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Research Article

Deep Learning: A Future Prognostic Tool in Medical Illness Prediction

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ABSTRACT

Artificial intelligence (AI) has a bright future in healthcare, as evidenced by its rapid growth and the gradual onset of AI research in the medical industry in recent years. The prediction of diseases and drugs has showed potential using deep learning. From a logistic regression model, to a machine learning model, and now to a deep learning model, improvements have been made in the ability to accurately predict medical illnesses. In this article, common illnesses, fundamental deep learning frameworks, and deep learning prediction techniques are all introduced to make a future prognosis and draw attention to issues with illness prognostication. It explains how well deep learning works for predicting diseases and demonstrates how deep learning and medicine will interact in the future. Medical research can benefit from deep learning's innovative feature extraction techniques.

Keywords: Deep Learning , Deep neural network, CNN, RNN, Autoencoder, GAN.

INTRODUCTION

People's concealed illness risks rise as a result of changing environmental factors and lifestyle choices as society develops. Health issues affecting the brain, heart, eyes, low vision, diabetes, as well as cancer, and so on have a global impact. Worldwide, 422 million individuals have diabetes, of which 90% have Type 2 diabetes [1]. Cardiac disease risk is increased by age-related heart senescence and function decrease. Heart disease is a leading cause of mortality worldwide [2]. The health and output of these conditions are impacted. In addition to raising health care and medical expenditures, it will exacerbate societal pressure. The goal of disease prediction is to calculate a person's chance of developing a disease in the future. There are several contributing variables for various illnesses in various populations. Identifying features with broad dimensions and separating complicated and changeable distinctions between individuals and diseases These jobs are challenging and expensive to complete manually.

The expansion of society has accelerated technical development. The gathering of medical data sets is made simpler. Worldwide medical organisations are always gathering health-related data. Various types of information are included in the realm of medicine [3]. Despite being a sort of fundamental data, they are incredibly effect sensitive. Data that is inaccurate or redundant due to timeliness or problems with personal security endanger privacy. Medical data is challenging to manually handle since it is high dimensional, diverse, irregular, and unstructured. Medical circumstances, the expertise of the diagnostician, and patient variations restrict medical diagnosis. People require supplementary ways to forecast and diagnose illnesses in light of the aforementioned problems [4].

As a method for learning to analyse complicated data, machine learning has quickly advanced, and deep learning has emerged as its most intriguing subfield. Deep learning outperforms older technological approaches in several areas, including the capacity to handle complicated data, the classification for extracting the key features from multidimensional data, the ability to deal with unstructured data, and the ability to classify data with more accuracy. This makes deep learning more accessible to more individuals. The deep learning field is developing. It has interfered with NLP, speech recognition, and picture recognition. With excellent results, deep learning has been used to forecast diseases [5]. Deep learning, which is better able to perform tasks, is extremely compatible with medical data.

A perceptron, sometimes referred to as an artificial neural network (ANN), is the building block of deep learning. A deep neural network (DNN) has evolved from a shallow model NN to a deep model as a result of shifts in people's desire for models, the expansion of data size, and advancements in computer capacity. A deep neural network consists of three layers: input, hidden, and output. The training algorithm for conventional multi-layer perceptron neural networks is back propagation.

Information is propagated both forward and backward in this way. Visually, it's comparable to teaching a computer to create a set of programmes that simulate the functions of the human brain in order to train its intelligence to mimic human vision, hearing, and other intelligent behaviours and develop over time. When making disease predictions, the computer can mimic medical professionals to diagnose diseases and build up prior experience to increase prediction accuracy, strengthening the model. Figure 1 shows the evolution of some of the network structure models developed by DNN [6] for use with clinical data and problems.

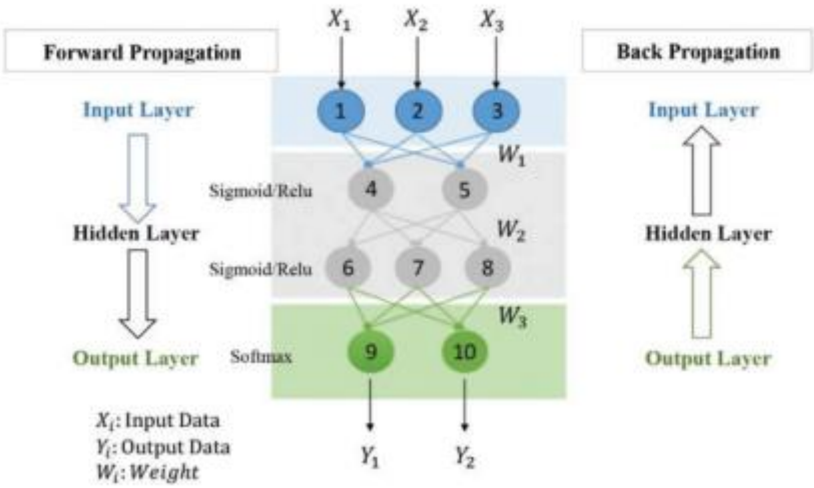


Figure 1: Deep neural network

Popular deep learning models and techniques are introduced in the second section of the paper, which is then followed by enhanced model frameworks and fundamental approaches to medical problem solving. The third section provides a succinct overview of illnesses, the exploration of deep learning approaches for disease prediction, and a summary of successes and improvements. The fourth section examines issues and difficulties with using deep learning to forecast diseases. The fifth section outlines potential applications for intelligent fusion in the future under the state of technology today. Text is summarised in the sixth section.

DEEP LEARNING MODELS

1.1 CNN

As the depth of the neural network with one fully connected layer increases, the size of the memory requirement and the cost of computation rise. The issues brought on by fully linked layers have been steadily addressed in order to promote neural network development. Local correlation and weight sharing are used in the construction of a convolutional neural network (CNN), which lowers the number of parameters and boosts training effectiveness. LeNet's 1998 plan laid the foundation for CNN. Convolutional, pooling, and completely linked layers are displayed in Figure. 2. Architectural modifications are output after fc, following convolution and pooling.

It wasn't further developed at the time because of the computational capacity and data volume. After overcoming some objective challenges and doing well in international contests, CNN swiftly rose to the top of the computer vision heap. A slew of improved CNN models, including VGG net [7], ResNet [8], DenseNet [9], as well as Xception [10] and many more followed shortly thereafter. CNN was first developed for computer vision, but research has proven it is useful in a variety of industries, including medicine [11,12]. Classification, prognosis of illness, [13], [14] visualisation, etc. Medical chest X-ray, CT, and other [15] imaging data may all be processed using CNN. The CNN model can understand medical images through the feature extraction as well as data fusion [16], whether there is a single image for disease diagnosis or a collection of many images for supplementary prediction. The fully linked layer outperforms conventional machine learning models in terms of illness classification [17].

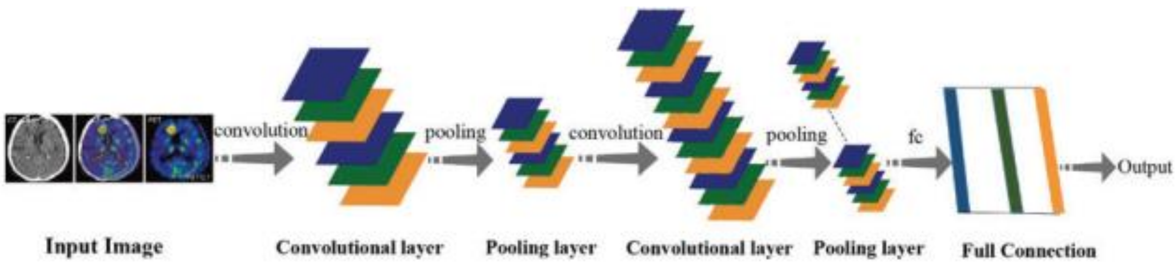


Figure 2: Flow diagram of the CNN

1.2 RNN

For task-based conversation, time series forecasting, etc., models must learn sequence features. Effective time series management is impossible due to the inability of neurons in any layer of a neural network to link that includes the intigrated layer. Unlike temporal data, geographical data can be handled by CNN. Recurrent neural networks (RNN) were developed to address a few of the aforementioned issues.

RNN is made up of neurons and feedback loops. When the prior and subsequent inputs are interdependent, RNN offers benefits [18]. Compared to other machine learning algorithms, RNN excels at handling massive data sets that are contaminated with delays and noise. Short-term memory problems [19] and gradient explosion problems that RNN encounters during training inspired the creation of LSTM and GRU, respectively. State vectors and gates are added by LSTM to RNN. Figure 3 the key components of an LSTM: input, forget, and output gates. GRU only has two gates: Reset and Update. Refresh and forgetfulness are managed by gating. Input data is represented by xt, the state vector by ht, and state vector changes under gate control by ht1 to ht. Tanh is the activation function. On long-term data, LSTM performs better than RNN. Images, images, and sounds are sent to it. GRU is employed in place of LSTM due to its huge model parameters and high computational cost. The gate control system used by GRU consists of reset gate and update gate. Despite having a simpler structure than LSTM, GRU is just as effective [20]. Vertical time stamps work nicely with both types. It's crucial to review old medical records or compile data from several time periods when forecasting the development of specific disorders [21]. RNN has a use [22]. To deal with the space-time complexity of medical data, RNN is typically combined with a convolutional neural network (CNN) or other models [23-26].

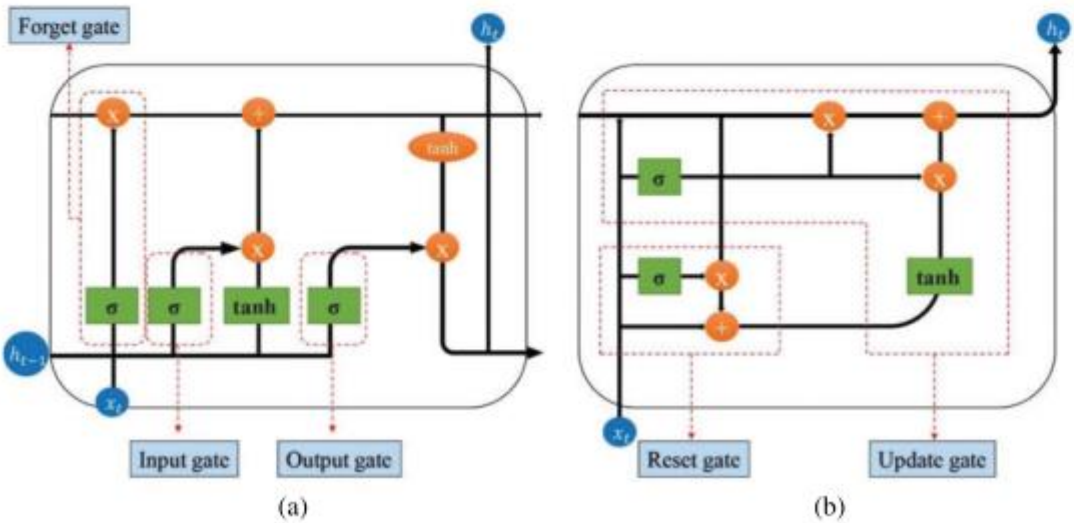


Figure 3: structural diagrams of (a) RNN and LSTM (b) GRU

1.3 Autoencoder (AE)

In reality, unlabelled data are present. It facilitates learning without supervision. Real medical data is difficult to categorise. To uncover greater value, technology is needed to automatically categorise or aggregate data. There are several methods connected to the medical environment for obtaining medical data. Data loss and distortion happen sometimes [27]. Autoencoder is a neural network model that reduces feature dimensionality, eliminates noise, and restores lost data efficiently using unsupervised learning as well as feature extraction [28]. Encoding and decoding are the two components of the traditional AE paradigm. 4. AE utilises x as the output and creates a mapping of f:x>x because the input data lacks label information. The network really consists of two components: f 1:x>z encoding and f:z>x decoding. Dimensionality is reduced by encoding to z, which is subsequently recovered to x. The input x and the desired outcome x should be as comparable as feasible in order to optimize the objective function (x, x). We use deep neural networks to train F1 as well as F2 and then couple them with other deep learning models to obtain representational data. The initial input x can indeed be retrieved more accurately than with machine learning. Numerous other models can be combined with the AE model [29]. In order to effectively analyse medical data with low recognition, a variety of AE designs, including the Sparse Auto encoder [30] and Variational Auto encoder (VAE) [31], may be created using changing medical data. (Figure 4)

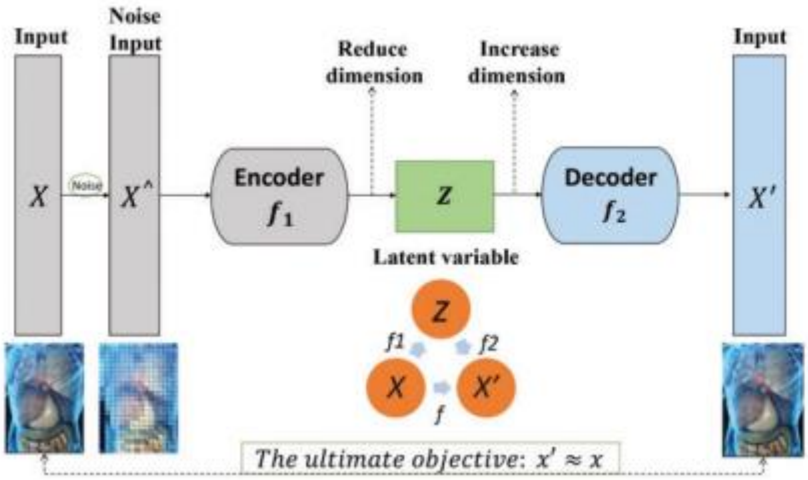


Figure 4: The flow diagram of the Autoencoder

1.4 GAN (Generative-Adversarial-Networks)

Using game theory GAN develops artificial images. Game theory is implemented in network training. Subnetworks for generation and discrimination are built up. Optimization is performed in a manner analogous to a competitive process on both the generative network as well as the discriminant network. Then, work together to get better. The discriminating network separates created samples from actual samples while the producing network learns the genuine sample distribution. The discriminating network is convolutional whereas the generating network is de-convolutional. Regardless of picture size or fidelity, GAN's performance has increased and made strides since it was initially suggested in 2014. Image processing, such as image-to-image translation, image restoration[32], [33], image resolution enhancement [34], medical image fusion, [35], [36] etc., is where GAN is most frequently used. Gan has been successfully applied to medical imaging [37]. Gradient loss and mode collapse are effects of traditional Gan training. The majority of improved techniques function well [38–40]. Despite being relatively new to medical imaging, GAN has already demonstrated its advantages. Once these problems are fixed, GAN will benefit the medical industry more.

1.5 Other Models and Methods

Recent years have seen the emergence of Deep Belief Networks (DBN) in medical research. When processing medical images, for instance, it enhances image fusion [41]. Parkinson's disease is easier to diagnose because to DBN voice processing [42]. In order to assist doctors absorb medical information more thoroughly, DBN may be utilised with regard to both supervised and unsupervised learning. It may be used in supervised learning serve as a classifier, and in unsupervised learning, it has the similar effects as AE.

Research applications are improved when many models are combined. Different models for solving problems are applied. Bagging increases accuracy compared to standalone models while RNN analyses vertical problems and CNN processes horizontal data [43].

Transfer learning has been increasingly popular in recent years and is frequently used in tandem with deep learning. The fact that deep learning needs so much information is one of its drawbacks. Transfer learning, like the "polymorphic" idea that suggests reusing models, may be performed with a small amount of data to save time and improve the model. DL models might benefit from more transfer learning [44]. Talo et al. [45] employ deep transfer learning to assist radiologists with MRI image diagnosis. The trained model is flexible enough to tackle novel challenges, medical researchers make use of transfer learning, and the baseline model is heavily modified to improve lesion identification in cancer images [46]. As the field of medical imaging evolves, transfer learning can help push forward ground breaking discoveries.

CLASSIFICATION OF ILLNESSES AND RELATED PREDICTION

1.6 Pneumonia

Numerous organs in the lungs get inflamed as a result of pneumonia. The most typical is bacterial pneumonia. Chest discomfort, fever, and breathing problems are more common in children and senior citizens. The proportion of pneumonia individuals to mortality is high globally. There are still risks to one's health and life despite the use of antibiotics and immunizations. COVID-19 is a mild-to-moderate respiratory disease. Influenza-related pneumonia [47] The effects of COVID-19 extend beyond the lungs. cardiovascular, nerve system of the head, [48], [49] etc. The emergence of new coronary pneumonia as a worldwide health issue on February 19 is crucial for pneumonia early detection and prediction.

Patients who have suffered significant lung injury may experience breathing problems as a result of pneumonia-related respiratory obstruction. A portable respiratory measuring device was created by Fan et al. [50] to enhance current ventilators. Radiologists can use deep learning to screen suspicious X-images of the lungs for the presence of pneumonia. With X-images, Voroshnina et al. [51] evaluated CNN. The data set includes 5863 X images that can clearly distinguish between healthy and sick lungs. By tweaking layers, optimizers, training parameters, and epochs, the author was able to find the optimum CNN model. With an accuracy of 89.24%, a 4-layer alternating Conv2D layer with a MaxPooling2D layer structure showed the best ability to diagnose pneumonia. By enhancing the CNN paradigm, Rajpurkar et al. [52] developed the 121-layer CheXNet network. The index outperformed the previous best model in detecting pneumonia from chest X-ray image data, outperforming radiologists. Qjidaa's team [53] employed the upgraded VGG16 network model to forecast pneumonia. This simple network can better extract picture features. According to the report, this model can spot lesions just as effectively as radiologists can. The external AUC and accuracy of this model for predicting chest radiographs are 95% and 87.5%, respectively. To track COVID-19, [54] comparisons with Xception, VGG16, as well as InceptionResnet-V2. When compared with the other models' accuracy (95.42% and 93.87% respectively), the CNN Xception algorithm has the highest accuracy (97.19%).

Pneumonia risk can be reduced by transfer learning [55]. To get around the problem of limited data, first construct a foundation for deep learning, and then use transfer learning to incorporate the learned parameters of other models into your own. A brand-new pneumonia predictor was suggested by Liang et al. [56]. Convolutional networks with residual structures, which lessen overfitting and avoid feature loss owing to model depth, make up the fundamental architecture. Transfer learning improves accuracy over Xception by 87.8% to 90.5%. Additionally combining transfer learning and deep learning is Chouhan et al. [57]. It extracts and categorises features using an ensemble model and As many as five deep learning models that have already been trained. Performance of the combined model outperforms that of a single model.

Fusion techniques have been developed in addition to the conventional solo approach. Convolutional and residual networks were integrated by Saul et al. [58] to categorise images. Figure 5. depicts the multi-view fusion paradigm proposed by Wu et al. [59] Accuracy of 78.73% was achieved by X-ray image analysis, which is higher than the best available independent model. which had a rate of 76.8%. ResNet50 makes up its base layer. The RGB channel picture of the original model is converted to a three-lungs view image. Utilizing medical images from a wider angle lessens single-factor issues, prevents overfitting, and enhances performance. In order to diagnose COVID-19, 495 high-resolution CT images were employed. This shows the promise of machine learning to effectively screen patients by training models on CT scans. Numerous patient information and privacy concerns are involved with COVID-19. In order to identify Hossain et al. [60] developed the B5G architecture to incorporate COVID-19 into everyday life and connect this with distributed ledgers technology to enhance data security.

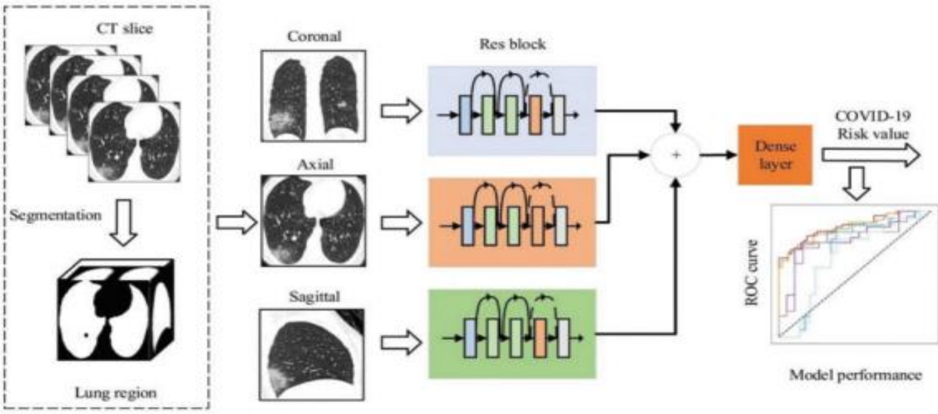


Figure 5: Deep learning fusion model with several views [59]

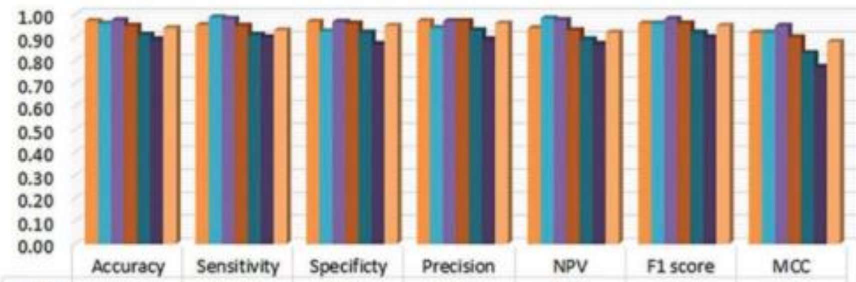
The COVID-19 outbreak affected the world economy and used up most of the medical resources. Quality and cost must coexist in harmony. A decision-making model and auction mechanism were suggested in reference [61] as a way to aid in product selection while fostering economy and quality. Deep learning models may be used to speed diagnosis and accurately forecast each patient's particular prognosis for COVID-19, which will lessen the strain on doctors and the paucity of medical resources [62]. Future studies should use DL along using medical records, X-rays, and CT scans. A more thorough diagnosis may be made by anticipating the patient's computed tomography (CT) scans, chest x-rays, and other information prevent single-information mistakes.

1.7 The Cardiovascular Disease (CVD)

Congenital heart defects, high blood pressure, irregular heartbeats, and coronary artery disease are all examples of cardiovascular disorders. Cardiovascular disease causes almost 18 million deaths annually, or 31% of all fatalities worldwide [63]. In our fast-paced environment, excessive job demands and inconsistent nutrition are prevalent. Cardiovascular illness is brought on by genes, inheritance, and overt markers like blood pressure and blood lipids. The most prevalent clinical arrhythmia, atrial fibrillation, results in organ embolization and brain thrombosis. Although clinical heart rate problems are not immediately apparent, general detection entails analysing heart rhythm variations [64]. A unique way for analyzing very complex characteristics in high dimensionality and identifying abnormal features is provided by deep learning. Arrhythmia and acute coronary syndrome can be found using an electrocardiogram (ECG) [65]. DNN was employed by Hannun et al. [65] to categorise ECG heart rhythm, outperforming cardiologists' sensitivity and lowering the rate of incorrect diagnoses of irregular heart rhythm. DL may speed up and increase the accuracy of CVD diagnosis, which aids in both prevention and therapy.

To predict CVD, several practises employ machine learning. Many DL techniques have exceeded conventional ML techniques because to deep learning. Seven models were utilised by Ayon et al. [66] to forecast CHD. With the use of five-fold and ten-fold cross-validation, the author evaluated the Statlog and Cleveland data sets. Only the indicators from the Statlog data set's five-fold cross-validation are recovered in Figure 6. In comparison to SVM, the top ML model, DNN has greater accuracy, sensitivity, and NPV. Similar to SVM in terms of F1 score, specificity, and precision. DNN does well in ten-fold cross-validation. The graph demonstrates that DNN's performance on several assessment metrics is constant and that, in actual use, its classification impact is more accurate. When working with bigger illness datasets, DL models outperform ML models.

Additionally, the clinical data on coronary heart disease frequently has poor data quality and uneven categories. Based on this issue, Dutta et al. [67] suggested a model for an effective neural network with convolutional layers that employs subsampling to resolve aberrant data types and contrasts them with many current machine learning techniques. While the accuracy rate while testing negative examples reaches 82%, greater than the best machine learning model's SVM 76%, it is equivalent to the best model in recall prediction (0.77). Additionally, the classification performance outperforms frequently employed machine learning methods. The MIT-BIH arrhythmia database was the first to evaluate all types of arrhythmia [68]. In classification to accomplish multi-level classification of heartbeat situations, Shi et al. [69] fused the threshold classifier on the hierarchical classifier with the enhanced XGBoost for the identification of aberrant heartbeats and the MIT-BIH "Atrial Fibrillation Database (AFDB)". A neural network with a complete connection layer was suggested by Wang et al. [70] to identify AAMI-standard aberrant heartbeats (N, S, V, F, and Q) represent a five-category classification of heartbeat types. The findings are optimised using two classifications, several data sets, and the fundamental structure's two layers of neural networks. A residual network was developed for transfer learning by Jin et al. [71]. Learning from and practicing on the domain may result in a 4.5 percent increase in average accuracy rate of the source data. The resolution of unlabeled and unbalanced data sets.



	Accuracy	Sensitivity	Specificty	Precision	NPV	F1 score	MCC
SVM	0.97	0.95	0.97	0.97	0.94	0.96	0.92
LR	0.96	0.99	0.93	0.94	0.98	0.96	0.92
DNN	0.97	0.98	0.97	0.97	0.97	0.98	0.95
DT	0.95	0.95	0.96	0.97	0.93	0.96	0.90
NB	0.91	0.91	0.92	0.93	0.89	0.92	0.83
RF	0.89	0.90	0.87	0.89	0.87	0.90	0.77
K-NN	0.94	0.93	0.95	0.96	0.92	0.95	0.88

Figure 6: Analysis of Statlog data for the ten-fold heart disease prediction algorithm [66].

RNN beats most ML algorithms for processing large amounts of massive data that is delayed and noise abnormally. The medical past of the patient can aid in predicting CVD. RNN can analyse data with time stamps. Real-time medical record monitoring and physical condition prediction are both possible with RNN's distinctive gate control mechanism. Anandajayam et al. [72] use the RNN algorithm to predict cardiovascular diseases using historical medical information of those who have a history of heart disease. RNN's accuracy is greater than 90%, which is superior to logistic regression's 85%. As demonstrated, RNN performs better when handling huge data sets. A dynamic LSTM model was built by Kuang et al. [73]. LSTM classification is enhanced by combined processing of input data at various periods. For earlier aberrant heartbeats, there were significant individual variations. The hybrid LSTM model, which can analyse ECG segments across time and employs active learning to automatically extract features, was proposed by Jin et al. [74]. It resolved issues connected to personal differences. More illness prediction situations may be handled when RNN and CNN are combined. Moreover, hybrid model performance may be enhanced through model combining techniques. By utilising numerous input layers, Shi et al., [75] suggested a system topology that blends LSTM and CNN. To reach a subject accuracy of 94.20%, automatic feature extraction is paired with manual features. A CNN-LSTM hybrid model known as twin-attentional convolutional-LSTM was developed by Jin et al. [76]. It exploits LSTM's capacity to gather time-domain data to make up for CNN's shortcomings in time-sensitive processing. Accuracy of the AFDB data set is 98.51%. CNN and GRU were employed by Ali et al. [77] to forecast cardiac disease. The resulting CNN-GRU ACU rate is 94.5%, higher than the LSTM and CNN-LSTM accuracy rates of 92% and 93.7%, respectively. This is accomplished by integrating the feature extraction methods for LDA and PCA, and then improving accuracy through k-fold cross-validation. Both supervised and unsupervised illness prediction may be performed using deep belief networks. A better DBN model with outstanding stability and prediction accuracy was proposed by Lu et al. [78] by combining unsupervised training with supervised optimization. The model's classification accuracy in the last test was 91.26. Deep learning can extract aberrant illness indicators and disease risk factors from a large set of indicators. To noninvasively identify blood vessel characteristics, Poplin et al. [79] monitored retinal characteristics. They classified a number of factors using retinal images and CNN to predict and verify cardiovascular classification influences.

RNN can be used to make early predictions when taking the characteristics of CVD into account, and its special processing technique for time series data can be used to look into the patient's medical background. EHR's widespread use presents a chance for RNN health. Future integration of RNN with EHR should enhance illness monitoring.

1.8 Alzheimer’s Disease (AD)

Cognitive and behavioural deterioration are two symptoms of the neurodegenerative illness known as Alzheimer's disease. Across 50 million individuals around the world experience AD. The initial death rate is minimal, but it nevertheless causes hardship for people and their families [80]. Although early symptoms are difficult to identify, they get worse over time. There is no treatment for early AD, which is easily missed. Early diagnosis helps the medical community manage with AD. A major problem for technology is early AD diagnosis and prevention. The overall course of AD patients from normal to MCI to AD was documented in reference [81]. MCI can stop AD degeneration in its tracks. The essay mentioned difficulties in predicting AD. Although there is no complete way to forecast A generation later, machine learning technology has been employed extensively in the automated categorization as well as early diagnosis of AD.

AD can be identified with MRI and PET multi-modality, high-dimensionality, as well as other complex properties characterise these two images [82]. Older processing techniques are cumbersome. Since its creation, more research have used deep learning models to analyse medical images of the brain. When several images were combined, Jo et al [82] analysis of the DL technique's and hybrid method's performance as well as the effects of various AD image data revealed that the hybrid approach performed better overall. Ji's [83] team suggested a 3D-CNN model that is superior for medical imaging analysis because it can extract features from Compared to a 2D model, time and space could capture more spatial details. Cheng’s team [84] to confirm the 3D-efficacy of CNN in AD MRI diagnostic uses the spatial and temporal characteristics of MRI. The ADNI contains Genetic, biospecimen, MRI, PET, and other diagnostics data related to AD. It accounts for the majority of AD effects and is a well-known resource for AD research. The 3D-densely CNN method in Figure. 7 was created by Wang et al. [85]. The accuracy of the classification tests on AD/MCI/Normal that the author performed using the ANDI dataset was 93%. The distinct distribution of the 18F-FDG PET picture in the low-metabolic brain can aid in the diagnosis of MCI and AD [86]. MRI is less sensitive than 18F-FDG PET for identifying AD/MCI [81]. Using the 18F-FDG PET images with the InceptionV3 CNN model, the DL method can accurately diagnose lesions.

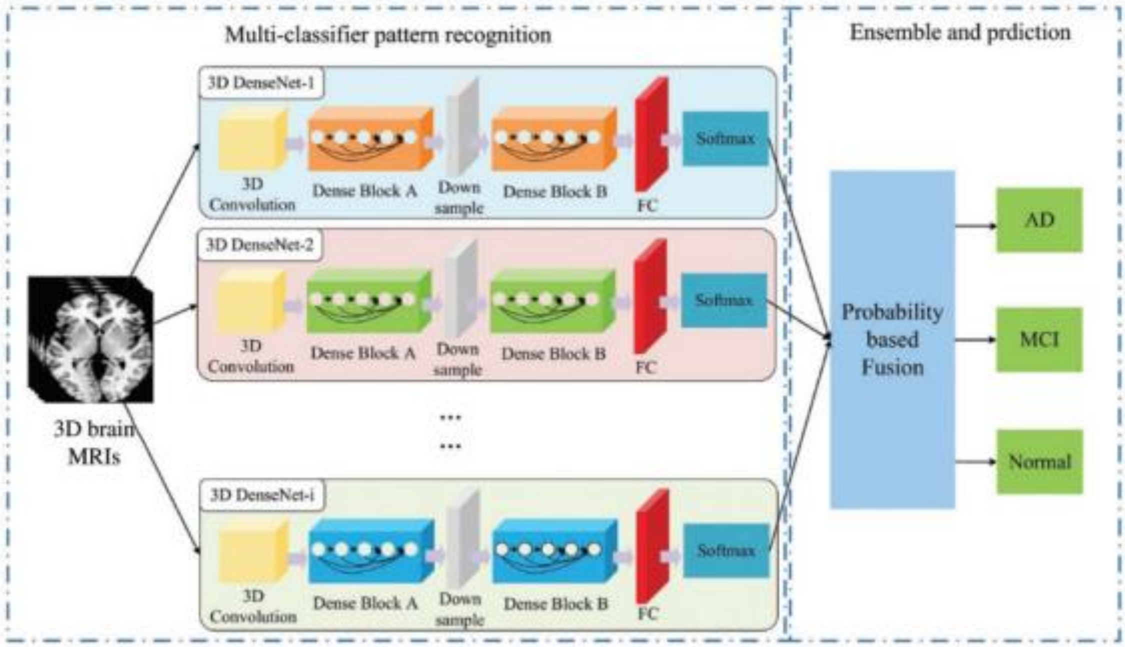


Figure 7: Wang suggested 3D-DenseNet aimed at the diagnosis of AD as well as MCI [85].

RNN and CNN were suggested as a combination by Cui et al. [87] to classify brain abnormalities. RNN extracts longitudinal features, whereas CNN learns spatial features. This approach outperforms CNN's [88]. In the bilateral hippocampi of AD/MCI patients, MRI images can reveal lesion features. Li et al. [89] achieved 91.0% AUC while diagnosing AD using a hybrid recurrent and convolutional neural network in comparison to healthy controls. hippocampus lesions in MRI.

These publications provide a more thorough processing of brain medical images by the deep learning model. Unlike conventional techniques and specialists, it can identify deeper forms of brain abnormality. The test findings of the model cannot give grounds for making decisions. In reality, it is challenging to match the demands for picture quality, and image set performance is unpredictable. Rapid changes are brought on by many brain disorders. Prediction for AD is still viable. AI can help with healthcare by advancing studies on AD prevention and therapy. It's also simpler to create DL technology.

1.9 Cancer

There are several disorders that fall under the umbrella of cancer. Primarily describes the uneven cell proliferation brought on by causes that induce illness and cells in tissue masses. Cancer ranks second in worldwide death rates [90]. Cancer, often known as tumour, is benign and malignant. Malignant tumours can harm other tissues and organs because they are tenacious, simple to recur, and simple to spread. Even though malignant tumours are challenging to treat, early discovery, prevention, and therapy can stop the tumour from getting worse [91], [92]. Early detection and screening can reduce cancer-related fatalities by 30% to 50%. Comprehensive prediction technology is needed due to the wide variety of malignant cells and the significant variances between cells. By automatically collecting crucial data, deep learning has demonstrated distinct improvements in the classification of cancerous lesions [93].

Complex disorders can't be studied using single-omics approaches [94]. Cancer is a condition that has a protracted course of development as well as the potential for several gene alterations. More data as well as associated genes are necessary for better knowledge. Accurate cancer detection will be facilitated by the multi-omics combined technique, which can get a additional complete stream of illness data [95]. There are tumour data collections on UCSC Xena. Multi-omics data are available in TCGA. It encourages multi-omics research on cancer. In order to analyse and fuse various omics structures, Tan et al [96] MOSAE's (Model for Multi-omics Supervised Auto encoding in Genomic Research was presented [96]. The ROC and AUC obtained using TCGA Pan-Cancer data to compare with six widely used machine learning models are better. Tong et al. [97] modified the original AE to accomplish various goals. CrossAE carried out multi-modal denoising while ConcatAE fused modal data. When put to the test with multi-omics data, these two models predict breast cancer superior than using only one model. Asada et al. [98] tested genes associated with lung cancer prognosis using ML and DL and revealed novel survival genes. After processing six multi-omics data sets using AE to decrease dimensionality and unify features, Takahashi's team [99] employed ML to create a lung cancer prognostic model. Several indications support the idea.

There is a dearth of recent research on deep learning and various omics for predicting cancer diagnosis. Data collection for cancer genomics is facilitated by current genomics technology. Future studies should concentrate on the integration of several omics employing DL to analyse multiple data sets. Cancerous cells can be identified from a wider range of angles, enabling precise cancer prediction, which is important for the irregular and variable growth of cancer.

When processing diseased cell data, DL models can better extract potential features, improve the data using Solve unlabeled as well as irregular data, or optimize noisy data using AE or GAN. to find cancer cells. Using CNN and VAE, Khamparia et al. [100] diagnose and categorise cervical carcinoma. The primary structure makes use of dense and Softmax layers for classification, The convolutional neural network to extract high-dimensional characteristics while reducing dimensionality and enriching the data. When the size is 3 3, which is superior, 99.4% accuracy is attained after applying filters and compared to the current approach. Iizuka et al. [101] to identify adenoma, adenocarcinoma, as well as non-tumor combine InceptionV3 and RNN. The WSI image dataset classification test's AUC is more than 96%. The ResNet101 model, used at the bottom layer by Khan et al. [102], extracts more detailed features than the conventional CNN model while using less input due to transfer learning. After applying the improved model to analyze the WCE image data, which comprises four stomach abnormalities, the accuracy performance increased from 87.45% to 99.46%. It is more accurate than any preceding methods when compared toward other neural networks.

Baptista et al [103] use of DL can identify cancerous tumours and anticancer medications forecast anti-cancer drug sensitivity lessened the constraints of clinical drug testing. The categorization of pharmacological responses using the Alex-NET framework, which was used by Mencattini et al. [104] to study cancer medication response at the cellular level, has a clear classification. Kuenzi et al. [105] investigate how medicines affect carcinogenesis in cells. Clinical cancer research should be reevaluated.

Breakthrough computer technology and medical innovations will result in new cancer therapies. Conventionally, radiologists manually diagnose cancer. A medical image's malignant region could only be twelve pixels wide. Manual diagnosis takes a lot of time and is unreliable. The standards are higher for radiologists. By taking both horizontal and vertical characteristics into account, deep learning could identify deeper lesions with cancer cells. Early and accurate cancer cell diagnosis may result from less strain on medical diagnoses [106].

1.10 Diabetes Mellitus

If your blood sugar levels spike dramatically, your insulin production is abnormal, or your body is unable to absorb glucose normally, you may have diabetes mellitus. If diabetes is not identified and treated in a timely manner, it can harm several organs and endanger human health. Diabetes can be of type 1 or type 2. Hereditary research is crucial to avoiding diabetes at its source since both forms have a genetic link. Diabetes-related features are screened using deep learning to diagnose and categorise illness.

The levels of Blood glucose are frequently used in medical diagnosis to check for diabetes, as well as ECG signals can be used to monitor diabetes. Diabetic lesions can be recognised via HRV abnormalities [107]. DNN was applied for diabetes feature monitoring by Ayon et al. [108] and was contrasted with other machine learning techniques. In comparison to the optimum SVM's 97.47% accuracy, five-fold cross-validation produces a result of 98.35%. To test BG, Padmapritha [109] used LSTM. [110] Li et al. suggested the CRNN. Blood glucose problems may be easily identified and predicted using CNN and an enhanced LSTM structure. CNN and LSTM were combined by Swapna et al. [107] to diagnose HRV data with 95.7% accuracy. With the use of Deep GRU and LSTM, Pavithra's team [111] tested diabetes The accuracy of GRU is higher than LSTM's. In order to create a training network that could accurately diagnose Type 2 diabetes and sleep apnea with 98.80% accuracy, Perdomo et al. [112] coupled DBNN with CNN.

In medical diabetes, diabetes monitoring equipment is employed. Diabetes treatment and management rates in China are below 50%. A disease analysis platform and essential tools are missing from real-time diabetes monitoring. Huge demand creates the environment for real-world IoT applications and fosters IoT growth globally. Deep learning's sophisticated processing techniques have also boosted medical therapy, resulting in smarter illness identification. Retinal fissures, facial features, and various perspectives can all be used to monitor diabetes. In actual practise, additional possibilities ought to be covered by a broader diagnostic model. AI will diagnose diabetes in the future.

1.11 Other Diseases

As mentioned below, deep learning technology is also employed to treat different ailments.

1.11.1 Hepatitis

The persistent inflammation that is hepatitis. Five categories make up medicine. Symptoms of various hepatitis kinds vary. Most people don't exhibit any early signs, thus further techniques are required. Hepatitis that is left untreated can cause liver cancer and liver cirrhosis to diagnose. Immunization and early detection enhance preventive and care. Using DNN, Jyoti et al. [113] were able to forecast hepatitis and compare different activation methods. The accuracy of the swish method was the highest prediction accuracy as 92.3%. To find liver lesions, Yang's team [114] used transfer learning in conjunction with a 7-layer AlexNet CNN framework. Accuracy while automating methods is on par with machine learning and neural networks. Xiao et al. [115], in their study of hepatobiliary diseases using eye feature images, used ResNet-101 to diagnose hepatitis, establishing the link between defective eye functioning and hepatobiliary disorders. Frid-Adar et al. [116] synthesised high-quality liver lesion images, combined them with CNN to complete the lesion classification, and achieved sensitivity and specificity values of 85.7% and 92.4%, respectively, which are higher than those of the comparison method (78.6% and 88.2%). This improved the quality of the medical data significantly. Based on observations made with Raman spectroscopy, Lu et al. [117] developed MSCIR. Normalized architecture now includes convolutional and recurrent neural networks (CNN and RNN) to improve data processing. 96.15 percent accuracy, compared to 91.53 percent accuracy using regular NN. Patients having type B pneumonia were identified by Wang et al. [118] using Raman spectroscopy, principal component analysis to reduce dimensionality, as well as a long short-term memory network to manage long-span data, with a 97.32% success rate. Minimizing dimensionality with principal component analysis is a technique used in both articles. It could be beneficial to switch to AE or Gan.

1.11.2 Infectious Disease

Multiple organs are harmed by the bacterial and viral infection. There are numerous channels for transmission, and there is no clear pattern. It's challenging to control once infected. It's important to recognise the signs of infectious characteristics and take immediate action. A viral infectious disease, COVID-19. To forecast and diagnose worldwide medical issues, several teams employ DL. BiPathCNN and viral sequences were utilised by Zhu et al. [119] to estimate the source and infectiousness of COVID-19. ResNet-50 and transfer learning were employed by Fu et al. [120] to diagnose viral pneumonia in CT images having prediction accuracy as 98.8%.

High-risk variables are found and managed with the use of AI. It enhances disease control and prevention [121]. When tested with ideal control settings, DNN and LSTM increase the ARIMA model's performance by 24% and 19%, respectively. When an infectious illness spreads, DNN remains constant, although LSTM is much precise. Since a decade, big data has aided in the fight against infectious diseases. Deeper mining has been made possible by big data to address unforeseen infectious disease issues. Big data processing can be aided by deep learning [122].

1.11.3 Kidney Disease

Inflammation and tissue damage are results of kidney diseases. CKD, or chronic kidney disease, is the usual one (CKD). Delaying detection and treatment may lead to kidney cancer. For the purpose of CKD detection, Alnazer et al. [123] assessed radiomics, etc. These intricate medical image sources can be used to examine kidney disease symptoms and aid in DL's disease research. In order to detect kidney abnormalities, Wu et al. [124] developed a multifunctional network (MF-Net) primarily made of CNN. This network achieved an average classification accuracy rate of 94.67% when compared to multiple fusion models. Convolutional neural networks were enhanced by Navaneeth et al. [125] using dynamic pooling. Proposed employing saliva urea levels to detect chronic renal illness, followed by SVM to reach 97.67% prediction accuracy, outperforming standard CNN's 96.12%. Bhaskar et al. [126] created an ammonia sensor, using the CNN-SVM model for classification, which has a 98.04% accuracy rate, and exploited irregularities in saliva urea to diagnose illnesses. Khamparia et al. [127] achieve 100% accuracy in CKD classification using stacked AutoEncoder for feature augmentation and Softmax as the classifier. An HMA model was suggested by Ma's team [128]. To forecast CKD, this model integrates many classifiers. Medical IoT ensures data accuracy and speeds up computation during the experiment. With the help of the medical Internet of Things and an adaptive hybridised deep CNN structure, Chen et al. [129] were able to predict and optimise their models for the detection of kidney disease.

TECHNICAL BARRIERS AND EXISTING ISSUES

1.12 Inadequate interoperability

Although DL models do well at feature extraction and classification, they are difficult to comprehend. Since deep learning and medicine are two separate fields of science, the research they conduct will be varied. Some illness prediction techniques distinguish between deep learning and medical expertise. The model's interpretability must be taken into consideration when integrating these two subjects. The interpretability of the model reveals how well humans comprehend the choice. Models need to explain "why," or how they make predictions. Some conventional statistical techniques choose features by hand using medical expertise. Deep learning is data-driven and seldom ever takes risk considerations or domain expertise into account.

Black boxes are what deep neural networks are. New data is added after the model has been trained, and predictions are then produced. The model just provides a forecast outcome based on input data; it does not explain how to predict that breeds mistrust. The model must be trustworthy in order to use deep learning for actual illness prediction and healthcare and realise disease prediction intelligence. Interpretability is necessary for deep learning model believability. Only until the model interpretability issue is resolved will deep learning be widely used in medical scenarios. Model interpretability should be emphasised in future research. Realistic requirements should be used to "humanise" the model, regardless of its criteria, scope, or interpretability role. Deep learning can only increase credibility after that. Give patients quick, precise, and illuminating diagnosis.

1.13 Problems with Clinical Deployment

The vast majority of DL related disease prediction techniques are still in the conceptual phase. There are several reasons for this.

1.13.1 Generalization Ability

Poor generalisation raises questions about the model's usefulness and accuracy. It is challenging to extract high-quality medical images and fulfil model input data requirements in places with inadequate medical equipment. Despite having advantages in a number of indicators, DNN is unstable when tested against various test sets [72]. More data is needed for DL. Denoising may be built into CNN or other deep learning models [130]. The usage of image enhancement technologies may also be used to magnify important features, increase the usability of images, and improve global or local picture features. Utilize existing picture fusion technologies to the fullest to improve diagnosis [131]. Class imbalance problems arise in small medical datasets. The generalizability of the approach should be enhanced by further study on data accessibility.

1.13.2 Stability

It is not known how stable the deep learning approach is. Deep learning needs to be very stable before it can be used in clinical settings. Medical data are unreliable and poor. The training sample could differ from the real sample when a neural network model is applied to a real medical scenario. When a model developed from training examples processes real samples, it could not be resilient, have aberrant features, or have insufficient classification accuracy. Inaccurate illness prediction, decreased algorithm performance and efficiency, and even patient safety are all risks if the model's stability cannot be assured. Make sure the model is stable before moving on to clinical application.

1.13.3 Privacy Security

Data protection and patient privacy should be taken into consideration because medical records and patient data are frequently used while utilising deep learning to detect illnesses. It's critical to safeguard patient privacy and stop data breaches. To process medical data, Lv et al. [132] recommended employing differential privacy technology. Telemedicine data is safeguarded by blockchain technology and conventional surveillance systems [60]. Technology should help with problems related to deep learning, just as technology should help with problems that have been supposedly created by technology. The goal of maintaining patient records within the institution of origin was achieved [133]. Deep learning integration research is still insufficient, and distributed technology is still autonomous. The privacy of doctors and patients should be protected in future studies [88]. The varying quality of medical data is influenced by medical disorders. We should create medical data application technologies that provide privacy and security using already available technology. To hasten clinical applications, let patients cease caring about their personal information.

The previous three points are influenced by other factors. Data that has been manually labelled is used to forecast diseases. Ethical problems will result from personal bias. To avoid dealing with personal feelings, this calls for a practical ethical framework, but reaching a global ethical agreement is challenging. Deep learning has a high applicability barrier, talent is in short supply, and most fields lack fundamental requirements. We still have a ways to go before we can adopt clinical practise associated with DL.

1.14 Training Models: A Challenge Task

Deep learning models with weaknesses include AE and GAN. Credibility of manufactured data is a problem. Convincingness is hampered by insufficient linkages and mappings. Urgent issues include instability and ambiguous assessment signs. When these problems are resolved, the healthcare technology will be more trustworthy. During model training, there is greater over-fitting and under-fitting under the characteristics of medical data [134]. Inadequate or redundant data in the training set will lead to the aforementioned problems. The issue can be resolved by modifying the model's structure and dataset size [135].

The largest obstacle to model training is still data quality. In order to forecast illness, DL models rely on reliable medical data. Although medical data may be easily obtained, the quality is poor. Medical specialists with experience are needed to classify a lot of medical data. Image processing is crucial [136], and separate organisations hold medical data sets. Numerous closed data sets aren't suitable for use in research. Additionally, inadequate training [137] prevents creativity.

2 A Possible Future Research

2.1 Advances in Precision Medicine Driven by Deep Learning

Precision medicine will be emphasised in future research. Precision medicine has made significant strides in several areas, including patient diagnosis, treatment, and prognosis management, thanks to the growth of big data. In comparison to conventional medical care, it is quicker and more efficient. Since 2015, many countries have prioritised precision medicine as a central tenet of their development strategies because of its potential to transform healthcare around the world [138]. Human health and medical treatment have transformed as a result of its diagnostic paradigm and fundamental ideas [139–141]. From an informatics viewpoint, Afzal et al. [138] addressed PM's evolution and potential future directions and offered Figure 8, which shows data sources, processing, applications, and services. Precision medicine and multi-domain applications will be combined in next-generation development. Systematic medical diagnosis and intelligent medical therapy may be accomplished using a set of comprehensive operation methodologies.

Similar to personalised care, precision medicine emphasises the study of individual characteristics [142], and hones the influence of each patient's particular circumstances on disease [143]. Clinical data analysis combined with genetic, environmental, and other level assessments of an individual's health have a greater resolution. In the case of complex diseases, for illustration, Panayides et al., [144] suggested using radio genomics in conjunction with precision medicine to detect abnormal diseases at an earlier stage in the treatment process. It's easiest to make a quick diagnosis at night, with the right patient and the right medication. Precision medicine is also useful in avoiding malignant disorders, including cancer [145,146], tumour [147], and others. Its approaches for illness diagnosis and treatment encourage disease prognosis. A growing field is precision medicine [148].

Precision medicine has advanced significantly in Western nations, but it is still in its infancy in Asia-Pacific. It is critical to guarantee the diversity and excellence of gene collections. The extraction must be firmly guaranteed to be in line with genetics found in the Asia-Pacific region. Precision medicine and AI are connected [138]. Precision medicine has benefited greatly from the quick development of AI and the availability of associated platforms [149]. The advent of a big-data age, with deep learning at its forefront, has had a significant impact on advancing precision medicine [150].

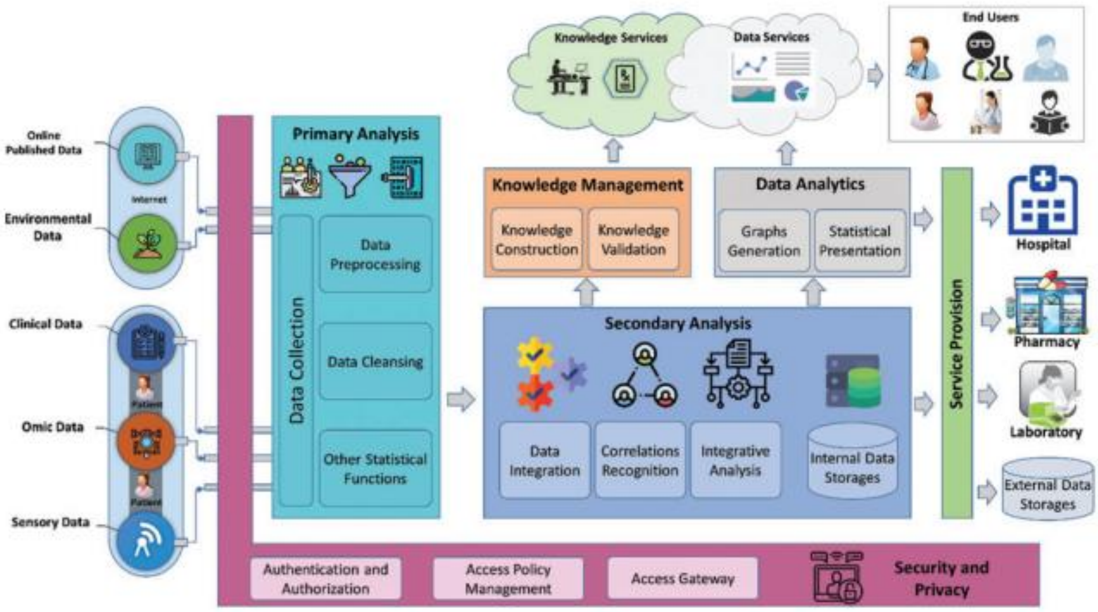


Figure 8: Framework for integrated precision medicine [138]

Precision medicine, big data, and deep learning must be approached fundamentally in order to address the remaining limitations between them [151]. Deep learning gives improved technological methods and improves medical multi-angle thinking. Accurate disease prediction is a crucial component of precision medicine because it illustrates the benefits of potential future medical treatment and supports the advancement of cutting-edge medical technology. The research level of various diseases is very variable, and the use of deep learning technology is still in its exploratory development stage for precision medicine [152–154]. Precision medicine should be the main topic of future AI medical research. Create a deep learning model for precision medicine by combining medical knowledge on pathogenic gene mutations. More complex and adaptable models. Precision medicine encourages the multifaceted use of deep learning, adjusting medical care to meet social requirements in the near future.

2.2 Combination of Medical and IoT sectors

The growth of the IoT is being boosted by the fact that it has reached maturity so quickly. Changes in functionality have been made to IoT applications as a result of 5G. Broader IoT coverage, low-latency and high-throughput performance, and rising demand for health and healthcare transformation all contribute to closer coordination between the medical and IoT sectors as well as DL methods. The Internet of Things and medicine are combined in e-healthcare. It can offer telemedicine system and platform, as well as "interaction" with medical information. The [155] healthcare system has assisted in tracking patients and keeping an eye on disease symptoms during the current COVID-19 outbreak. AI and IoT integration has enhanced illness prediction. The cloud-based EPL system created by Hossain [156] can interpret both voice and EEG inputs. An IoT-based eHealth system was suggested by Bisio et al. [157] to remotely monitor the rehabilitation of stroke patients. When compared to more traditional medical systems, it allows for remote monitoring. After the promotion, DL will be able to efficiently process data to provide comprehensive, remote rehabilitation services for patients.

IoMT has grown rapidly in recent years [158]. Intelligent home devices [159], [160] and wearable medical devices (such as a bracelet, belt, glasses for diagnosis and treatment, intelligent underwear, etc.) have emerged as significant sources of medical data. A medical system that can recognise and understand emotions was developed by Reference [161]. Easy to use and constantly updated data make it possible to track ones every day actions. Evolving processing of data with deep learning empowers real-time patient monitoring systems [162]. A new category of smart medical equipment is proposed in reference [163] that utilises deep learning techniques for disease monitoring. By gathering complete patient data, this enhances the detection system's performance. Using sensors, it's also feasible to follow critical postoperative physical indications. The longitudinal timeline data stream is analysed with the DL approach to remotely monitor patient recovery. IoT medical gadgets with deep learning promote symbiotic development. Figure 9 shows how personal medical information is collected at the terminal and sent through networks. The IoMT platform gets personal data. On its platform, IoMT processes enormous amounts of data using DL. Medical procedures that must be performed, including hospital and system interfaces. This is the IoT and DL framework for healthcare.

It is recommended that in future work, Internet-of-Things-based intelligent data processing is implemented to provide better-quality baseline data for models using deep learning. A smart city is needed at the same time as even more IoT healthcare system platforms. An interactive medical platform and smart medical care are essential for a smart city. The [164] medical monitoring framework achieves 93% accuracy in voice case monitoring while concurrently receiving voice and EGG signals. It lessens interactivity issues. The IoT platform is made more secure, which broadens application coverage and improves user experience [165]. Intelligence is necessary for both urban development and future medical health. For complete medical intelligence, the medical IoT and deep learning need to be better integrated. A new technological model eases the strain on medical resources and aids in disease diagnosis.

2.3 Specialized Model Improvement

Deep learning's architecture is very flexible. Changeable features vary by model. They can be modified as necessary. The general model can be used to implement the actual needs regardless of the data or scene. This function is appropriate for the medical industry and may take into account various illnesses, patient variations, and intricate medical circumstances.

Gradient disappearance throughout gradient propagation is a potential issue in DL models with deeper levels, which are a result of complex structures as well as high-dimensional features. The characteristics of medical data should inform the construction of a DL model [166-168]. Factoring in training data, optimization strategies, training times, the influence of parameters, etc. Enhance the classifier by better utilising medical data features, eliminating unnecessary parameters, and preventing overfitting. Medical data, like that found in electronic health records presented as a time series, can be used in conjunction with transfer learning to develop a framework that incorporates various models [169]. The training of unnecessary parameters should be minimised, and the use of existing data for model expansion should be maximised. A more robust integrated framework can be developed by combining transfer learning with the association of IoT hardware [170] as well as a big data foundation.

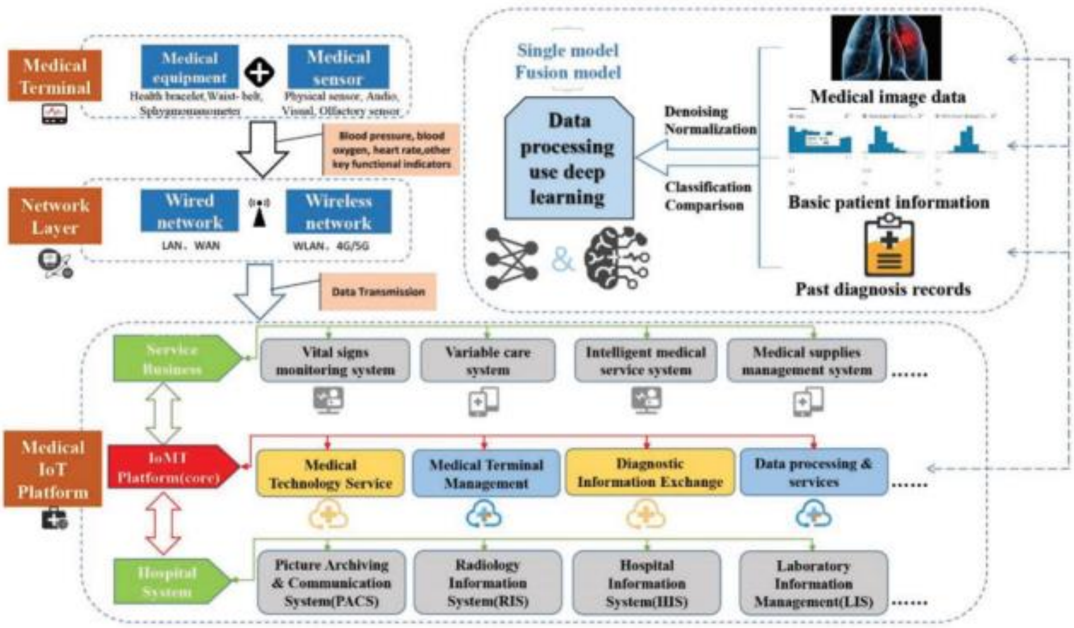


Figure 9: The structure of a medical IoT platform

Multiple risk factors exist for each disease. No one truth exists, as well as no universally accepted method of making medical diagnoses. The aftereffects of one disease can occasionally trigger the onset of others. This limits their utility. Because each disease has its own unique characteristics, the DL model needs to be developed with its own set of usage data as well as prediction methods in order to see widespread use. With the goal of expanding model research and developing more targeted approaches to treating disease.

CONCLUSION

Big data and the Internet of Things will pave the way for future medical breakthroughs. Given the high dimensionality and inherent uncertainty of medical data, advances will be driven by deep learning's novel feature processing approach and flexible model structure. In this article, we'll take a look at some of the most well-known deep learning frameworks and prediction techniques for a variety of diseases, as well as the best approach to making that all-important issues in medicine and the bounds of deep learning were discussed. It is predicted that fusing personalised therapy with genetic disease research, as well as the Internet of Things with intelligent medical platforms and equipment, and ideas for improving medical data models will be beneficial in the future. It is likely that in the future, deep learning will be used in all stages of disease diagnosis, from ancillary diagnosis to final decision making. There are additional DL models for various diseases. Models that are able to learn from one another contribute to a more reliable DL network. The development of clinical applications and medical diagnosis will be bolstered by this cutting-edge medical system.

FUNDING AND/OR CONFLICTS OF INTERESTS/COMPETING INTERESTS

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Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

REFERENCES

[1] Cho, N., Shaw, J. E., Karuranga, S., Huang, Y., da Rocha Fernandes, J. D. et al. (2018). IDF diabetes atlas: Global estimates of diabetes prevalence for 2017 and projections for 2045. Diabetes Research and Clinical Practice, 138, 271–281. DOI 10.1016/j.diabres.2018.02.023.

[2] Steenman, M., Lande, G. (2017). Cardiac aging and heart disease in humans. Biophysical Reviews, 9(2), 131–137. DOI 10.1007/s12551-017-0255-9.

[3] Shickel, B., Tighe, P. J., Bihorac, A., Rashidi, P. (2017). Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE Journal of Biomedical and Health Informatics, 22(5), 1589–1604. DOI 10.1109/JBHI.2017.2767063.

[4] Sun, W., Cai, Z., Li, Y., Liu, F., Fang, S. et al. (2018). Data processing and text mining technologies on electronic medical records: A review. Journal of Healthcare Engineering, 2018, 9. DOI 10.1155/2018/4302425.

[5] Cao, C., Liu, F., Tan, H., Song, D., Shu, W. et al. (2018). Deep learning and its applications in biomedicine. Genomics, Proteomics & Bioinformatics, 16(1), 17–32. DOI 10.1016/j.gpb.2017.07.003.

[6] Shrestha, A., Mahmood, A. (2019). Review of deep learning algorithms and architectures. IEEE Access, 7, 53040–53065. DOI 10.1109/ACCESS.2019.2912200.
[7] Dumoulin, V., Visin, F. (2016). A guide to convolution arithmetic for deep learning. arXiv preprint arXiv:1603.07285v2.
[8] Kaur, T., Gandhi, T. K. (2019). Automated brain image classification based on VGG-16 and transfer learning. 2019 International Conference on Information Technology, pp. 94–98. Bhubaneswar, India, IEEE.
[9] Huang, G., Liu, Z., van der Maaten, L., Weinberger, K. Q. (2017). Densely connected convolutional networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4700–4708. Honolulu, HI, USA.
[10] Kassani, S. H., Kassani, P. H., Khazaeinezhad, R., Wesolowski, M. J., Schneider, K. A. et al. (2019). Diabetic retinopathy classification using a modified xception architecture. 2019 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), pp. 1–6. Ajman, United Arab Emirates, IEEE.
[11] Tang, S., Yuan, S., Zhu, Y. (2020). Convolutional neural network in intelligent fault diagnosis toward rotatory machinery. IEEE Access, 8, 86510–86519. DOI 10.1109/ACCESS.2020.2992692.
[12] Khare, S. K., Bajaj, V. (2020). Time-frequency representation and convolutional neural networkbased emotion recognition. IEEE Transactions on Neural Networks and Learning Systems, 1–9. DOI 10.1109/TNNLS.2020.3008938.
[13] Siddiqi, R. (2019). Automated pneumonia diagnosis using a customized sequential convolutional neural network. Proceedings of the 2019 3rd International Conference on Deep Learning Technologies (ICDLT 2019), pp. 64–70. New York, NY, USA.
[14] Zhang, N., Cai, Y. X., Wang, Y. Y., Tian, Y. T., Wang, X. L. et al. (2020). Skin cancer diagnosis based on optimized convolutional neural network. Artificial Intelligence in Medicine, 102, 101756. DOI 10.1016/j.artmed.2019.101756.
[15] Hossain, M. S., Amin, S. U., Alsulaiman, M., Muhammad, G. (2019). Applying deep learning for epilepsy seizure detection and brain mapping visualization. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 15(1s), 1–17. DOI 10.1145/3241056.
[16] Zhang, Y., Liu, Y., Sun, P., Yan, H., Zhao, X., Zhang, L. (2020). IFCNN: A general image fusion framework based on convolutional neural network. Information Fusion, 54, 99–118. DOI 10.1016/j.inffus.2019.07.011.
[17] Sharma, H., Jain, J. S., Bansal, P., Gupta, S. (2020). Feature extraction and classification of chest X-ray images using cnn to detect pneumonia. 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), pp. 227–231. Noida, India, IEEE.
[18] Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. Physica D: Nonlinear Phenomena, 404, 132306. DOI 10.1016/j.physd.2019.132306.
[19] Long, D., Zhang, R., Mao, Y. (2019). Recurrent neural networks with finite memory length. IEEE Access, 7, 12511–12520. DOI 10.1109/ACCESS.2018.2890297.
[20] Lynn, H. M., Pan, S. B., Kim, P. (2019). A deep bidirectional GRU network model for biometric electrocardiogram classification based on recurrent neural networks. IEEE Access, 7, 145395–145405. DOI 10.1109/ACCESS.2019.2939947.
[21] Cui, Y., Zhao, S., Wang, H., Xie, L., Chen, Y. et al. (2018). Identifying brain networks at multiple time scales via deep recurrent neural network. IEEE Journal of Biomedical and Health Informatics, 23(6), 2515–2525. DOI 10.1109/JBHI.2018.2882885.
[22] Choi, E., Bahadori, M. T., Schuetz, A., Stewart, W. F., Sun, J. (2016). Doctor ai: Predicting clinical events via recurrent neural networks. Machine Learning for Healthcare Conference, pp. 301–318. Los Angeles, CA, PMLR 56.
[23] Banerjee, I., Ling, Y., Chen, M. C., Hasan, S. A., Langlotz, C. P. et al. (2019). Comparative effectiveness of convolutional neural network (CNN) and recurrent neural network (RNN) architectures for radiology text report classification. Artificial Intelligence in Medicine, 97, 79–88. DOI 10.1016/j.artmed.2018.11.004.
[24] Zhang, P., Wang, X., Zhang, W., Chen, J. (2018). Learning spatial–spectral–temporal EEG features with recurrent 3D convolutional neural networks for cross-task mental workload assessment. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 27(1), 31–42. DOI 10.1109/TNSRE.2018.2884641.
[25] Qin, C., Schlemper, J., Caballero, J., Price, A. N., Hajnal, J. V. et al. (2018). Convolutional recurrent neural networks for dynamic MR image reconstruction. IEEE Transactions on Medical Imaging, 38(1), 280–290. DOI 10.1109/TMI.2018.2863670.
[26] Liang, G., Hong, H., Xie, W., Zheng, L. (2018). Combining convolutional neural network with recursive neural network for blood cell image classification. IEEE Access, 6, 36188–36197. DOI 10.1109/ACCESS.2018.2846685.
[27] Kim, J. C., Chung, K. (2020). Multi-modal stacked denoising autoencoder for handling missing data in healthcare big data. IEEE Access, 8, 104933–104943. DOI 10.1109/Access.6287639.
[28] Chen, M., Shi, X., Zhang, Y., Wu, D., Guizani, M. (2017). Deep features learning for medical image analysis with convolutional autoencoder neural network. IEEE Transactions on Big Data, 1, 1. DOI 10.1109/TBDATA.2017.2717439.

[29] Azarang, A., Manoochehri, H. E., Kehtarnavaz, N. (2019). Convolutional autoencoder-based multispectral image fusion. IEEE Access, 7, 35673–35683. DOI 10.1109/ACCESS.2019.2905511.

[30] Zhang, J., Lin, F., Xiong, P., Du, H., Zhang, H. et al. (2019). Automated detection and localization of myocardial infarction with staked sparse autoencoder and treebagger. IEEE Access, 7, 70634–70642. DOI 10.1109/ACCESS.2019.2919068.

[31] Wei, R., Mahmood, A. (2021). Recent advances in variational autoencoders with representation learning for biomedical informatics: A survey. IEEE Access, 9, 4939–4956. DOI 10.1109/ACCESS.2020.3048309.

[32] Yeh, R. A., Chen, C., Yian Lim, T., Schwing, A. G., Hasegawa-Johnson, M. et al. (2017). Semantic image inpainting with deep generative models. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 5485–5493. Honolulu, HI, USA.

[33] Zhou, Z., Wang, Y., Guo, Y., Qi, Y., Yu, J. (2019). Image quality improvement of hand-held ultrasound devices with a two-stage generative adversarial network. IEEE Transactions on Biomedical Engineering, 67(1), 298–311. DOI 10.1109/TBME.2019.2912986.

[34] Bing, X., Zhang, W., Zheng, L., Zhang, Y. (2019). Medical image super resolution using improved generative adversarial networks. IEEE Access, 7, 145030–145038. DOI 10.1109/ACCESS.2019.2944862.

[35] Huang, J., Le, Z., Ma, Y., Fan, F., Zhang, H. et al. (2020). MGMDcGAN: Medical image fusion using multigenerator multi-discriminator conditional generative adversarial network. IEEE Access, 8, 55145–55157. DOI 10.1109/ACCESS.2020.2982016.

[36] Li, Y., Zhao, J., Lv, Z., Li, J. (2021). Medical image fusion method by deep learning. International Journal of Cognitive Computing in Engineering, 2, 21–29. DOI 10.1016/j.ijcce.2020.12.004.

[37] Yi, X., Walia, E., Babyn, P. (2019). Generative adversarial network in medical imaging: A review. Medical Image Analysis, 58, 101552. DOI 10.1016/j.media.2019.101552.

[38] Yang, Z., Chen, Y., Le, Z., Fan, F., Pan, E. (2019). Multi-source medical image fusion based on wasserstein generative adversarial networks. IEEE Access, 7, 175947–175958. DOI 10.1109/ACCESS.2019.2955382.

[39] Hong, H., Li, X., Wang, M. (2019). Gane: A generative adversarial network embedding. IEEE Transactions on Neural Networks and Learning Systems, 31(7), 2325–2335. DOI 10.1109/TNNLS.2019.2921841.

[40] Wang, C., Xu, C., Yao, X., Tao, D. (2019). Evolutionary generative adversarial networks. IEEE Transactions on Evolutionary Computation, 23(6), 921–934. DOI 10.1109/TEVC.2019.2895748.

[41] Kaur, M., Singh, D. (2020). Fusion of medical images using deep belief networks. Cluster Computing, 23(2), 1439–1453. DOI 10.1007/s10586-019-02999-x.

[42] Al-Fatlawi, A. H., Jabardi, M. H., Ling, S. H. (2016). Efficient diagnosis system for Parkinson's disease using deep belief network. 2016 IEEE Congress on Evolutionary Computation, pp. 1324–1330. IEEE.

[43] Dua, M., Makhija, D., Manasa, P. Y. L., Mishra, P. (2020). A CNN–RNN–LSTM based amalgamation for Alzheimer's disease detection. Journal of Medical and Biological Engineering, 40(5), 688–706. DOI 10.1007/s40846-020-00556-1.

[44] Khan, S., Islam, N., Jan, Z., Din, I. U., Rodrigues, J. J. C. (2019). A novel deep learning based framework for the detection and classification of breast cancer using transfer learning. Pattern Recognition Letters, 125, 1–6. DOI 10.1016/j.patrec.2019.03.022.

[45] Talo, M., Baloglu, U. B., Yıldırım, Ö., Acharya, U. R. (2019). Application of deep transfer learning for automated brain abnormality classification using MR images. Cognitive Systems Research, 54, 176–188. DOI 10.1016/j.cogsys.2018.12.007.

[46] Hu, Z., Tang, J., Wang, Z., Zhang, K., Zhang, L. et al. (2018). Deep learning for image-based cancer detection and diagnosis–A survey. Pattern Recognition, 83, 134–149. DOI 10.1016/j.patcog.2018.05.014.

[47] Zhu, N., Zhang, D., Wang, W., Li, X., Yang, B. et al. (2020). A novel coronavirus from patients with pneumonia in China, 2019. New England Journal of Medicine, 382, 727–733. DOI 10.1056/NEJMoa2001017.

[48] Bansal, M. (2020). Cardiovascular disease and COVID-19. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14(3), 247–250. DOI 10.1016/j.dsx.2020.03.013.

[49] Nishiga, M., Wang, D. W., Han, Y., Lewis, D. B., Wu, J. C. (2020). COVID-19 and cardiovascular disease: From basic mechanisms to clinical perspectives. Nature Review Cardiology, 17, 543–558. DOI 10.1038/s41569-020-0413-9.

[50] Fan, D., Yang, J., Zhang, J., Lv, Z., Huang, H. et al. (2018). Effectively measuring respiratory flow with portable pressure data using back propagation neural network. IEEE Journal of Translational Engineering in Health and Medicine, 6, 1–12. DOI 10.1109/JTEHM.2017.2688458.

[51] Voroshnina, N., Shabley, A., Vaulin, S. (2020). Neural network approach for prediction of pneumonia. 2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon), pp. 1–5. Vladivostok, Russia, IEEE.

[52] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H. et al. (2017). Chexnet: Radiologist-level pneumonia detection on chest X-rays with deep learning. arXiv preprint. arXiv: 1711.05225.

[53] Qjidaa, M., Ben-Fares, A., Mechbal, Y., Amakdouf, H., Maaroufi, M. et al. (2020). Development of a clinical decision support system for the early detection of COVID-19 using deep learning based on chest radiographic

images. 2020 International Conference on Intelligent Systems and Computer Vision (ISCV), pp. 1–6. Fez, Morocco, IEEE.
[54] Phankokkruad, M. (2020). COVID-19 pneumonia detection in chest X-ray images using transfer learning of convolutional neural networks. Proceedings of the 3rd International Conference on Data Science and Information Technology, pp. 147–152. Xiamen, China.
[55] Raghu, M., Zhang, C., Kleinberg, J., Bengio, S. (2019). Transfusion: Understanding transfer learning for medical imaging. arXiv preprint. arXiv: 1902.07208.
[56] Liang, G., Zheng, L. (2020). A transfer learning method with deep residual network for pediatric pneumonia diagnosis. Computer Methods and Programs in Biomedicine, 187, 104964. DOI 10.1016/j.cmpb.2019.06.023.
[57] Chouhan, V., Singh, S. K., Khamparia, A., Gupta, D., Tiwari, P. et al. (2020). A novel transfer learning based approach for pneumonia detection in chest X-ray images. Applied Sciences, 10(2), 559. DOI 10.3390/app10020559.
[58] Saul, C. J., Urey, D. Y., Taktakoglu, C. D. (2019). Early diagnosis of pneumonia with deep learning. arXiv preprint. arXiv: 1904.00937.
[59] Wu, X., Hui, H., Niu, M., Li, L., Wang, L. et al. (2020). Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: A multicentre study. European Journal of Radiology, 128, 109041. DOI 10.1016/j.ejrad.2020.109041.
[60] Hossain, M. S., Muhammad, G., Guizani, N. (2020). Explainable AI and mass surveillance systembased healthcare framework to combat COVID-19 like pandemics. IEEE Network, 34(4), 126–132. DOI 10.1109/MNET.011.2000458.
[61] Abdulsalam, Y., Hossain, M. S. (2020). COVID-19 networking demand: An auction-based mechanism for automated selection of edge computing services. IEEE Transactions on Network Science and Engineering, 1–1. DOI 10.1109/TNSE.2020.3026637.
[62] Chowdhury, M. E., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A. et al. (2020). Can AI help in screening viral and COVID-19 pneumonia? IEEE Access, 8, 132665–132676. DOI 10.1109/ACCESS.2020.3010287.
[63] Timmis, A., Townsend, N., Gale, C. P., Torbica, A., Lettino, M. et al. (2020). European society of cardiology: Cardiovascular disease statistics 2019. European Heart Journal, 41(1), 12–85. DOI 10.1093/eurheartj/ehz859.
[64] Shi, H., Wang, H., Qin, C., Zhao, L., Liu, C. (2020). An incremental learning system for atrial fibrillation detection based on transfer learning and active learning. Computer Methods and Programs in Biomedicine, 187, 105219. DOI 10.1016/j.cmpb.2019.105219.
[65] Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C. et al. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine, 25(1), 65–69. DOI 10.1038/s41591-018-0268-3.
[66] Ayon, S. I., Islam, M. M., Hossain, M. R. (2020). Coronary artery heart disease prediction: A comparative study of computational intelligence techniques. IETE Journal of Research, 66, 1–20. DOI 10.1080/03772063.2020.1713916.
[67] Dutta, A., Batabyal, T., Basu, M., Acton, S. T. (2020). An efficient convolutional neural network for coronary heart disease prediction. Expert Systems with Applications, 159, 113408. DOI 10.1016/j.eswa.2020.113408.
[68] Moody, G. B., Mark, R. G. (2001). The impact of the MIT-bIH arrhythmia database. IEEE Engineering in Medicine and Biology Magazine, 20(3), 45–50. DOI 10.1109/51.932724.
[69] Shi, H., Wang, H., Huang, Y., Zhao, L., Qin, C. et al. (2019). A hierarchical method based on weighted extreme gradient boosting in ECG heartbeat classification. ComputerMethods and Programs in Biomedicine, 171, 1–10. DOI 10.1016/j.cmpb.2019.02.005.
[70] Wang, H., Shi, H., Lin, K., Qin, C., Zhao, L. et al. (2020). A high-precision arrhythmia classification method based on dual fully connected neural network. Biomedical Signal Processing and Control, 58, 101874. DOI 10.1016/j.bspc.2020.101874.
[71] Jin, Y., Qin, C., Liu, J., Lin, K., Shi, H. et al. (2020). A novel domain adaptive residual network for automatic atrial fibrillation detection. Knowledge-Based Systems, 203, 106122. DOI 10.1016/j.knosys.2020.106122.
[72] Anandajayam, P., Krishnakoumar, C., Vikneshvaran, S., Suryanaraynan, B. (2019). Coronary heart disease predictive decision scheme using big data and RNN. 2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), pp. 1–6. Pondicherry, India, IEEE.
[73] Kuang, J. W., Yang, H. Z., Liu, J. J., Yan, Z. J. (2019). Dynamic prediction of cardiovascular disease using improved LSTM. International Journal of Crowd Science, 3(1), 14–25. DOI 10.1108/IJCS-01-2019-0002.
[74] Jin, Y., Qin, C., Liu, J., Li, Z., Shi, H. et al. (2021). A novel incremental and interactive method for actual heartbeat classification with limited additional labeled samples. IEEE Transactions on Instrumentation and Measurement, 70, 1–12. DOI 10.1109/TIM.2021.3069021.
[75] Shi, H., Qin, C., Xiao, D., Zhao, L., Liu, C. (2020). Automated heartbeat classification based on deep neural network with multiple input layers. Knowledge-Based Systems, 188, 105036. DOI 10.1016/j.knosys.2019.105036.

[76] Jin, Y., Qin, C., Huang, Y., Zhao, W., Liu, C. (2020). Multi-domain modeling of atrial fibrillation detection with twin attentional convolutional long short-term memory neural networks. Knowledge-Based Systems, 193, 105460. DOI 10.1016/j.knosys.2019.105460.

[77] Ali, A. A., Hassan, H. S., Anwar, E. M. (2020). Heart diseases diagnosis based on a novel convolution neural network and gate recurrent unit technique. 2020 12th International Conference on Electrical Engineering, pp. 145–150. Cairo, Egypt, IEEE.

[78] Lu, P., Guo, S., Zhang, H., Li, Q., Wang, Y. et al. (2018). Research on improved depth belief network-based prediction of cardiovascular diseases. Journal of Healthcare Engineering, 2018, 1–9. DOI 10.1155/2018/8954878.

[79] Poplin, R., Varadarajan, A. V., Blumer, K., Liu, Y., McConnell, M. V. et al. (2018). Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. Nature Biomedical Engineering, 2(3), 158–164. DOI 10.1038/s41551-018-0195-0.

[80] Lyu, M. J., Yuan, S. M. (2020). Cloud-based smart dog music therapy and pneumonia detection system for reducing the difficulty of caring for patients with dementia. IEEE Access, 8, 20977–20990. DOI 10.1109/ACCESS.2020.2969482.

[81] Ding, Y., Sohn, J. H., Kawczynski, M. G., Trivedi, H., Harnish, R. et al. (2019). A deep learning model to predict a diagnosis of Alzheimer disease by using 18F-fDG PET of the brain. Radiology, 290(2), 456–464. DOI 10.1148/radiol.2018180958.

[82] Jo, T., Nho, K., Saykin, A. J. (2019). Deep learning in Alzheimer's disease: Diagnostic classification and prognostic prediction using neuroimaging data. Frontiers in Aging Neuroscience, 11, 220. DOI 10.3389/fnagi.2019.00220.

[83] Ji, S., Xu, W., Yang, M., Yu, K. (2012). 3D convolutional neural networks for human action recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(1), 221–231. DOI 10.1109/TPAMI.2012.59.

[84] Cheng, D., Liu, M., Fu, J., Wang, Y. (2017). Classification of MR brain images by combination of multicNNs for AD diagnosis. Ninth International Conference on Digital Image Processing (ICDIP 2017), vol. 10420, pp. 1042042. Hong Kong, China, International Society for Optics and Photonics.

[85] Wang, H., Shen, Y., Wang, S., Xiao, T., Deng, L. et al. (2019). Ensemble of 3D densely connected convolutional network for diagnosis of mild cognitive impairment and Alzheimer's disease. Neurocomputing, 333, 145–156. DOI 10.1016/j.neucom.2018.12.018.

[86] Riederer, I., Bohn, K. P., Preibisch, C., Wiedemann, E., Zimmer, C. et al. (2018). Alzheimer disease and mild cognitive impairment: Integrated pulsed arterial spin-labeling MRI and 18F-fDG PET. Radiology, 288(1), 198–206. DOI 10.1148/radiol.2018170575.

[87] Cui, R., Liu, M. (2019). RNN-Based longitudinal analysis for diagnosis of Alzheimer's disease. Computerized Medical Imaging and Graphics, 73, 1–10. DOI 10.1016/j.compmedimag.2019.01.005.

[88] Ahmed, O. B., Benois-Pineau, J., Allard, M., Amar, C. B., Catheline, G. (2015). Classification of Alzheimer's disease subjects from MRI using hippocampal visual features. Multimedia Tools and Applications, 74(4), 1249–1266. DOI 10.1007/s11042-014-2123-y.

[89] Li, F., Liu, M., Alzheimer's Disease Neuroimaging Initiative. (2019). A hybrid convolutional and recurrent neural network for hippocampus analysis in Alzheimer's disease. Journal of Neuroscience Methods, 323, 108–118. DOI 10.1016/j.jneumeth.2019.05.006.

[90] Siegel, R. L., Miller, K. D., Jemal, A. (2020). Cancer statistics. CA: A Cancer Journal for Clinicians, 70(1), 7–30. DOI 10.3322/caac.21590.

[91] Tiwari, A., Srivastava, S., Pant, M. (2020). Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019. Pattern Recognition Letters, 131, 244–260. DOI 10.1016/j.patrec.2019.11.020.

[92] Tsherniak, A., Vazquez, F., Montgomery, P. G., Weir, B. A., Kryukov, G. et al. (2017). Defining a cancer dependency map. Cell, 170(3), 564–576. DOI 10.1016/j.cell.2017.06.010.

[93] Sultan, H. H., Salem, N. M., Al-Atabany, W. (2019). Multi-classification of brain tumor images using deep neural network. IEEE Access, 7, 69215–69225. DOI 10.1109/ACCESS.2019.2919122.

[94] de Anda-Jáuregui, G., Hernández-Lemus, E. (2020). Computational oncology in the multi-omics era: State of the art. Frontiers in Oncology, 10, 423. DOI 10.3389/fonc.2020.00423.

[95] Hasin, Y., Seldin, M., Lusis, A. (2017). Multi-omics approaches to disease. Genome Biol, 18, 83. DOI 10.1186/s13059-017-1215-1.

[96] Tan, K., Huang, W., Hu, J., Dong, S. (2020). A multi-omics supervised autoencoder for pan-cancer clinical outcome endpoints prediction. BMC Medical Informatics and Decision Making, 20(3), 1–9. DOI 10.1186/s12911-020-1114-3.

[97] Tong, L., Mitchel, J., Chatlin, K., Wang, M. D. (2020). Deep learning based feature-level integration of multi-omics data for breast cancer patients survival analysis. BMC Medical Informatics and Decision Making, 20, 225. DOI 10.1186/s12911-020-01225-8.

[98] Asada, K., Kobayashi, K., Joutard, S., Tubaki, M., Takahashi, S. et al. (2020). Uncovering prognosisrelated genes and pathways by multi-omics analysis in lung cancer. Biomolecules, 10(4), 524. DOI 10.3390/biom10040524.

[99] Takahashi, S., Asada, K., Takasawa, K., Shimoyama, R., Sakai, A. et al. (2020). Predicting deep learning based multi-omics parallel integration survival subtypes in lung cancer using reverse phase protein array data. Biomolecules, 10(10), 1460. DOI 10.3390/biom10101460.

[100] Khamparia, A., Gupta, D., Rodrigues, J. J., de Albuquerque, V. H. C. (2020). DCAVN: Cervical cancer prediction and classification using deep convolutional and variational autoencoder network. Multimedia Tools and Applications, 80, 1–17. DOI 10.1007/s11042-020-09607-w.

[101] Iizuka, O., Kanavati, F., Kato, K., Rambeau, M., Arihiro, K. et al. (2020). Deep learning models for histopathological classification of gastric and colonic epithelial tumours. Scientific Reports, 10(1), 1–11. DOI 10.1038/s41598-020-58467-9.

[102] Khan, M. A., Sarfraz, M. S., Alhaisoni, M., Albesher, A. A., Wang, S. et al. (2020). Stomachnet: Optimal deep learning features fusion for stomach abnormalities classification. IEEE Access, 8, 197969–197981. DOI 10.1109/ACCESS.2020.3034217.

[103] Baptista, D., Ferreira, P. G., Rocha, M. (2021). Deep learning for drug response prediction in cancer. Briefings in Bioinformatics, 22(1), 360–379. DOI 10.1093/bib/bbz171.

[104] Mencattini, A., Di Giuseppe, D., Comes, M. C., Casti, P., Corsi, F. et al. (2020). Discovering the hidden messages within cell trajectories using a deep learning approach for in vitro evaluation of cancer drug treatments. Scientific Reports, 10, 7653. DOI 10.1038/s41598-020-64246-3.

[105] Kuenzi, B. M., Park, J., Fong, S. H., Sanchez, K. S., Lee, J. et al. (2020). Predicting drug response and synergy using a deep learning model of human cancer cells. Cancer Cell, 38(5), 672–684. DOI 10.1016/j.ccell.2020.09.014.

[106] Coccia, M. (2020). Deep learning technology for improving cancer care in society: New directions in cancer imaging driven by artificial intelligence. Technology in Society, 60, 101198. DOI 10.1016/j.techsoc.2019.101198.

[107] Swapna, G., Vinayakumar, R., Soman, K. P. (2018). Diabetes detection using deep learning algorithms. ICT Express, 4(4), 243–246. DOI 10.1016/j.icte.2018.10.005.

[108] Ayon, S. I., Islam, M. (2019). Diabetes prediction: A deep learning approach. International Journal of Information Engineering & Electronic Business, 11(2), 21–27. DOI 10.5815/ijieeb.2019.02.03.

[109] Padmapritha, T. (2019). Prediction of blood glucose level by using an LSTM based recurrent neural networks. 2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES), pp. 1–4. Krishnankoil, India.

[110] Li, K., Daniels, J., Liu, C., Herrero, P., Georgiou, P. (2019). Convolutional recurrent neural networks for glucose prediction. IEEE Journal of Biomedical and Health Informatics, 24(2), 603–613. DOI 10.1109/JBHI.2019.2908488.

[111] Pavithra, M., Saruladha, K., Sathyabama, K. (2019). GRU based deep learning model for prognosis prediction of disease progression. 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), pp. 840–844. Erode, India, IEEE.

[112] Perdomo, O., Rios, H., Rodríguez, F. J., Otálora, S., Meriaudeau, F. et al. (2019). Classification of diabetesrelated retinal diseases using a deep learning approach in optical coherence tomography. Computer Methods and Programs in Biomedicine, 178, 181–189. DOI 10.1016/j.cmpb.2019.06.016.

[113] Jyoti, O., Islam, N., Hasnain, F. M. S. (2020). Prediction of hepatitis disease using effective deep neural network. 2020 IEEE International Conference for Innovation in Technology (INOCON), pp. 1–5. Bangluru, India, IEEE.

[114] Yu, Y., Wang, J., Ng, C. W., Ma, Y., Mo, S. et al. (2018). Deep learning enables automated scoring of liver fibrosis stages. Scientific Reports, 8, 16016. DOI 10.1038/s41598-018-34300-2.

[115] Xiao, W., Huang, X., Wang, J. H., Lin, D. R., Zhu, Y. et al. (2021). Screening and identifying hepatobiliary diseases through deep learning using ocular images: A prospective, multicentre study. The Lancet Digital Health, 3(2), e88–e97. DOI 10.1016/S2589-7500(20)30288-0.

[116] Frid-Adar, M., Diamant, I., Klang, E., Amitai, M., Goldberger, J. et al. (2018). GAN-Based synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing, 321, 321–331. DOI 10.1016/j.neucom.2018.09.013.

[117] Lu, H., Tian, S., Yu, L., Lv, X., Chen, S. (2020). Diagnosis of hepatitis B based on Raman spectroscopy combined with a multiscale convolutional neural network. Vibrational Spectroscopy, 107, 103038. DOI 10.1016/j.vibspec.2020.103038.

[118] Wang, X., Tian, S., Yu, L., Lv, X., Zhang, Z. (2020). Rapid screening of hepatitis B using Raman spectroscopy and long short-term memory neural network. Lasers in Medical Science, 35(8), 1791–1799. DOI 10.1007/s10103-020-03003-4.

[119] Zhu, H., Guo, Q., Li, M., Wang, C., Fang, Z. et al. (2020). Host and infectivity prediction of wuhan 2019 novel coronavirus using deep learning algorithm. BioRxiv, DOI 10.1101/2020.01.21.914044.

[120] Fu, M., Yi, S. L., Zeng, Y., Ye, F., Li, Y. et al. (2020). Deep learning-based recognizing covid- 19 and other common infectious diseases of the lung by chest CT scan images. MedRxiv. DOI 10.1101/2020.03.28.20046045.
[121] Chae, S., Kwon, S., Lee, D. (2018). Predicting infectious disease using deep learning and big data. International Journal of Environmental Research and Public Health, 15(8), 1596. DOI 10.3390/ijerph15081596.
[122] Wong, Z. S., Zhou, J., Zhang, Q. (2019). Artificial intelligence for infectious disease big data analytics. Infection, Disease & Health, 24(1), 44–48. DOI 10.1016/j.idh.2018.10.002.
[123] Alnazer, I., Bourdon, P., Urruty, T., Falou, O., Khalil, M. et al. (2021). Recent advances in medical image processing for the evaluation of chronic kidney disease. Medical Image Analysis, 69, 101960. DOI 10.1016/j.media.2021.101960.
[124] Wu, Y., Yi, Z. (2020). Automated detection of kidney abnormalities using multi-feature fusion convolutional neural networks. Knowledge-Based Systems, 200, 105873. DOI 10.1016/j.knosys.2020.105873.
[125] Navaneeth, B., Suchetha, M. (2020). A dynamic pooling based convolutional neural network approach to detect chronic kidney disease. Biomedical Signal Processing and Control, 62, 102068. DOI 10.1016/j.bspc.2020.102068.
[126] Bhaskar, N., Manikandan, S. (2019). A deep-learning-based system for automated sensing of chronic kidney disease. IEEE Sensors Letters, 3(10), 1–4. DOI 10.1109/LSENS.2019.2942145.
[127] Khamparia, A., Saini, G., Pandey, B., Tiwari, S., Gupta, D. et al. (2020). KDSAE: Chronic kidney disease classification with multimedia data learning using deep stacked autoencoder network. Multimed. Tools Appl., 79, 35425–35440. DOI 10.1007/s11042-019-07839-z.
[128] Ma, F., Sun, T., Liu, L., Jing, H. (2020). Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network. Future Generation Computer Systems, 111, 17–26. DOI 10.1016/j.future.2020.04.036.
[129] Chen, G., Ding, C., Li, Y., Hu, X., Li, X. et al. (2020). Prediction of chronic kidney disease using adaptive hybridized deep convolutional neural network on the internet of medical things platform. IEEE Access, 8, 100497–100508. DOI 10.1109/ACCESS.2020.2995310.
[130] Collins, F. S., Varmus, H. (2015). A new initiative on precision medicine. New England Journal of Medicine, 372(9), 793–795. DOI 10.1056/NEJMp1500523.
[131] Li, Y., Lv, Z., Zhao, J., Pan, Z. (2019). Improving performance of medical image fusion using histogram, dictionary learning and sparse representation. Multimedia Tools and Applications, 78(24), 34459–34482. DOI 10.1007/s11042-019-08027-9.
[132] Lv, Z., Piccialli, F. (2020). The security of medical data on internet based on differential privacy technology. ACM Transactions on Internet Technology (TOIT), 1–10. DOI 10.1145/3382769.
[133] Kumar, R., Khan, A. A., Kumar, J., Zakria, A., Golilarz, N. A. et al. (2021). Blockchain-federated-learning and deep learning models for COVID-19 detection using CT imaging. IEEE Sensors Journal, 1–1. DOI 10.1109/JSEN.2021.3076767.
[134] Hesamian, M. H., Jia, W., He, X., Kennedy, P. (2019). Deep learning techniques for medical image segmentation: Achievements and challenges. Journal of Digital Imaging, 32(4), 582–596. DOI 10.1007/s10278-019-00227-x.
[135] Shen, D., Wu, G., Suk, H. I. (2017). Deep learning in medical image analysis. Annual Review of Biomedical Engineering, 19, 221–248. DOI 10.1146/annurev-bioeng-071516-044442.
[136] Yang, X., Zhang, T., Xu, C., Yan, S., Hossain, M. S. et al. (2016). Deep relative attributes. IEEE Transactions on Multimedia, 18(9), 1832–1842. DOI 10.1109/TMM.2016.2582379.
[137] Levine, A. B., Schlosser, C., Grewal, J., Coope, R., Jones, S. J. et al. (2019). Rise of the machines: Advances in deep learning for cancer diagnosis. Trends in Cancer, 5(3), 157–169. DOI 10.1016/j.trecan.2019.02.002.
[138] Afzal, M., Islam, S. R., Hussain, M., Lee, S. (2020). Precision medicine informatics: Principles, prospects, and challenges. IEEE Access, 8, 13593–13612. DOI 10.1109/ACCESS.2020.2965955.
[139] Llovet, J. M., Montal, R., Sia, D., Finn, R. S. (2018). Molecular therapies and precision medicine for hepatocellular carcinoma. Nature Reviews Clinical Oncology, 15(10),599–616. DOI 10.1038/s41571-018-0073-4.
[140] Le Tourneau, C., Borcoman, E., Kamal, M. (2019). Molecular profiling in precision medicine oncology. Nature Medicine, 25, 711–712. DOI 10.1038/s41591-019-0442-2.
[141] Wang, Y., Sun, S., Zhang, Z., Shi, D. (2018). Nanomaterials for cancer precision medicine. Advanced Materials, 30(17), 1705660. DOI 10.1002/adma.201705660.
[142] Fujiwara, N., Friedman, S. L., Goossens, N., Hoshida, Y. (2018). Risk factors and prevention of hepatocellular carcinoma in the era of precision medicine. Journal of Hepatology, 68(3), 526–549. DOI 10.1016/j.jhep.2017.09.016.
[143] Zhang, S., Bamakan, S. M. H., Qu, Q., Li, S. (2018). Learning for personalized medicine: A comprehensive review from a deep learning perspective. IEEE Reviews in Biomedical Engineering, 12, 194–208. DOI 10.1109/RBME.2018.2864254.

[144] Panayides, A. S., Pattichis, M. S., Leandrou, S., Pitris, C., Constantinidou, A. et al. (2018). Radiogenomics for precision medicine with a big data analytics perspective. IEEE Journal of Biomedical and Health Informatics, 23(5), 2063–2079. DOI 10.1109/JBHI.2018.2879381.

[145] Loomans-Kropp, H. A., Umar, A. (2019). Cancer prevention and screening: The next step in the era of precision medicine. NPJ Precision Oncology, 3(1), 1–8. DOI 10.1038/s41698-018-0075-9.

[146] Regel, I., Mayerle, J., Mahajan, U. M. (2020). Current strategies and future perspectives for precision medicine in pancreatic cancer. Cancers, 12(4), 1024. DOI 10.3390/cancers12041024.

[147] Steuer, C. E., Ramalingam, S. S. (2018). Tumor mutation burden: Leading immunotherapy to the era of precision medicine. J. Clin. Oncol., 36(7), 631–632. DOI 10.1200/JCO.2017.76.8770.

[148] Hamamoto, R., Suvarna, K., Yamada, M., Kobayashi, K., Shinkai, N. et al. (2020). Application of artificial intelligence technology in oncology: Towards the establishment of precision medicine. Cancers, 12(12), 3532. DOI 10.3390/cancers12123532.

[149] Ahmed, Z., Mohamed, K., Zeeshan, S., Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database, 2020, baaa010. DOI 10.1093/database/baaa010.

[150] Hulsen, T., Jamuar, S. S., Moody, A. R., Karnes, J. H., Varga, O. et al. (2019). From big data to precision medicine. Frontiers in Medicine, 6, 34. DOI 10.3389/fmed.2019.00034.

[151] Prosperi, M., Min, J. S., Bian, J., Modave, F. (2018). Big data hurdles in precision medicine and precision public health. BMC Medical Informatics and Decision Making, 18, 139. DOI 10.1186/s12911-018-0719-2.

[152] Hey, S. P., Gerlach, C. V., Dunlap, G., Prasad, V., Kesselheim, A. S. (2020). The evidence landscape in precision medicine. Science Translational Medicine, 12(540). DOI 10.1126/scitranslmed.aaw7745.

[153] Dienstmann, R., Vermeulen, L., Guinney, J., Kopetz, S., Tejpar, S. et al. (2017). Consensus molecular subtypes and the evolution of precision medicine in colorectal cancer. Nature Reviews Cancer, 17(2), 79–92. DOI 10.1038/nrc.2016.126.

[154] Dayem Ullah, A. Z., Oscanoa, J., Wang, J., Nagano, A., Lemoine, N. R. et al. (2018). SNPnexus: Assessing the functional relevance of genetic variation to facilitate the promise of precision medicine. Nucleic Acids Research, 46(W1), W109–W113. DOI 10.1093/nar/gky399.

[155] Tebeje, T. H., Klein, J. (2020). Applications of e-health to support person-centered health care at the time of COVID-19 pandemic. Telemedicine and E-Health, 27, 150–158. DOI 10.1089/tmj.2020.0201.

[156] Hossain, M. S. (2017). Cloud-supported cyber–Physical localization framework for patients monitoring. IEEE Systems Journal, 11(1), 118–127. DOI 10.1109/JSYST.2015.2470644.

[157] Bisio, I., Garibotto, C., Lavagetto, F., Sciarrone, A. (2019). When eHealth meets IoT: A smart wireless system for post-stroke home rehabilitation. IEEE Wireless Communications, 26(6), 24–29. DOI 10.1109/MWC.001.1900125.

[158] Dubey, H., Monteiro, A., Constant, N., Abtahi, M., Borthakur, D. et al. (2017). Fog computing in medical internet-of-things: Architecture, implementation, and applications. in Handbook of Large-Scale Distributed Computing in Smart Healthcare, pp. 281–321. Cham: Springer.

[159] Moore, C. (2020). Medical internet of things-based healthcare systems: Wearable sensor-based devices, patient-generated Big data, and real-time clinical monitoring. American Journal of Medical Research, 7(1), 41–47. DOI 10.22381/AJMR7120206.

[160] Harvey, P., Toutsop, O., Kornegay, K., Alale, E., Reaves, D. (2020). Security and privacy of medical internet of things devices for smart homes. 2020 7th International Conference on Internet of Things: Systems, Management and Security (IOTSMS), pp. 1–6. Paris, France, IEEE.

[161] Hossain, M. S., Muhammad, G. (2017). Emotion-aware connected healthcare big data towards 5G. IEEE Internet of Things Journal, 5(4), 2399–2406. DOI 10.1109/JIOT.2017.2772959.

[162] Zhou, Z., Yu, H., Shi, H. (2020). Human activity recognition based on improved Bayesian convolution network to analyze health care data using wearable IoT device. IEEE Access, 8, 86411–86418. DOI 10.1109/ACCESS.2020.2992584.

[163] Fouad, H., Hassanein, A. S., Soliman, A. M., Al-Feel, H. (2020). Analyzing patient health information based on IoT sensor with AI for improving patient assistance in the future direction. Measurement, 159, 107757. DOI 10.1016/j.measurement.2020.107757.

[164] Hossain, M. S., Muhammad, G., Alamri, A. (2019). Smart healthcare monitoring: A voice pathology detection paradigm for smart cities. Multimedia Systems, 25, 565–575. DOI 10.1007/s00530-017-0561-x.

[165] Al-Garadi, M. A., Mohamed, A., Al-Ali, A. K., Du, X., Ali, I. et al. (2020). A survey of machine and deep learning methods for internet of things (IoT) security. IEEE Communications Surveys & Tutorials, 22(3), 1646–1685. DOI 10.1109/COMST.2020.2988293.

[166] Alloghani, M., Baker, T., Al-Jumeily, D., Hussain, A., Mustafina, J. et al. (2020). Prospects of machine and deep learning in analysis of vital signs for the improvement of healthcare services. Nature-Inspired Computation in Data Mining and Machine Learning, pp. 113–136. Cham: Springer.

[167] Wang, T., Lei, Y., Tian, Z., Dong, X., Liu, Y. et al. (2019). Deep learning-based image quality improvement for low-dose computed tomography simulation in radiation therapy. Journal of Medical Imaging, 6(4), 043504. DOI 10.1117/1.JMI.6.4.043504.
[168] Mohan, S., Thirumalai, C., Srivastava, G. (2019). Effective heart disease prediction using hybrid machine learning techniques. IEEE Access, 7, 81542–81554. DOI 10.1109/ACCESS.2019.2923707.
[169] Liu, Y., Kang, Y., Xing, C., Chen, T., Yang, Q. (2020). A secure federated transfer learning framework. IEEE Intelligent Systems, 35(4), 70–82. DOI 10.1109/MIS.2020.2988525.
[170] Chen, Y., Qin, X., Wang, J., Yu, C., Gao, W. (2020). Fedhealth: A federated transfer learning framework for wearable healthcare. IEEE Intelligent Systems, 35(4), 83–93. DOI 10.1109/MIS.2020.2988604.