used by different scholars to summarize and examine credible scientific literature. Different conclusions and theories that are presented in traditional papers by various researchers can be examined using a thorough and accurate analysis in a systematic review approach. A researcher can conduct systematic reviews and meta-analyses with a level of accuracy that can guide research in a well-organized way by using the PRISMA approach. TABLE 1. Different published articles were selected for the literature review along with frequency.

VII. LITERATURE SEARCH

Based on our research questions, eight databases were selected for accurate review in this study: BMC, Springer, ACM, IEEE, Elsevier, Google Scholar, Wiley digital library, and ACM. The literature search was conducted using terms such as "fuzzy logic," "machine learning," "deep learning," and "disease prediction," based on predetermined queries and aims. A search approach identified and retrieved prior helpful articles. The search method has been displayed for each journal listed in Table 1. After extracting 150 articles from 2009 to 2019, the PRISMA diagram in Figure 7 shows the complete selection process.

Table 1: Different published articles selected for the literature review Along with frequency.

Publisher	**Articles**	**Percentage**
Elsevier	11	23.40
IEEE	18	35.29
Springer	10	19.60
ACM	5	9.80
BMC	1	1.96
IOSPress	1	1.96
BioMed central	3	5.88
Wiley online library	2	3.92
Total	**51**	**100**

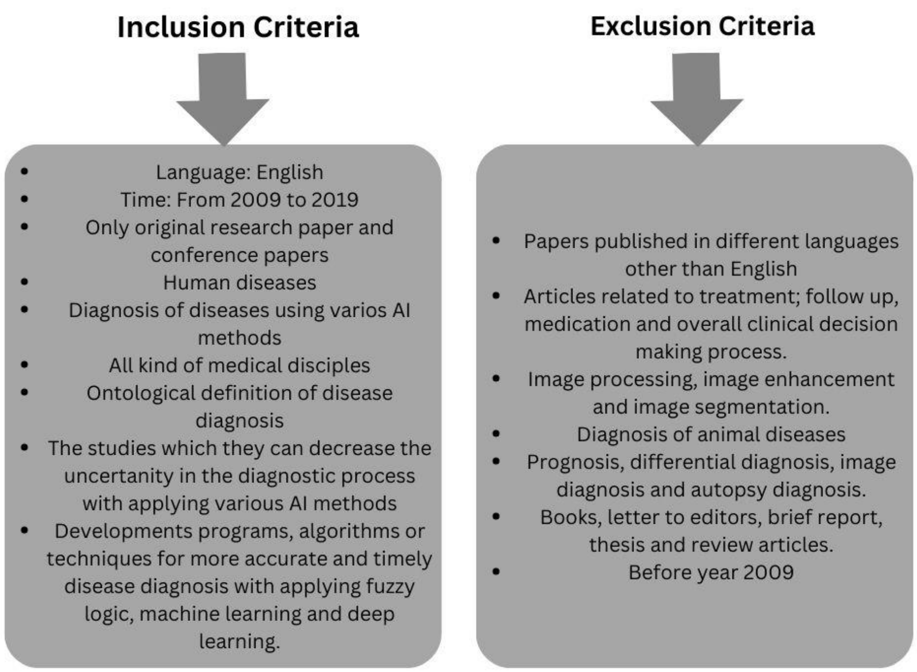


Figure 7: Article selection process

Table 2: Search Strategy In Different Databases

Data base	**Search strategy**
IEEE	(Fuzzy logic, machine learning and deep learning) AND (Disease diagnosis)
ELSEVIER	Pub date>2009 and Ai technique and Disease diagnosis
Springer	(Fuzzy logic, machine learning and deep learning) AND (Disease diagnosis) and pub date 1/1/9 to 1/11/20
BMC	Ai technique in abstract and disease diagnosis in abstract
Taylor and Francis	Ai method and disease diagnosis
Google scholar	AI method and disease diagnosis anywhere in the article

A) Distribution of Papers by Journals

Seven reputable publications have been chosen for the study's article search. All of the database providers are displayed in the table below. Table 1 lists the publications whose names were chosen, the quantity of articles chosen, and the corresponding percentages. IEEE, Elsevier, and Springer ranked first, second, and third, respectively, with 35.29%, 23.40%, and 19.60%, as indicated in Table 1.

B) Study Selection and Eligible Papers

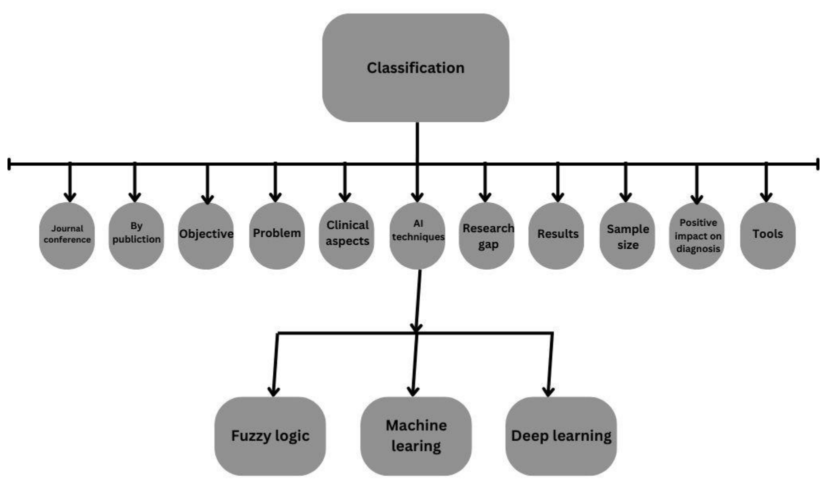
This section considered the findings from eighty research publications. These research publications were selected or given consideration in accordance with inclusion and exclusion criteria, as illustrated in Fig. 7. Chapters from books, theses, and summary reports were excluded, and only papers meeting the qualifying requirements were included. Excluded were newsletters, journal editorials, and publications written in languages other than English. The following factors were taken into consideration for inclusion: the author's reference, the year the work was published, whether it was part of a journal or conference proceeding, the definition of the diseases, including their types and complications, the objectives of the research, any gaps in the knowledge, the kinds of fuzzy, machine, and deep learning methods that were employed, the outcomes, and the concluding remarks, In light of this, 105 articles were included and 15 scholarly works were eliminated.

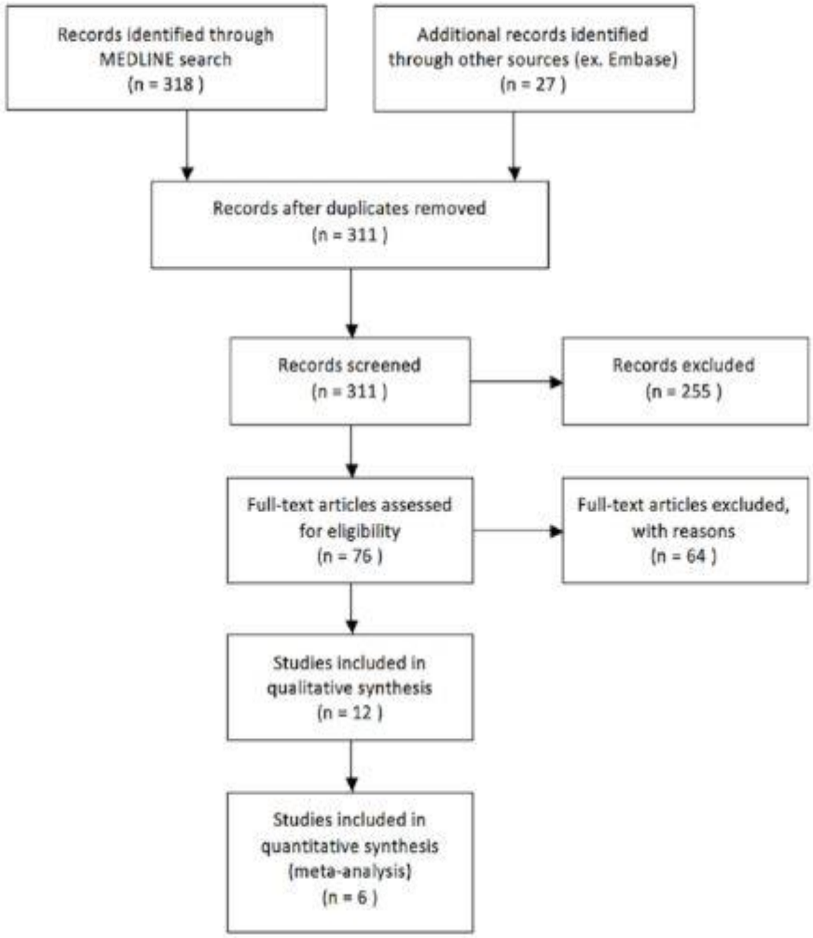
Only 80 papers met the qualifying requirements after all the articles were reviewed; these were the articles that were selected for further examination and analysis. In addition, we went ahead and carefully examined the chosen papers' abstracts and summaries to find out if they met all of the inclusion requirements. At this point, all irrelevant and unimportant articles were eliminated. Likewise, while choosing relevant publications, all scholarly research papers that did not meet the disease diagnostic inclusion criteria were eliminated. 89 publications all met the inclusion criteria, were deemed appropriate for our investigation, and were included in the systematic review. Table 2 presents the principal.

C) Extraction and Summarizing of Data

In the penultimate phase, we went over every paper, which included 95 publications, to finish the final analysis and attain the intended outcome. The collected publications for the study were carefully examined to determine the response to the important inquiries in accordance with the research's needs. In accordance with the current standards, a form was developed to extract the data required for the included articles' classification, examination, and incorporation. The data extraction form that was modeled greatly aided in achieving the intended outcomes and coming to the right conclusion. The criteria that were taken into consideration included the author's citation, the year the work was published, whether it was part of a journal or conference proceeding, the definition of the disease, its types and complications, the objectives of the research, any gaps in the knowledge, the methods that were used—fuzzy logic, machine learning, and deep learning—the results, the conclusions, and the positive impact on the diagnosis process. A classification chart is shown in Fig. 8. Following a comprehensive examination of all the articles gathered, 80 scholarly research papers published between 2009 and 2019 that were published in 30 international scientific journals and ten ongoing conferences were considered for this systematic investigation. After carefully going over each chosen article, we kept the ones that used deep learning, machine learning, and fuzzy logic to diagnose diseases. However, even though using the PRISMA method and choosing articles correctly takes time, this approach is still a highly effective research methodology since it is structured and requires us to incorporate those publications in the study that directly address the topic of the systematic review.

Figure 8. PRISMA methods for review





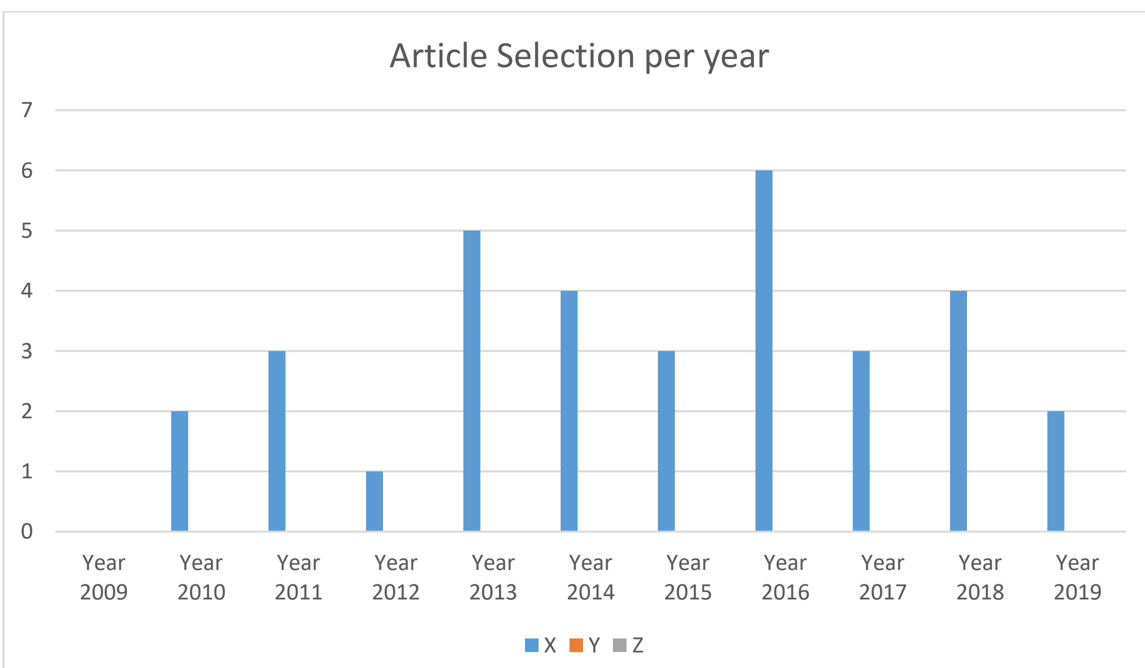


Figure 9. Article Selection per Year

VIII. DISCUSSIONS AND FUTURE RESEARCH DIRECTIONS

A) Research Findings and Lessons Learned

The purpose of this study was to examine how AI techniques affect different disease diagnoses. There aren't many published review articles assessing the usefulness of AI techniques in healthcare. We were able to find and examine 51 papers from January 2009 to December 2019 that used various AI techniques for diagnosing different diseases for this review study. A total of 105 articles were located in the eight most popular databases that were examined for this review. The publications were thoroughly examined in order to categorize the most popular AI methods for medical diagnostic systems. We were composing this review paper at the start of 2020, thus we were unable to find any articles that had been released that year. Initially, we conducted our research with the aim of identifying the mechanisms that had the biggest impact on the diagnosis of the condition. As a result, based on our investigation, we looked at relevant classifications for the study of AI methods including machine learning, deep learning, and fuzzy logic. As seen by Table 3, the findings demonstrate how well-liked deep learning is among current researchers, particularly in the field of medical science.

Table 3. The distribution of AI methods by medical disciplines.

Disease name	Fuzzy logic	Machine learning	Deep learning
Cardiology	2	2	2
Neurology	2	2	2
Dermatology	0	2	2
Breast Cancer	2	2	2
Diabetics	2	2	2
Kidney disease	2	2	2
Arthritis	0	1	0
Liver cancer	0	0	1
Thyroid	0	0	1
Dental disease	2	2	0
Ebola	1	0	0
Asthma	1	0	0
Cholera	2	0	0
Influenza	0	1	0
Skin cancer	0	0	2

Classifying the percentage of articles produced annually is the subject of another category. Our research's review of papers over the past few years shows how quickly the field of artificial intelligence (AI) in disease diagnosis has grown. As seen in Fig. 9, the results reveal that the average published volume increased from 1% in 2009 to 20% in 2019. AI is favored by investigators because it facilitates early disease detection and yields positive outcomes that enhance the diagnosing process. Three popular AI approaches—fuzzy logic, machine learning, and deep learning—were taken into consideration based on our investigation to analyze the publications in the healthcare industry and provide findings. We took into account how articles that documented. In such complicated instances, artificial intelligence is a boon. Considering the applicability of these methods to healthcare, we have examined a number of AI strategies. The most popular method was connected to the application of AI technology in the field of cardiovascular medicine. We covered cardiology using three primary AI approaches: deep learning, machine learning, and fuzzy logic. We merely looked at a handful of the many cardiovascular illnesses that are covered by cardiology. Certain AI techniques are not as good at detecting certain diseases or yielding satisfactory results. Examine the top articles using various AI algorithms about a range of diseases, including cholera, liver cancer, breast cancer, dental issues, cardiology, Alzheimer's disease, and Ebola. This study improved our knowledge of how well AI methods work in diagnostic exams. Consequently, knowledge from this research is useful for those in therapeutic fields. Furthermore, we were able to identify the fields and illnesses that have rejected AI approaches and which have employed them based on the research's findings. Additionally, Tables 4, 5, and 6 provide a brief summary of the reviewed articles for the available studies that used deep learning, machine learning, and fuzzy logic, respectively.

Table 4: Fuzzy logic method review

Study	Disease	Research goals	Methodology	Findings
26	Heart Disease	To measure the accuracy of the framework system for heart disease.	Neuron-Fuzzy Integrated system and tool used in MATLAB.	The results produced by this study by applying neuron-fuzzy integrated systems matched with the expert’s opinion.
27	Cardiology	The main goal of this research is to reduce time in the processing of ECG signal by	The algorithm is used for the signal classification and the correlation is Gustafson Kassel fuzzy clustering.	Only twenty samples to determine the case using the fuzzy clustering algorithm. This algorithm is used. It takes a little measure of memory to store the

		minimizing the number of data samples, without losing any essential bit and analysing the heart signals.		information and requires littler processing. in this manner producing the reaction in a small period.
28	Ebola	The prime objective of this study is to develop a fuzzy system to diagnose EBOLA with useful recommendations.	Fuzzy expert system was used along with The Root Sum Square.	The accomplishment of Ebinformatics shows thy possibilities of applying an informatics device as a method for encouraging basic tasks, for example, understanding findings, forecasting, and suitable suggestions.
30	Brain tumor	To improve the segmentation process.	clustering algorithms Fuzzy C Means is used along with tools Genetic Algorithm (GA), and Particle Swarm Optimization (PSO).	The results have provided substantial evidence that for brain tumor segmentation. The performance accuracy is 0.95 and the rate of error is reduced to 13%. Tumor diagnosis reached to very high rate of 98%.
31	Parkinson disease	The fuzzy k-nearest neighbor system was used for detecting Parkinson's disease.	The proposed FKNN-based system is compared with the support vector machines based methods. To further enhance the diagnostic correctness for the detection of PD.	The FKNN-based framework gets an accuracy of up to 96.07% this method can ensure a reliable diagnostic model for the detection of PD.
32	Asthma disease	The prime goal of this study is to design a system that assists in the diagnosis of adult Asthma by use of Neuron-Fuzzy Logic. This model is helpful in diagnosing Asthma and will get accurate results.	Self-Organizing Map (SOM).Learning Vector Quantization. Back-Propagation Algorithm. along with Neuron-Fuzzy Fitting.	Tool The effectiveness of this model assed based on a dataset of asthmatic patients. And use Back-Propagation to produce results and best validation performance at 535 samples.
33	Breast cancer	To achieve high accuracy in results we applied Fuzzy Logic to automatic BI-RADS categorization of breast lesions.	They proposed a fuzzy inference system. The fuzzy Omega algorithm was used to generate the membership function.	Initially domain expert investigated the images and produced results assessed into the Fuzzy Omega algorithm. The results are compared with the previous study and achieve a very high accuracy of 0.76.
34	Breast cancer	The developed information-based framework used as a medical decision Support assistant to assist medical experts in the healthcare.	Clustering method Expectation-Maximization is used for clustering. Fuzzy rules are designed based Classification and Regression Trees. The rules generated by the CART algorithm are used to classify breast cancer disease.	Two data sets to evaluate breast cancer from the UCI data repository. The outcome produced from this dataset indicates fuzzy rule-based techniques achieved good prediction accuracy for breast cancer.
35	Liver disease	The objective of this research is to develop a fuzzy expert system for the detection of Cirrhosis which is one of the most common diseases that arises in the liver.	Mamdani Fuzzy Logic was parameters along with Fuzzy Logic tools Identify risk status with max-min method.	centroid technique improves outcomes with defuzzification.
36	Diabetes Disease	To diagnosis diabetic Fuzzy Expert System Used to Investigate the diabetes data.it is set off fuzzy membership function and rules.	The fuzzy mechanism consists of fuzzy inference. Collection of rules. Also, use fuzzy T-norm and T-Conorm operators. To convert fuzzy values into a	'The developed model obtains much more accurate results than previous models.

			crisp set Defuzzification has been used.	
37	Diabetes Disease	This model is proposed to get exact results as Clinical experts conclude related Diabetes Mellitus	The fuzzy Hierarchical Model IS designed to measure the results.	The outcome based on 311 records is equivalent to a clinical expert.
38	Diabetes Disease	Early detection of the pre-diabetic condition and comparing the results with the crisp method.	Associative classification techniques depend on fuzzy logic-based.	The proposed technique can make sense of specific hazard factors like Age. Glucose. DPF. BMI. And BP alongside its right unsafe estimations to anticipate prediabetes in an enhanced manner than the crisp method.
39	Dental disease	The research aims to propose a Fuzzy Expert System for the detection of periodontal dental illness by examining and building up a PC program to help dental specialists with examination, findings, and treatment of the disease.	Mamdani Fuzzy Logic with 5 input variables and 164 rules along with a fuzzy logic toolbox.	Dental Disease identification time is minimized.
40	Dental disease	The designed system problem was DDS.	To perform the segmentation process they use a semi-supervised fuzzy clustering algorithm.	The accuracy of the used DDS algorithm is compared with other algorithms. DDS achieved 0.92 highest accuracy greater than other algorithms like prim spanning tree, fuzzy k-nearest neighbor, and affinity propagation clustering.
41	Cholera	fuzzy expert system for the diagnosis and monitoring of cholera.	Mamdani Fuzzy Logic parameter. utilize MATLAB with a max-min approach and centroid.	MATLAB achieved an outcome of 0.05 better as indicated in the calculated results.
42	Cholera	Analysis cholera based on the FC algorithm.	Fuzzy Classifier Algorithm With five input parameters and one outcome parameter Fuzzy Logic Toolbox.	Simulation results were satisfactory for diagnosing cholera.

B) Open Problems And Future Trends

AI algorithms have the ability to significantly improve medical diagnostic systems, as shown by the advancements and discussion in this paper. However, in order to fully utilize AI's potential for extracting fresh insights from the corresponding medical data, AI-based diagnostic systems need to solve the following significant problems.

C) Explainable Diagnosis

AI models' internal, ambiguous decision-making process is a common source of criticism. Explainable AI, in this sense, is concerned with applying logic and clarity to the actions of statistical black-box AI learning techniques, especially deep learning. Therefore, in addition to identifying issues with pattern recognition, AI systems ought to include causal models of the world that facilitate comprehension and explanation. This becomes much more crucial when we look for ways to use AI in medical diagnostics. Scholars contend that it's critical to consider AI that goes even beyond explainable. Causability will ultimately lead to explainable diagnoses that include metrics for explanation quality.

Table 5: Machine learning method review.

Study	Disease	Research Goals	Methodology	Findings
50	Kidney Disease	The main objective is to make a comparative study between the performance of SVM and KNN and make a classification on the basis of its precision, correctness and completion time for the predication of CKD.	Classification, SVM, KNN.	From the outcome of the test, it is evident that the KNN give better results in comparison to SVM in terms of classification.
51	Kidney Disease	Provide assistance to doctors in	So far 4 types of machine	SVM shows

		deciding the accurate treatment methods for chronic diseases related to kidneys he using clinical	learning methods have been invented viz: KNN (K-nearest neighbors). SVM (support vector machine), decision tree classifiers and LR(logistic regression)	Maximum in comparison to the other three methods at 0.99 whereas the sensitivity of Logistic recorded at 0.94, Decision Tree recorded at 0.93 and KNN recoded at 0.96.
52	Breast Cancer	The aim of this particular study is to identify diseases related to breast cancer based 23 and determine the characteristics of the tumor	Algorithms generated related to K-SVM (K-means and sup-Port vector machine)	30 Investigation on the Wisconsin Diagnostic Breast Cancer (WDBC) data set carried out in this method and recorded 97.38% Accuracy may be considered as better results.
53	Breast Cancer	In this comparative study of Performance among various machine learning algorithms done viz: SVM. Decision Tree, NB and k-NN on the Wisconsin Breast Cancer datasets. Subsequently effectiveness and efficacy of all algorithms with respect to their precision, accuracy, and specificity in classifying data is recorded	WEKA data mining tool.	It's observed that SVM perform better with the highest degree of accuracy of 97.135 with the minimum uncertainty.
55	ARTHRITIS	Design a model to analyze the predicted improvement in ARTHRITIS patient	On the dataset of arthritis Simple The CART Algorithm and WEKA technique are used in tandem.	This method provides assistance to treat more critical cases of Arthritis or solve its queries.
56	Diabetics	Early detection of Diabetes Mellitus to decrease the death rates.	SVM	SVM is a useful device to examine diabetes and the result yields 94% accuracy and its sensitivity and specificity were recorded at 93% and 94% respectively.
57	Diabetics	The objective of this research is to make a comparative study between algorithms and their performances which are useful in the detection of diabetes.	KNN, SVM, RF, J48Decision Tree;	Research result indicates that Decision tree 148 gives better outcomes with 73.82% accuracy in comparison to other methods.
58	Parkinson’s disease	Voice data examination is a very critical aspect in the current decade for studying and determining suitable diagnostic techniques for Parkinson s disease	In this study for statistical analysis Orange v2.0b and WEKA 9.4.10 has been used whereas for classification SVM. KNN classified has been used.	In this technique, Parkinson's disease is diagnosed with the help of a voice dataset using machine learning algorithms.
59	Parkinson’s disease	The main objective of this study is to analyze the viability of an overseeing machine learning algorithm for the assisted diagnosis of patients who already	SVM	The algorithm provides excellent discrimination of PD patients from PSP patients at an individual level, Accuracy,

		tested positive for Progressive Supra nuclear Palsy and Parkinson's disease		Specificity, and Sensitivity > 90%
60	Influenza	To reduce uncertainty and vague data in the detection process by applying fuzzy methods	Machine learning classifier	In the case of data with missing values ML constantly provide enhanced performance
61	Liver cancer	Developed a model to detect the normal and abnormal regions.	Neutral network classifier, fuzzy c means multinomial multivariate Bayesian	This model provides a mechanism to get results with more

Table 6: Deep Learning Methods

Study	Disease	Research Goals	Methodology	Findings
69	Skin disease	The study aims to analyze the efficiency of universal building skin disease detection system using DCNN.	23,000 skin disease images extracted from the Dermnet and OLE dataset to assist the performance of the CNN framework.	the system obtained high accuracy in the detection of skin diseases.
70	Skin Cancer	It is difficult to recognize melanoma during its initial stages by manual examination. Hence development of an automated system was required to assist early diagnosis of skin cancer.	A classifier system has been developed based on a multiclass linear Support Vector Machine. This system is trained with CNN features extracted from the skin images dataset.	The outcome of this system shows very high performance related to accuracy, specificity and sensitivity.
71	Breast Cancer	To diagnose breast cancer CAD strategy has been designed based on a deep belief network along with a backpropagation supervised path.	Backpropagation neural network.	The proposed model provides an accuracy of 0.99 in results over Previously published models.
72	Breast Cancer	This method helps to detect the region of the tumor.	This study utilized different K means, closing, Dilation and Canny edge detection algorithms.	The outcome described that K Means algorithm is more accurate in diagnosing tumor.
73	Diabetes	This study proposed a methodology to classify diabetic disease HRV signals using a deep learning frame-works.	Heart rate variabilities, ECG, CNN, LSTM.	Developed to assist doctors in diagnosing diabetes using ECG signals. It achieves accuracy up to 0.95.
74	Diabetes	The goal of this study is to propose a framework that is able to prognosticate the possibility of diabetes in patients with maximum accuracy.	Decision tree, SVM, and Naive Bayes.	Results obtained show Naive Bayes outperforms with an accuracy of 0.76.
75	Heart disease	The study showed how deep learning is used to diagnosis automated cardiac recognizing variabilities in heart sounds.	Deep convolutional neural network	The overall result achieved with this model is 0.83.
76	Heart disease	The objective of this study is to design deep neural network learning to diagnose patients and aid the clinical expert in enhancing the correctness and reliability of heart disease detection and prognosis in patients.	Deep neural network learning.	The model acquires an accuracy of 0.83, sensitivity of 0.93 and precision of 0.79.
1	Liver Cancer	The objective is to investigate lung cancer using deep learning algorithms on the LIDC database.	CNN, DBNs, Stacked DE noising Auto encoder.	The correctness of CNN, DBNs, and SDAE are 0.79 and 0.81. And 0.79 respectively.

D) Quality Of Training

In order to obtain the necessary diagnostic capability, the success of deep learning and machine learning algorithms is mostly dependent on the availability of high-quality training models. Furthermore, the issue of data scarcity is crucial. as the foundation of AI-based medical solutions is data. There are initiatives underway to generate more annotated data through alternative techniques like image synthesis and information augmentation. Whether they are appropriate for AI-based medical diagnostics is unclear, though.

E) Clinical Translation

Rapid advancements in AI research have been made in the field of medical diagnostics, and systems that diagnose disorders in retinal images, recognize the brain, and detect different cancer metastases have demonstrated the potential for their deployment. However, there are still a lot of changes and phases that the use of AI-based systems in healthcare settings will go through. As previously stated, current research mostly focuses on maximizing the effectiveness of intricate machine learning models, ignoring their explainability. Consequently, doctors find it difficult to understand these models and find it difficult to put their trust in them. Hence, it is imperative that medical professionals and AI model experts maintain dependable and trustworthy communication channels in order to effectively integrate AI-powered diagnostic capabilities into clinical settings.

F) Medial Data Characteristics

Medical data should be of a high caliber since it serves as the foundation for mining the knowledge necessary to diagnose diseases. Furthermore, a variety of data sources, including real-time sensors, frequently provide a large number of medical data. As such, maintaining the quality of the data is a difficult effort. Having medical data stored on the cloud appears to be a more practical choice due to the increasing use of mobile sources and sophisticated applications that require remote access to healthcare data. Despite the introduction of numerous solutions to address cloud storage problems, none of them can accurately handle all elements of medical data characteristics due to the extra requirement of maintaining compliance with medical data security rules.

G) Standardization And Interoperability

Regarding the diagnosis, there are numerous methods that suppliers may provide a wide variety of diagnostic items while including a set of AI algorithms chosen from a variety of techniques. They might not, however, abide by the norms and guidelines for appropriate interfaces and related protocols across various computer frameworks. This gives rise to interoperability problems. It will take quick action to establish the technical requirements for AI-based diagnosis and medicine in order to handle system diversity. Various technical and medical organizations can collaborate in this area, such as the World Health Organization, the World Health Professionals Alliance, and the AI group managed by the International Organization for Standardization.

H) Secure Diagnosis

Deep learning approaches in particular, as well as AI methods in general, are highly application-specific; that is, a model developed for one diagnosis may not be suitable for another. To be used for various diseases, the algorithms typically need to be retrained using the appropriate medical data; otherwise, incorrect diagnosis will be inevitable. Furthermore, even a small alteration in the hyperparameters might cause a significant shift in the model's performance and a poor diagnosis. For instance, reinforcement learning is not stable at all, in contrast to supervised learning, which is thought to be stable because of fixed data sets. Further understanding of this is necessary in order to optimize AI algorithms for the diagnosis of certain diseases. The protection of the diagnostic systems is a crucial component of secure diagnosis. The assailants utilize the characteristics of the AI programs that compromise the system. An advertiser might, for instance, tamper with the training parameters and trick the diagnostic system into learning the reverse of what is intended. Therefore, conducting a thorough investigation is crucial. the features of AI algorithms, reevaluate their respective functions in diagnostic systems and deal with the associated difficulties.

IX. CONCLUDING REMARKS

Recent developments in AI methods enable the effective use of AI in healthcare. The question of whether AI expert systems will eventually take the place of human doctors has even become a major topic of conversation. However, we take into account the possibility that an AI expert system could help a human doctor make a better choice—or perhaps take the place of human judgment in specific circumstances. A variety of AI methods can assist in extracting pertinent information from a vast quantity of clinical data. Furthermore, AI techniques are trained to generate outcomes with a high degree of accuracy and the capacity to learn from their mistakes. This survey examines the application of three AI methods to the diagnosis of illness. In order to reduce misdiagnosis mistakes, we evaluate the influence of AI approaches and their consistency on disease diagnosis in this review using the PRISMA method. We came up with a search strategy in order to achieve the main objective. Several scientific publications, such as Elsevier, Google Scholar, IEEE, Science Direct, Web of Science, Wiley Online Library, and Science Direct, were selected for this prospect in order to retrieve published scientific papers from 2009 to 2019. The distribution of all the retrieved papers is based on the following factors: authors, years of publication, different AI tools, fuzzy, machine learning, and deep learning methods; different types of diseases; outcomes; and, lastly, the impact of AI techniques used in disease diagnosis. The findings indicate a sharp increase in the number of papers published in the medical profession. Finding out which AI technique, in the opinion of the majority of the researchers, was the most successful in diagnosing diseases was another goal of this study. Our investigation led us to the conclusion that using AI in healthcare might improve the diagnosis process and help identify diseases early on, which would allow doctors to select the best course of action. Another important idea to have in mind is that we looked into three AI approaches—fuzzy logic, machine learning, and deep learning—that are frequently applied in the healthcare industry and that we employed to get our findings. Additionally, an analysis was conducted on each AI technique's impact based on the frequency of influence reported in articles. Using AI diagnostic criteria, we analyzed major medical fields relating to cardiology, neurology, cancer, kidney disease, diabetes, cholera, and dental illness, in that order. In addition, we found that the publications varied greatly according to the illness kind. This study shows that AI may be used to detect any type of disease or to identify specific diseases, as we can use a variety of AI methodologies. The effectiveness of illness detection by AI is unavoidable. The majority of the researchers in this review make use of programs like MATLAB, which is another noteworthy conclusion. Python, Java, and C# are used in AI architecture design. This study is not without its limits. The PRISMA method used AI algorithms to examine health-related papers that were only published within a particular decade. The primary review focus was on articles published between 2009 and 2019, while a few carefully chosen articles released in 2020 were also taken into account. In order to demonstrate the applicability of AI techniques in the diagnosis of Parkinson's and Alzheimer's diseases, we plan to take a more comprehensive approach to the diagnosis in future research. Furthermore, the functions of AI methods for sensors-based computing framework-based diagnostic systems will also looked into. A thorough evaluation of the financial implications of AI in healthcare is another area we plan to concentrate on in the future.

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