

An Effectiveness of AI Approaches in Human Disease Diagnosis for Increasing Efficiency of Medical Systems- Review



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An Effectiveness of AI Approaches in Human Disease Diagnosis for Increasing Efficiency of Medical Systems- Review

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Abstract— This review discussed the artificial intelligence techniques used in the medical examination, the models used for artificial intelligence algorithms in the medical examination, how the data were classified, as we gain a deeper understanding of disease biology and how diseases affect an individual, so, we provided an overview of the research related to the use of models used for artificial intelligence algorithms in the detection of human diseases and also compared the results obtained through artificial intelligence techniques, and how effective those algorithms were in medical detection and prediction. of recent research in the areas of Breast Cancer, Diabetes Disease, DR, Lung Cancer, Diabetes mellitus, COVID19, Heart disease, Diabetes diagnoses, Cervical Cancer and Phthalic acid. there is a need for artificial intelligence (AI) to be able to support predictions for personalized treatments. Healthcare applications and systems are being introduced along with the adoption of cloud computing in healthcare so, medicine has entered the digital age with data from new modalities, as well as new sources such as wearables and the Internet of Things.

Keywords —, Diabetic Retinopathy (DR), Deep learning (DL), K-SVM-related algorithms generated (K-means and support vector machine), Deep learning-based measure (DML), Consecutive Long-Term Memory Model (CSO-CLSTM).

I. INTRODUCTION

In the age of digital technology, we will be able to tailor medical treatment to the needs of individuals and groups of patients. Healthcare professionals in the 21st century face many technological advances and large amounts of data. Combined with digital medical records [16]. Innovative technologies such as blockchain and AI [17] have emerged as promising solutions to combat the global coronavirus pandemic in 2020 Blockchain can combat epidemics by enabling early detection of outbreaks, ensuring medical data is requested, and ensuring reliable medical supply as AI provides smart solutions to identify symptoms caused by the virus, treatments and how to make supportive drugs [19]. By perceiving the disease's symptoms, AI-based software diagnoses the ailment even before it occurs.

Furthermore, AI is always learning and has a better possibility of producing more accurate findings than before Disease detection and treatment is usually a difficult and complicated procedure since several diseases have very similar symptoms [30]. Various AI algorithms assist clinicians in analyzing medical imaging such as MRIs, x-rays, and CT scans and diagnosing particular diseases based only on symptoms. Another important use of AI is the Internet of Medical Things, which uses IOT Devices to collect healthcare data [3]. Both diagnosis and disease treatment are highly robust while Artificial Intelligence (AI) models, surgical gadgets, and mixed reality apps are used CDSS particular results, such as hepatitis, lung tumor, and skin cancer diagnosis, are achieved utilizing AI.[1]

A- The power of AI in healthcare

Machine learning models may be trained on a significant quantity of medical data [20]. The classification of medical data is based on the viewpoint of a human medical professional. Many advancements in information and communication technology have recently occurred, altering the world [18], within healthcare systems, digital technologies are generating vast amounts of data [19]. In order to popularize AI in healthcare and by developing interpretable algorithms including AI training in medical education for many solutions that can aid in medical diagnosis and prediction, big data analytics techniques allow extracting value from data that has four: Variety, speed and honesty [2]. In the world of machine learning, medical diagnosis is a difficult issue.

B- Healthcare data into digital data

The healthcare industry is undergoing a fundamental shift. Within healthcare systems, digital technologies are generating vast volumes of data [19]. As artificial intelligence (AI) pervades all aspects of social and economic life and other areas [20]. In order to popularize AI in healthcare and by developing interpretable algorithms including AI training in medical education for many solutions that can aid in medical diagnosis and prediction, big data analytics techniques allow extracting value from data that has four: Variety, speed and honesty

[1]. Many advancements in information and communication technology have recently occurred, altering the world [18]. The classification of medical data is based on the viewpoint of a human medical professional. [19]

C- The importance of Human diseases diagnosis

Diagnosis is described as the process of determining the pathophysiology of a disease based on its indications and symptoms. Diagnosis is also described as the process of determining which disease an individual has based on their symptoms and indicators. The importance of illness diagnosis cannot be overstated [3]. In the world of machine learning, medical diagnosis is a difficult issue. Machine learning models may be trained on a significant quantity of medical data. The classification of medical data is based on the viewpoint of a human medical professional [2]. AI tactics have resulted in success. AI applications in health care. As a result, it received a hearty welcome [3]. AI expert systems are being debated as to whether or not they will eventually replace human doctors. However, we must not overlook the fact that, in some circumstances, an AI expert system can aid a human doctor in making better decisions or even replace human judgment. The influence and balance of AI strategies in diagnosing the disease to reduce errors in misdiagnosis, as well as the application of the PRISMA approach, are examined.

II. RELATED WORKS AND MECHANISM

In this section, we discuss AI approaches for illness diagnosis, as well as pertinent survey studies on the diagnostic process and our addition to the existing work. The current state of machine learning models with optimization strategies for classifying medical data is discussed in this work. Attempt to provide an overview of recent research in the areas of Breast Cancer, Diabetes Disease, DR, Lung Cancer, Diabetes mellitus, COVID19, Heart disease, Diabetes diagnoses, Cervical Cancer and Phthalic acid. AI has entered many fields and is emerging in healthcare, providing significant support in streams of personalized treatments, and facing challenges in the era of big data such as vital signal monitors, molecular assays, lab tests, pumps, and medicine. nowadays medicine with rapid technological developments, modern sciences in genomics, imaging and new sources for example wearable devices and the Internet of things [9], medicine relies on very large medical images as in recent years deep CNNs have achieved remarkable success in medical image analysis, [27] All images and data recorded in electronic medical records AI strategies have been able to overcome seeing large amounts of different sources and are still undergoing improvements and training that reduce problems and help health care [9]. Disease diagnosis in healthcare plays a vital role [2] The implications of AI should be considered on a large scale, especially since it is already at a large scale, and its importance lies in allowing users to translate ideas and conceptual goals into concrete tactics that can be implemented in real-world systems [26]. In prenatal diagnosis, ultrasound examination is highly recommended as it is critical for accurate identification of fetal brain ultrasounds Difficulties in determining standard levels of fetal brain ultrasounds

(FBSPs) have two types First, it is not easy to detect features of fetal brain tissue Fetal brain Because the fetal brain tissue is not mature and the amount of classified image data is limited and for prohibitive assembly costs a differential convolutional neural network (Differential-CNN) has been proposed to automatically select six standard fetal brain planes (FBSPs) from non-standard planes [27].

Artificial intelligence diagnostic criteria were connected to heart and nerve disease, most malignancies and renal disease, diabetes, cholera, and dental disorders, among other clinical areas studied [3]. within the domain names of diabetes diagnostic and prediction tactics based on statistics mining, as well as their categorization based on the underlying models employed Based on a literature analysis of information mining-based totally approaches for diabetes detection, categorization, and prediction, a complete taxonomy of regularly used diabetes diagnostic and prediction processes has been developed. In addition, numerous methods were examined based on characteristics like algorithm/model, data entry format (data entry), plug-and-play capabilities, and so on. This research concludes that, in order to appropriately detect, categorize, and forecast illness, we should preprocess the data and use hybrid approaches, which employ numerous models in tandem rather than a single model, based on this evaluation and evaluation. We want to integrate dimensionality reduction, denoising, feature selection, and feature extraction methodologies with classification and prediction algorithms for preprocessing for the greatest overall performance and results.

A. AI APPROACHES USED IN DETECTION OF HUMAN DISEASES

a) CNN for diabetic retinopathy diagnosis.

Diabetic retinopathy used in [5] by Applying Kaggle dataset of retina pictures to teach an ensemble of 5 deep Convolution Neural Network (CNN) models (Resnet50, Inceptionv3, Xception, Dense121, Dense169) to encode the rich functions and enhance the type for special stage of DR, Figure2 shows how It works Qummar, S. et al. [5].

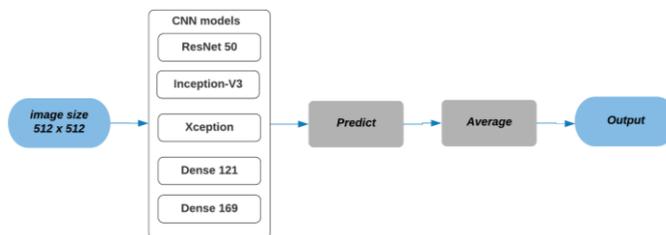


Figure1- 5 Deep Convolution Neural Network (CNN) Models [5].

While DR has 5 stages or classes, specifically normal, mild, moderate, severe and PDR (Proliferative Diabetic Retinopathy). The main idea in this paper is how to detection all stage of DR spatially the mild stage by divide the image and compare it with the images that have in the database Figure3 shows how it works by divide Image and rotate. Also, how to early

be controlled it and how can find the differentiate between mild stage and normal stage, accuracy of this model was 93%.

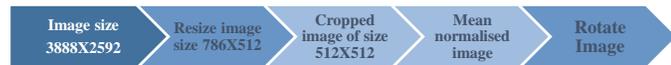


Figure2-Shows how it works by divide image and rotate by 5 steps showed [5].

b) SVM for diabetes diagnosis

To control diabetes numerous facts mining and machine learning strategies had been used for the prognosis, Barakat, N et al. [7] suggested using SVMs for the diagnosis of diabetes. they use an extra explanation module, which converts the "black box" model of SVM right into a file A clean illustration of the SVM diagnosis (classification) resolution. The accuracy of this model was 94% In Shi et al [14], there study suggested effective intelligence in a framework for predicting DEHP toxicity. The framework was designed by integrating a Harris hawks' optimization (HHO) profile using a support vector machine (SVM), which is called SGLHHO-SVM.

The main proposed methodology is that the developed SGLHHO integrates a collection mechanism, two core operators extracted from the salp swarm algorithm and a gray wolf optimizer to enhance and restore the search ability of the original HHO [14]. SVM can separate samples related to the highest classification accuracy by hyperplane when w and b can be obtained. Regarding kernel technologies, SVM can also solve nonlinear classification. The nonlinear function can be modeled as follows:

$$g(x) = \text{sgn}\left(\sum_{i=1}^n a_i y_i K(x^i, x) + b\right) \quad (1)$$

Where: $K(x, x_i)$ is the kernel function and $K(x, x_i) = \exp(-\gamma \|x - x_i\|^2)$.

c) 3d CNN for lung Cancer diagnosis

Lung Cancer is primarily based totally on deep CNN. their machine analyzes and provides CT scans immediately accurately represent calibrated possibility rating suspicion. machines include a Computer-Aided detection unit (CADE) to detect and cut suspicious lung nodules also a computer-assisted diagnostic unit (CADx) that performs each the extent of the nodules Evaluation and category of malignancies on the patient degree through evaluation of suspicious lesions of Cade. Both CADE and CADx modules obtain comparable or higher performance One of the first-rate CADE and CADx structures posted on LUNA16 and Kaggle Data Science Bowl standards [6]. This model was providing a complete probabilistic lung diagnostic machine, accuracy of this model was 94% Ozdemir, O et al. [6].

d) CSO-CLSTM for heart disease and diabetes diagnosis

Heart disease and diabetes diagnoses CSO-LSTM model's Mansour et al [12], performance was verified using healthcare data. The CSO-LSTM model achieved a maximum accuracy of 96.16 % percent and 97.26 % percent on, respectively, during the experiment. This proves that the model offered is effective. Performance can be enhanced in the future by adopting feature selection techniques that lessen the curse of dimensionality and computing complexity. Table1-show a heart disease & diabetic illness dataset, the average performance of current and suggested CSO-CLSTM methods was compared [28]

Algorithm	CSO-CLSTM	SVM	KNN	NB-A	FNCA	J48
Illness	Heart disease					
Sensitivity	98.62	83.14	92.10	87.90	95.50	94.20
Specificity	96.94	82.40	87.70	84.80	92.86	91.00
Accuracy	97.26	76.70	89.00	79.80	93.30	92.40
Illness	Diabetic disease					
Sensitivity	96.38	83.22	92.04	87.32	NA	94.42
Specificity	94.30	81.68	87.04	84.48	NA	91.04
Accuracy	96.16	77.34	88.80	79.14	NA	92.08

Table1-show a heart disease & diabetic illness dataset, the average performance of current and suggested CSO-CLSTM methods was compared [28]

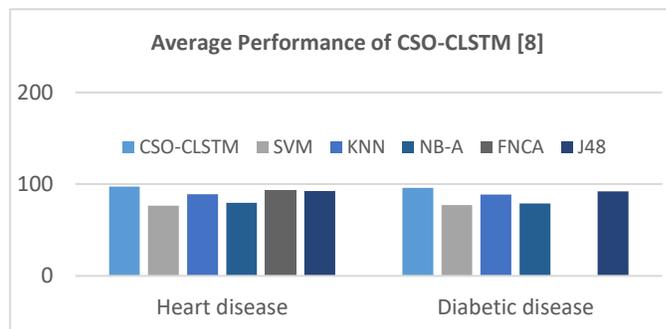


Figure3- Analysis of the average classifier performances on the Diabetes & heart disease dataset gave the following results [28].

The average classifier performances on the Diabetes & heart disease dataset gave the following results [28]. Furthermore, hybrid meta heuristic algorithms can overcome the drawbacks of the CSO method, such as its slow search precision and high likelihood of entering local optima [2] The condition is diagnosed using the suggested Crow Search Optimization approach, which is based on the CSO-CLSTM. A CSO is used to track both the 'weights' and 'bias' characteristics of the CLSTM version in order to obtain a greater category of clinical facts [2] In addition, to avoid outliers, these research panels used the (iForest) isolation strategy. The CSO program enables significant research into the diagnostic implications of CLSTM release. Healthcare facts are used to confirm the overall performance of the CSO-LSTM version. During the trial, CSO-LSTM version had the greatest accuracy ratings in

identifying heart disease and diabetes, with 96.16 percent and 97.26 percent, respectively Raf, et al [2].

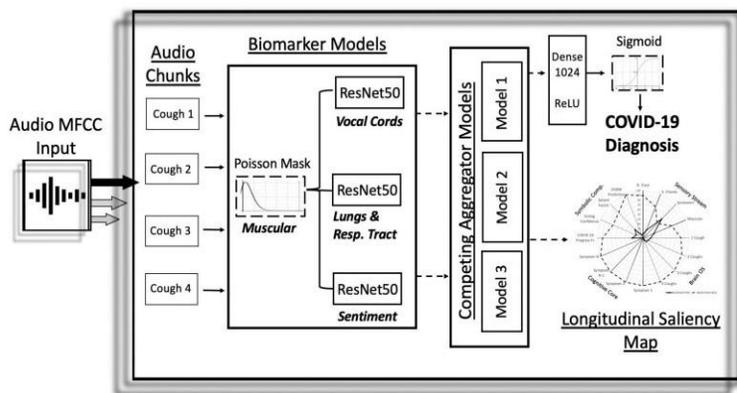


Figure4: COVID-19 discriminator architecture overview using cough recordings as input and COVID-19 diagnostic and longitudinal saliency map as output [8].

e) *AI speech processing framework, CNN for COVID19 diagnosis*

Diagnosis of COVID19 used AI speech processing framework and CNN, based totally at the cough sound only, wherein numerous sounds of itching have been gathered from infected people, and via way of means of comparison, the analysis is made, in particular with the ones infected asymptomatic. Accuracy of this model was 98,5% who has COVID-19 and 100% For asymptomatic. Three ResNet50s in a parallel plane make up the CNN architecture. Figure4 shows a ResNet50 Parallel series model with 77,2048 4-d tensor output layers. Pre-screening for diagnosis with a salinity map for vital indicators When preprocessing, it starts with a recording of one or more coughs, then goes through a two-step preprocessing procedure that includes recording and input into a CNN-based form. Each cough recording is separated into 6-second audio clips for output, which are then padded as appropriate, processed with an MFCC program, and then passed on afterwards. The result of these processes becomes the input to CNN. Then there's a dense bilayer with Sigmoid activation, followed by 1024 deep linked (dense) neural network layers with ReLU activation. For binary classification, the complete architecture is trained using the COVID-19 cough dataset. numerous types of A topic salience map are created by aggregating the output of a portion of a CNN structure using competing schemas. This paper's conclusions and presentation are primarily based on the outputs of the first audio group Laguarda, J et al [8].

f) *Neural Networks detecting possible falls in elderly individuals*

Several research have been conducted with the goal of detecting possible falls in elderly individuals using various types of sensors and algorithms [10]. proposed system can be classified into: a wearable-based system, a camera-based system, and an ambience device the concept involves categorizing a fall with very low-resolution heat sensors and

then alerting the care workers [11]. We also compare the performance of three recurrent neural networks for fall detection: long short-term memory (LSTM), gated recurrent unit (GRU), and Bi-LSTM [10]. When compared to LSTM and GRU, the Bi-LSTM algorithm produces excellent results because the use of their data is influenced by prior and new information. The user's privacy was not jeopardized as a result of the information received through this system, which is another benefit of this alternative.[11]

g) *The AVE algorithm for invasive cervical cancer diagnosis.*

The AVE algorithm has been shown to be effective in detecting confirmed cancers (i.e., directly precursor to invasive cervical cancer). It is based on the deep science of automatic visual assessment and in a study Pal et al [13], presented a new and innovative method for the detection of cervical cancers using DML that does not include any effort to mark cervical boundaries, this paper presented a pioneering initiative to study the effectiveness of a deep metric learning algorithm for classification of cervical images. The result of the experiment showed that deep metric learning with combined loss reduction performs better than the previously proposed AVE method in the waiting test set. In addition, the current frame reduces the annotation work at the ROI image level. The training loss is designed in a way such that the positive distance is minimized and the negative distance is maximized. Mathematically, the contrastive loss ($L_{contrastive}$) is defined as:

$$L_{contrastive} = [d_p - m_{pos}]_+ + [m_{neg} - d_n]_+ \quad (2)$$

Where m_{pos} means the positive distance's upper limit, m_{neg} denotes the negative distance's lower limit, d_p denotes positive distance, d_n denotes negative distance, and $[x]_+ = \max(0, x)$. while DML with n-pair embedding loss DML with n-pair embedding loss [13].

h) *Ultrasound detection for prenatal diagnosis*

A differential convolutional neural network (CNN) has been developed. For the correct measurement of the head and the diagnosis of brain lesions, accurate determination of the sound waves of the fetal brain is critical. A differential convolutional neural network (Differential-CNN) has been developed to automatically recognize six standard fetal brain planes (FBSPs) from non-standard planes. Additional differential feature maps are generated from the initial CNN feature maps using differential operators in the differential CNN framework The differential convolution maps will provide high-definition performance. A data set of 30,000 2D ultrasound images from 155 fetuses between 16 and 34 weeks of age was generated to evaluate the performance of these algorithms. The accuracy was found to be 92.93% in trials. It also showed that CNN differentiation can be used to facilitate the deployment of automated detection Qummar, S., et al [29]

B. Classifying and analysis data with experimental results

Here is a summary of the results of the mentioned studies. Table2 includes the most important algorithms mentioned in each study and the accuracy result for each algorithm and Figure 10 shows effectiveness of mentioned algorithms that used in detection of human diseases:

Table2-CLASSIFYING AND ANALYSIS DATA WITH EXPERIMENTAL RESULTS

Ref	Research problem	Algorithm/Tools/Model /Classifier	Dataset	Accuracy
[3]	Breast Cancer	Fuzzy Logic /Omega algorithm	Images	76%
		K-SVM	Wisconsin Diagnostic Breast Cancer (WDBC) data set	97.38
		backpropagation neural network.	backpropagation	99%
[3]	Diabetes Disease	SVM	Blood Samples	93%
		ECG, CNN, LSTM,	Heart rate variability	95%
[5]	DR	(CNN) models (Resnet50, Inceptionv3, Xception, Dense121, Dense169)	Kaggle	93%
[6]	Lung Cancer	CNN	Kaggle	94%
[7]	diabetes mellitus	SVM	Blood Samples	94%
[8]	COVID19	CNN	Cough sound only	98,5%
[12]	Heart disease	CSO-LSTM	Healthcare data. During the experimentation	96.16 %
	Diabetes diagnoses			97.26 %
[13]	Cervical Cancer	KNN	Cervical Cancer Data Images	90%
		DML		
[14]	Phthalic acid	SVM	Blood samples	95%

III. Weaknesses And Strengths in Mentioned Studies

The classification of findings after the experiment for artificial intelligence techniques applied in the field of medical care is shown in this review. The use of metric learning techniques [13] may lead to more advanced, it has been observed that some misclassification It still exists. So, a possible reason for this is a possible lack of proper generalization during training. The application of the proposed system in the real world is to act as an intelligence assistant to the physician who also evaluates the woman, The images used in the system can be acquired using a variety of devices, such as a smartphone and digital Camera, or colposcope with the ability to take pictures. Weaknesses lie in the steps to address this discrepancy in addition to the imbalance of data and regional differences in the appearance of the cervix. Experimental results have indicated that the proposed [14] SGLHHO can perform much better than others on improving these functions.

In addition, SGLHHO was also used to search for the best parameters and sub-features of SVM; RESULT The SGLHHO-SVM has been successfully used to predict DEHP toxicity. Also, an accurate comparison was made between SGLHHO-SVM and other competitive algorithm rhythms. In addition, the results also confirmed that SGLHHO-SVM achieved higher prediction accuracy with more stable property to work in the future, but there are still several aspects that need to be investigated where it should be noted that more influencing factors and coefficients are entered, thus parallel computing can Reduces computational burden in the process of specific applications. SGLHHO-SVM can be used to predict more diseases to extend the application of this algorithm, such as clustering and segmentation of the cross-sectional image as well as more data samples that can be collected to build a more effective and reliable framework.

IV. CRITERIA OF AN EFFECTIVE FRAMEWORK FOR RESPONSIBLE AI

The majority of AI development and complexity of AI's impacts. Given the black-boxed nature of certain AI models, which may make decision-making processes and outcomes opaque, this process requires exposing and then seeking to minimize bias in algorithms, as well as working to enhance interpretability or explain ability. Privacy, dependability, and safety are other often mentioned concerns [20]. However, these well-known difficulties, which are prevalent in AI ethics research, are only a small part of the social and ethical dangers and implications associated with AI. Broad It should think about AI's ramifications broadly, It should allow users to translate conceptual ideas and objectives into concrete tactics that may be executed in real-world systems. Flexibility It should be flexible enough to work with a wide range of AI systems. lifespan and on a regular basis. Guided It should be simple to use and comprehend, with enough documentation.

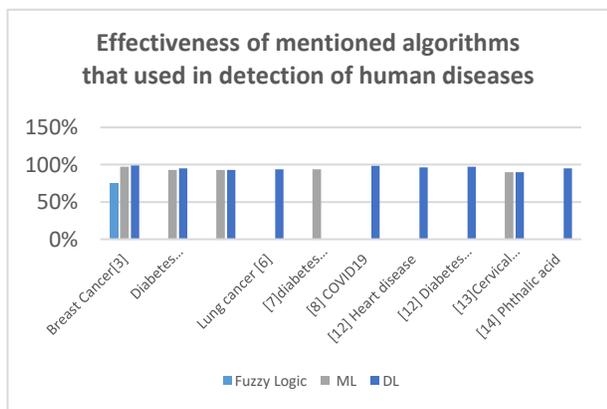


Figure 5- show effectiveness of mentioned algorithms that used in detection of human diseases

A) Importance of Artificial Intelligence and Big Data in Healthcare

Big data and blockchain have left their imprint on the sector. Huge volumes of data are created in the healthcare business. Health records, diagnostic testing, and the Internet of Wearables devices are all examples [23]. As a result, the information is gathered, merged, and double-checked.

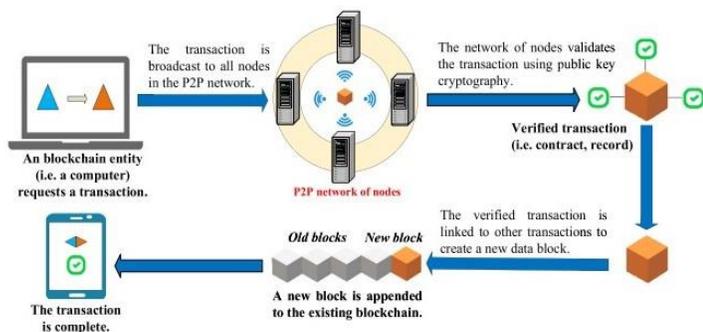


Figure 5- The blockchain operating idea [31].

Intelligence and related health are gaining relevance from a number of sources. The usage of data, on the other hand, is a difficult procedure [30]. Technology Cloud computing allows users to access information stored from anywhere at any time. It may be utilized by people or businesses to improve productivity and performance while lowering costs and complexity. [18], there are several issues connected with keeping data on the cloud, the most significant of which is ensuring the privacy of customers' data against unwanted access and harmful assaults. Additionally, the availability of the owners' data at any moment is a concern. [23].

b) Blockchain and AI in Healthcare Systems

Blockchain is based on the principle of decentralization. In fact, its database is dispersed among a network of participants rather than being housed in a single location [24]. This decentralized idea provides excellent security for the stored database so that there is no single point of failure, and for the purpose of importance, the blockchain is accessible to all network members. The notion of how the blockchain works is depicted because this is possible through a technique known as consensus. In principle, everyone has access to the public blockchain, and anybody may join and make transactions on any of the blockchains [17].

ML and DL are two significant technologies that have been applied to solve challenges in recent research [24]. The goal of machine learning in general is to grasp the structure of data and match it to models that people can articulate and use [25]. ML allow computers to train on data inputs and use statistical analysis methods to generate output values that fall inside a

certain range. Anyone may join, make transactions, and participate in the consensus process on a public blockchain since it is accessible to the public. Figure 5 depicts the blockchain concept. is a visual representation of how blockchain works.

In general, blockchains may be classified as public (permissionless) or private (permissioned) [31]. On the other hand, private blockchains are a closed network managed by a single entity. To provide authorization to a participant, a validation method must be employed. A blockchain is made up of three main components: data blocks, distributed ledgers (databases), and consensus methods. Blockchain's ability to keep the chronological sequence of data records, such as COVID-19 data, is a distinguishing advantage. These data items are kept on the chain in chronological order indefinitely. Each data record (medical data) on the blockchain can be saved as a transaction.

A block is made up of several transactions, while a blockchain is made up of multiple blocks connected together [32]. The hash of the previous block is stored in the header field of each block. The smart contract and its execution provide the same results, which are reflected and recorded on the blockchain. The Internet of Things (IoT) and blockchain can collaborate [33]. The usage of blockchain and AI platforms to avoid COVID-19 is also a challenge.

CONCLUSION

Many artificial intelligence algorithms utilized in medical detection of a variety of human illnesses, categorization data, and experimental findings in this review, demonstrating that the best accuracy was achieved. Backpropagation Neural Network for Breast Cancer 99 percent, Diabetes Disease 95% accuracy rate by ECG, CNN, LSTM, DR 93 % with CNN models, Lung Cancer for 94 % using CNN, diabetes mellitus 94 % accuracy using SVM, by using CNN for COVID19 the model achieved 98.5%, heart disease 96.16 %, and Diabetes diagnoses 97.26 %. For Cervical Cancer, both are utilizing CSO-LSTM, and both are using KNN and DML. Phthalic acid has a final accuracy of 95% when using SVM. Also, the strengths and weaknesses in the mentioned studies and summarized the effectiveness of those algorithms in medical detection and prediction and it was discussed. While recent technological advances in the areas of big data, analytics, and artificial intelligence (AI) have opened up new avenues of competition, where data is used strategically and treated as an ever-changing asset capable of unleashing, our future work is Building a model for detection and prediction of brain and neurodegenerative diseases.

DECLARATIONS

- ETHICS APPROVAL AND CONSENT TO PARTICIPATE: Not applicable.
- HUMAN AND ANIMAL RIGHTS: No animals/humans were used for studies that are basis of this research.
- CONSENT FOR PUBLICATION: Not applicable.

- AVAILABILITY OF DATA AND MATERIALS: The authors confirm that the data supporting the findings of this research are available within the article.
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