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Image classification based deep learning: A Review

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Abstract—The image classification is a classical problem of image processing, computer vision and machine learning fields. Image classification is a complex procedure which relies on different components. In this paper we study the image classification using deep learning. computer vision science, image classification implementation, and deep neural networks are presented. This article discusses The development of a Convolutional Neural Network (CNN) and its various architectures, which have shown great efficiency and evaluation in image classification. A literature review is conducted to illustrate the significance and the details of Convolutional Neural Networks in various applications.

Keywords:— *Computer Vision; Machine Learning; Image Classification; Deep Learning; CNN.*

1. Introduction

The World Health Organization (WHO) estimated that around 34% of all global deaths in 2018 were due to mis-judgement of patient medical record. Naming it the world's number one killer because it causes huge portion. Therefore, it is crucial and urgent to improve and accelerate all parts of clinical diagnosis, with the goal of widespread and early diagnosis of correct abnormalities across the population[1].

Artificial intelligence (AI) has been a growing trend lately. One of the tasks which can be achieved by AI is computer vision, which is the ability for computers to process and analyze images, aiming to mimic human vision. Machine Learning (ML) is an application of AI that can be able to function without being specifically programmed, that learn from data and make predictions or decisions based on past data[2].

One of the main tasks of computer vision is image classification, which is the process of labelling images into "classes". For example, if there are images of multiple objects, and those images need to be categorized into "classes", for instance "car", "plane", "ship", or "house", that is image classification[3].

ML uses three learning approaches, namely, supervised learning, unsupervised learning, and semi supervised learning. The ML techniques include the extraction of features and the selection of suitable features for a specific problem requires a domain expert. Deep learning (DL) techniques solve the problem of feature selection. DL is one part of ML, and DL can automatically extract essential features from raw input data [4].

Imaging techniques are used to capture anomalies of the human body. The captured images must be understood for diagnosis, prognosis, and treatment planning of the anomalies. Medical image understanding is generally performed by skilled medical professionals. However, the scarce availability of human experts and the fatigue and rough estimate procedures involved with them limit the effectiveness of image understanding performed by skilled medical professionals. Convolutional neural networks (CNNs) are effective tools for image understanding[5].

DL has two properties: (1) multiple processing layers that can learn distinct features of data through multiple levels of abstraction, and (2) unsupervised or supervised learning of feature presentations on each layer. A number of recent review papers have highlighted the capabilities of advanced DL Architectures in the medical field MRI [6], Radiology [7], Cardiology [8], and Neurology[9].

2. Digital Image processing:

Digital image processing means the set of techniques used to modify a digital image in order to improve it , or to reduce its size or to get information out of it .image processing can be divided into four fields :Restoration and enhancement image , image analysis ,image coding with data compression , image synthesis [10].

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Examples of images around us:

- Natural photographic images,
- Artistic and engineering drawings,
- Scientific images (satellite, medical, etc.).

2.1 How computers see images:

Digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called picture elements, image elements, pels and pixels. Pixel is the term used most widely to denote the elements of digital image.

An image is a two-dimensional function that represents a measure of some characteristic such as brightness or color of a viewed scene. An image is a projection of a 3-D scene into a 2D projection plane. An image may be defined as a two-dimensional function f(x,y), where x and y are spatial (plane) coordinates, and the amplitude off at any pair of coordinates (x,y) is called the intensity of the image at that point.

The term gray level is used often to refer to the intensity of monochrome images. Color images are formed by a combination of individual 2-D images. For example: The RGB color system, a color image consists of three (red, green and blue) individual component images[3][11].

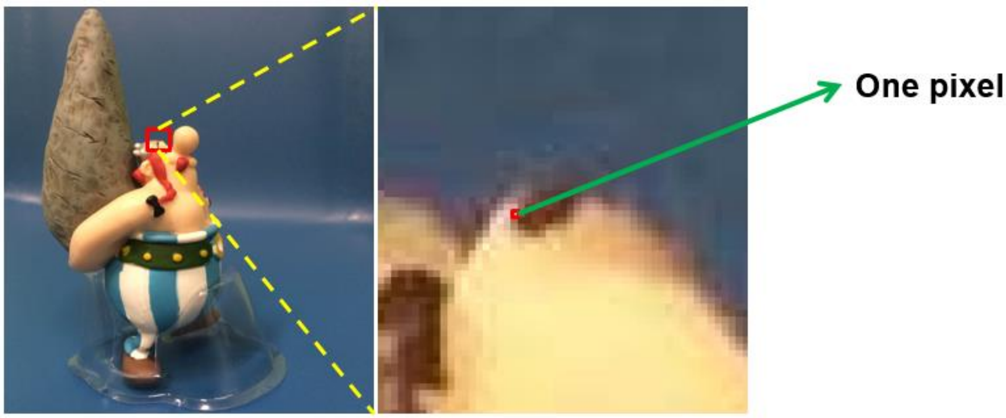

Fig 1. Digital image

Applications of digital images in different fields:

Digital image processing has a broad spectrum of applications, such as:

- Remote sensing
- Image transmission and storage for business applications
- Medical processing
- RADAR (Radio Detection and Ranging)
- SONAR (Sound Navigation and Ranging)
- Acoustic image processing (The study of underwater sound is known as underwater acoustics or hydro acoustics.)
- Robotics and automated inspection of industrial parts.

Images acquired by satellites are useful in tracking of

- Earth resources
- Geographical mapping
- Prediction of agricultural crops
- Urban growth and weather monitoring
- Flood and fire control.

Space image applications include:

- Recognition and analysis of objects contained in images obtained from deep space-probe missions.
- Image transmission and storage applications occur in broadcast television
- Teleconferencing
- Transmission of facsimile images (Printed documents and graphics) for office automation.

Communication over computer networks

- Closed-circuit television-based security monitoring systems and
- In military communications.

Medical applications:
- Processing of chest X- rays
- Cine angiograms
- Projection images of trans axial tomography
- Medical images that occur in radiology nuclear magnetic resonance (NMR)
- Ultrasonic scanning

3. What Is Image Classification?

Image classification is the process of separating pixels into different sets based on the values of their data [12].To classify a pixel to a particular class then the pixel should satisfy some certain rules in order to fit that particular class[13]. The classes may be known if the user was able to determine the classes of the data based on the training data, else the classes are unknown.[10][14]

In general, the process of image classification is to extract image features then classify the extracted features. Therefore, how to extract image features and analyze image features is the key point of image classification.[15]

The traditional classification methods use low-level or mid-level features to represent an image. The low-level features usually are based on grayscale density, color, texture, shape, and position information, which are defined by human (also known as hand-crafted features).The mid-level features, as well as learning-based features, commonly are distilled by bag-of-visual word (BoVW) algorithms, which are effective and popular in image classification or retrieval framework in the past few years.[16]

In computer vision, after extracting the features, a classifier (e.g., SVM, random forest etc.) is usually used to assign the label to the different type of objects. The traditional image classification is shown in Fig (a). Different from the traditional image classification method, the deep learning method combines the process of image feature extraction and classification on one network .The deep learning classification process is showing in Fig(b).[17]

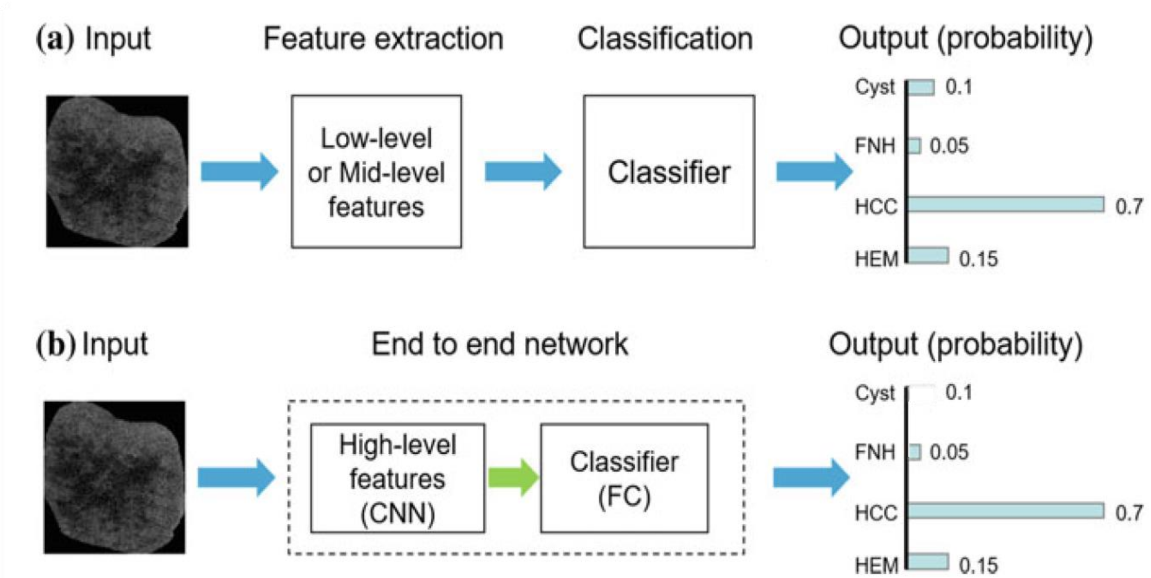

Fig 2. image classification frameworks. (a) traditional classification method (b)deep learning method

The high-level features representation of deep learning has proven to be superior to hand-crafted low-level features and mid-level features and achieved good results in image recognition and image classification. Image classification techniques are divided into two parts , supervised and unsupervised techniques based on the prior knowledge of the classes[18]. Important aspects of accurate classification (Learning techniques and Feature sets).

3.1 Types of learning: -

- Supervised Learning
    - Learning process designed to form a mapping from one set of variables (data) to another set of variables (information classes).
    - A teacher is involved in the learning process
- Unsupervised learning
    - Learning happens without a teacher
    - Exploration of the data space to discover the scientific laws underlying the data distribution

3.2 Features:

Features are attributes of the data elements based on which the elements are assigned to various classes. E.g., in satellite remote sensing, the features are measurements made by sensors in different wavelengths of the electromagnetic spectrum –visible/ infrared / microwave/texture features .
In medical diagnosis, the features may be the temperature, blood pressure, lipid profile, blood sugar, and a variety of other data collected through pathological investigations. The features may be qualitative (high, moderate, low) or quantitative. The classification may be presence of heart disease (positive) or absence of heart disease (negative).

4. Machine Learning

Machine learning (ML) and artificial intelligence (AI) are techniques that have been in existence for quite a while. Machine Learning is an intersection of various sub-fields 'statistical', 'probabilistic', 'computer science', and 'algorithmic', making it a capable tool to understand the hidden insights significant for developing intelligent applications[19].
In recent days, ML and AI are more often applied in various sectors to improve performance and increase production. Advancements in the field of AI has indicated the rising development of artificial neural network (ANN) and convolutional neural networks (CNN) that resembles the biological neural network.

These developing techniques can perform better than the initial artificial intelligence and machine learning models. The convolutional neural network is an essential topic in these days, mainly when designing a deep learning system that handles images as its input[20][21].
Four of the most popular and influential machine learning algorithms in data mining are presented and reviewed[22]:

1- Decision Trees
2- Neural Networks
3- Support Vector Machines
4- K-Nearest-Neighbor.

5. What is deep learning:

Deep learning is way of classifying, clustering, and predicting things by using a neural network that has been trained on vast amounts of data. Deep learning architectures learn features through layer by layer[23]. For example, when a convolutional network learns from images, it tends to learn patterns, textures, edges, and brightness in the first few layers. These features from images are used for processing many different types of natural images, and therefore they can be reused.[2][24][25]

Different from the traditional image classification method, the deep learning method combines the process of image feature extraction and classification on one network.

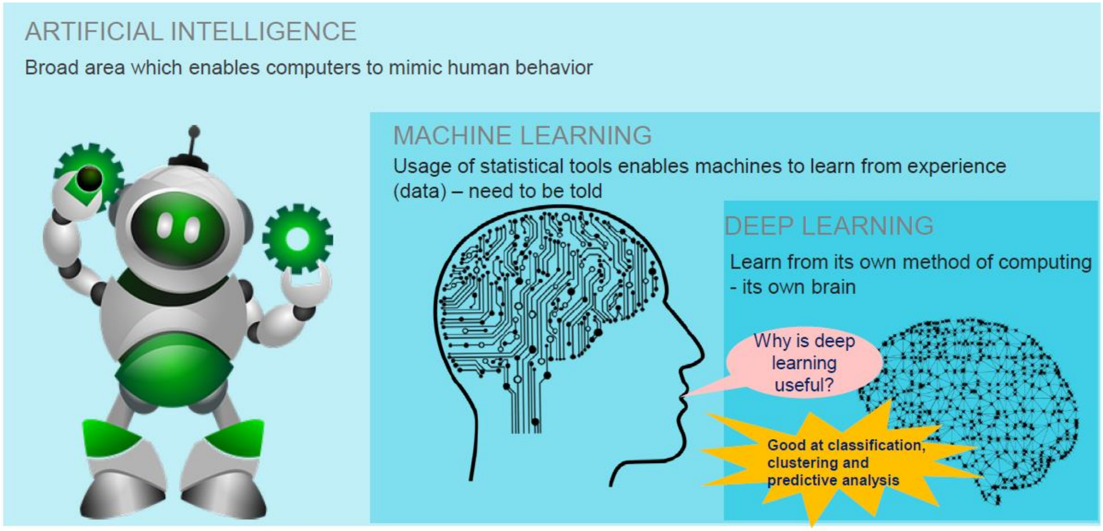

Fig 3. Artificial intelligence, machine learning and deep learning

5.1 Deep learning architecture:

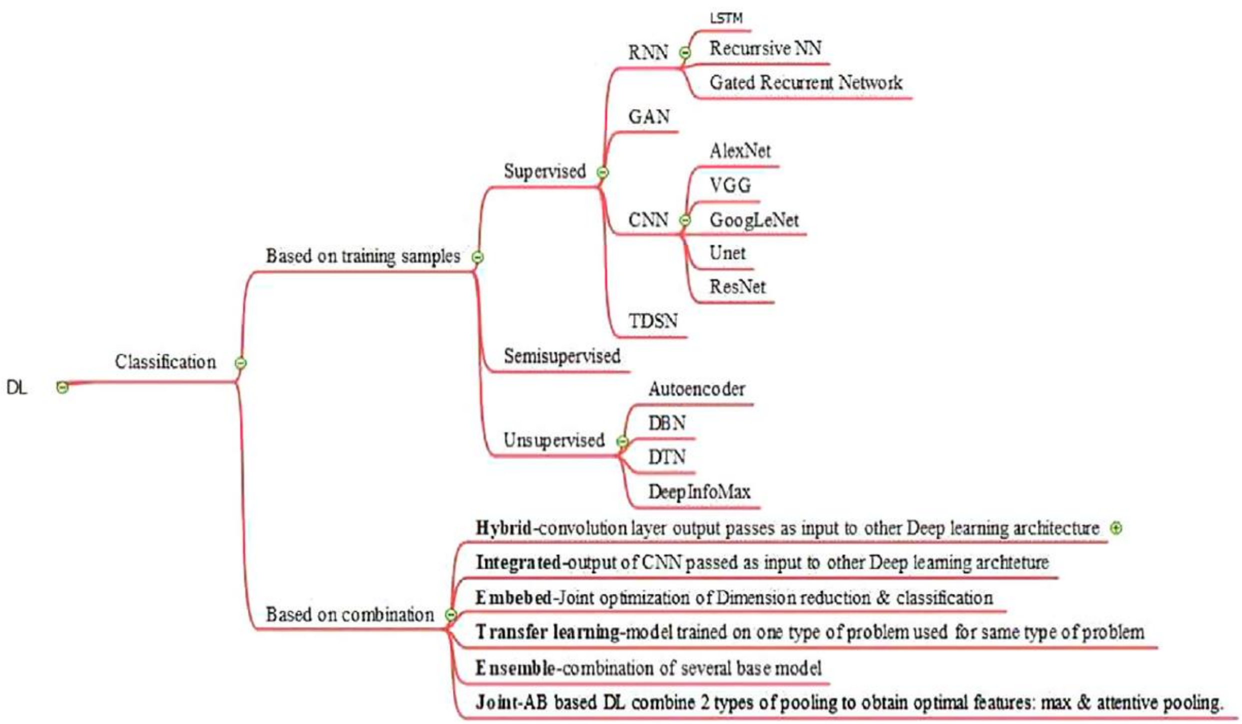

Fig 4. Breakdown of deep learning methods that are commonly used for health domain

The section describes categorization of DL architecture as shown in Fig 4 .
DL architecture can be divided into supervised DL and unsupervised DL [26]:
Supervised DL models are:

- recurrent neural networks (RNNs),

- long short-term memory (LSTM),
- gated recurrent unit (GRU),
- convolutional neural networks (CNNs),
- generative adversarial network (GAN).

Unsupervised deep learning models are:

- deep belief networks (DBN),
- Deep Transfer Network (DTN),
- Tensor Deep Stack Networks (TDSN),
- autoencoders (AE).

5.2 Convolutional neural network CNN:

CNN contains multiple layers which are arranged in a hierarchical fashion. Each layer learns specific features of the image. It consists of convolutional layers, pooling layers, dropout layers, and an output layer, the convolutional neural network structure is an improvement of the traditional artificial neural network (ANN) [27][28] [29].

In fact, the convolutional neural network is still a hierarchical network as the ANN, but the function and form of the layer have changed. It can be divided into two parts: feature extraction part (convolution layers and pooling layers) and classification part (fully connected layers). The image is first passed through a series of convolution, pooling layers for feature extraction and then is passed through fully connected layers for classification[30][31].

5.2.1 Convolution Layer

The image through the convolution layer can be seen as a process of extracting features of the image. Before understanding the convolution layer, let's compare the difference between images in human vision and computer vision. For example, an apple's grayscale image is visually identified by brightness, size, and contour. In computer vision, this apple image is a matrix with only numbers, as shown in Fig[32].

Fig 5. Images in human vision (left) and computer vision (right)

When a computer learns an image, it needs to extract the features of the image from this matrix. Convolution of the image is such a process. Taking a 5×5 image as an example, we choose a 3×3matrix called a filter (or convolution kernel) that slides along the image with a step size of 1.

Each time the filter slides, the filter multiply its values by the value of the image and all these multiplications are summed up. The resulting value is an element of the feature matrix. After passing the entire image, the feature matrix of the image can be finally obtained. The process of convolution is shown in Fig 5 [33].

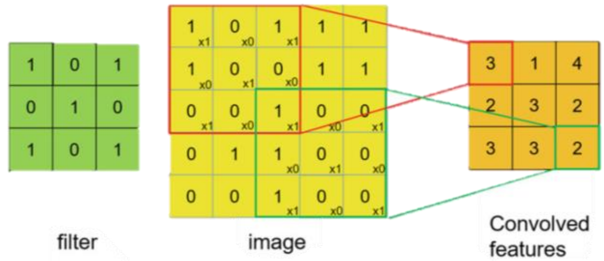

Fig 6. Convolution layer

5.2.2 Pooling Layer

In convolutional neural networks, a pooling layer is often added between convolution layers[34]. The pooling layer can very effectively reduce the size of the parameter matrix and reduce the number of parameters in the last fully connected layer. Using the pooling layer can speed up the calculation and prevent over-fitting. In the field of image recognition, sometimes the size of the trained image is too large, we need to add a pooling layer between the convolution layers to reduce the number of training parameters. Pooling is done in every depth dimension, so the depth of the image remains the same. The most common pooling form is the max pooling. The process of max pooling is as follows: We do the max pooling of a 4 × 4 matrix. The filter size is 2 × 2, the step size is set to 2, and the filter slides along the matrix. For each step, the maximum value in the filter region is used as an element of the pooled matrix. Repeat this process until the filter goes through the entire matrix. The pooling process is shown in Fig7 [28].

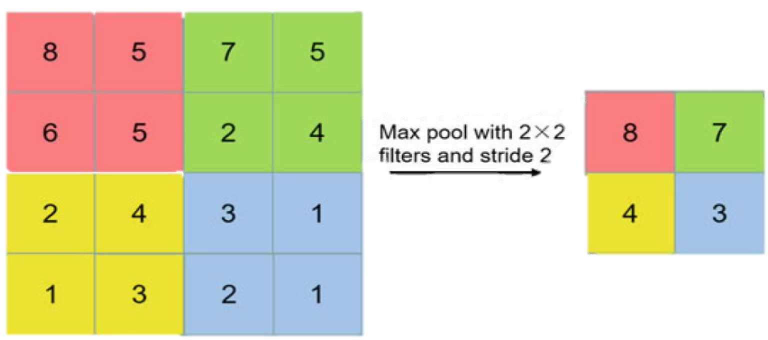

Fig 7. pooling layer

5.2.3 Fully Connected Layer

Fully connected layer is often used in classification task, which is the final part of convolutional neural network, it takes the outputs of formal layers as inputs, and maps them into the targets of classification task. For instance, as shown in Fig8. let's say we got 5 outputs from the formal convolution layers and pooling layers, and we will map them into three categories, the 5 outputs, as we know, that is the key features which can help us to determine the input image belongs to which category, and the three categories are the targets for the classification task, which is also the outputs of fully connected layer. Weights and bias of fully connected layer, together with the key features will do the linear combinations to output the 3 categories, in order to finish the classification task[35].

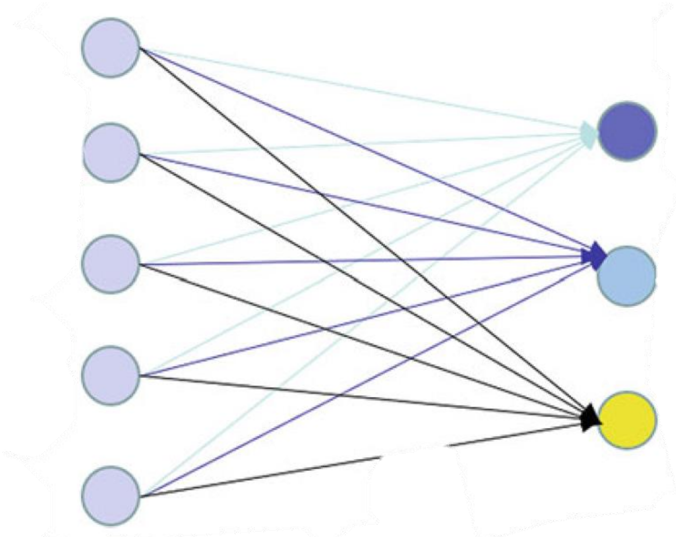

Fig 8. Fully connected layer

5.3 Some of the popular CNN architectures:

AlexNet

With the development of neural networks, researchers have started applying DCNN to medical fields[36][37]. The network structure of AlexNet is shown in Fig9. AlexNet is an 8-layer structure, in which the first 5 layers are convolution layers, and the latter 3 layers are fully connected layers. There are 60 million learning parameters in the network and 650,000 neurons. AlexNet is connected in a separate GPU at Layers 2, 4, and 5, and Layer 3 is fully connected to the previous 2 GPUs. The size of the kernel in the same convolution layer is the same. For example, Alex Net's first convolution layer contains 96 kernels that are 11 × 11 × 3 in size. The first two convolution layers are followed by the overlapping pooling layer, and the third, fourth, and fifth convolution layers are all directly connected. The fifth convolution layer is followed by an overlapping max pooling layer whose output enters two fully connected layers. The final fully connected layer provides 1000 types of tags to the softmax. The max pooling layer is typically used to down sample the width and height of the tensor while maintaining the depth. The overlapping pooling layer is similar to the max pooling layer, except those adjacent pooled windows overlap each other. The pooling window used by AlexNet is a window with a size of 3 × 3 and an adjacent window stride of 2. In the case of the same output size, compared to the non-overlapping pooled window with a size of 2 × 2 and an adjacent window stride of 2, the overlapping pooled windows can respectively reduce the first and fifth error rates by 0.3% and 0.4%[38][29].

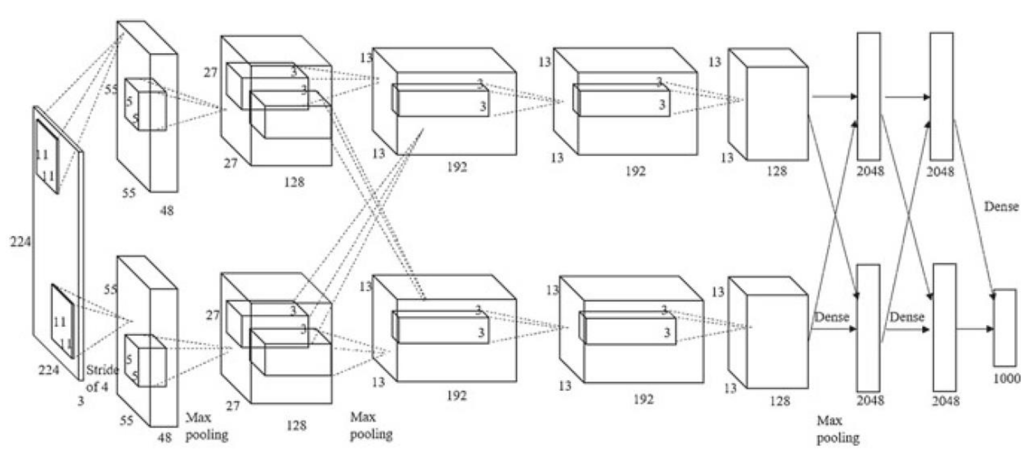

Fig 9. the network structure of Alex Net

VGG (Visual Geometry Group):

It consists of 13 convolution layers (in VGG16) & 16 convolution layers (in VGG19), 3 dense layers, pooling, and three ReLU units, very small receptive fields. It is used for large scale object recognition. Google Net. It consisted of 22 layers deep CNN and 4 million parameters. It contains more filters per layer and stacked convolutional layers. It used batch normalization, image distortions, and RMSprop[29][39].

ResNet (Residual Neural Network):

It contains gated units or gated recurrent units and has a strong similarity to recent successful elements applied in RNNs. It can train 152 layers NN. It has lower complexity than VGG Net[40][41].

UNet:

It consists of three units: contraction, bottleneck, and expansion. The contraction section is made of many contraction blocks. Each block is arranged in a hierarchal fashion. In which the max-pooling layer is arranged after two convolution layers. Each block is followed by kernels, whose number is increasing in multiple of 2. It helps in learning the complex structures. The bottommost layer mediates between the contraction layer and the expansion layer. It consists of two CNN layers followed by the up-convolution layer. It performs segmentation and classification in a single step[42].

RNN:

Recurrent neural networks and its one-directional and bidirectional variants, such as long short-term memory (LSTM) and gated recurrent units (GRU), recursive Neural Networks (recursive NN), Bidirectional RNNs (BiRNN).The one-dimensional RNN learns from the past to predict the future. Though, the Bidirectional RNN learns from the future to fix the past. The RNN is very efficient to capture long term dependencies.[43]

GAN:

It is used to generate synthetic training data from original data using latent distribution. It composed of two networks, a generator, which deployed to generate synthetic data from noise and a discriminator, which differentiates the real and synthetic instances of data. Together these two adversarial networks improve the quality of generated data.[44]

AEs:

They are composed of an encoder and decoder. AEs discover meaningful representations of data by mapping lower dimensional inputs to outputs. They utilize the latent representation of input to reconstruct output. They learn only those features of data that are necessary to reconstruct the input. Such algorithms are utilized to learn features that can be subsequently utilized in conjunction with deep learning techniques.[45]

DBN:

It consists of two networks, The Belief Networks and Restricted Boltzmann Machines which stacked each other. Belief network is an acyclic graph composed of layers of stochastic binary units with weighted connections. Boltzmann Machine is a stochastic RNN with stochastic binary units and undirected edges between Units. It is suitable for large-scale problems.[46]

DTN:

It composed of two layers: feature extraction layer, which learns a shared feature subspace in which the marginal distributions of the source and the target samples are drawn close and a discrimination layer, which match conditional distributions by classifier transduction. Its computational complexity O(n). It is suitable for large-scale problems.[47]

TDSN:

It contains two parallel hidden representations which are combined using a bilinear mapping. This arrangement provides a better generalization as compared to single module architecture. It deduces the biases of the generalizer (s) with respect to the learning set. It works effectively and better than a cross-validation strategy when used with multiple generalizers as compared to individual generalizers.

Deep InfoMax (DIM):

It maximizes the mutual information between an input and the output of a highly flexible convolutional encoder by training another neural network that maximizes a lower bound on a divergence between the product of marginal of the encoder input and output. The estimates obtained by another network can be used to maximize the mutual information of the features in the encoder with the input. The memory requirement of DIM is less because it only requires encoder not decoder.[48][49]

Combined DL models:

DL models can be combined in five different ways: hybrid model – in this model, the output of convolution layer is directly passed as input to other DL architecture such as residual attention network, recurrent convolutional neural network (RCNN) and inception recurrent residual convolutional neural network (IRRCNN) model ; Integrated model – in this model, the output of one DL model is passed as input to other DL model; Embedded model – in this model, the dimension reduction model and classification model are jointly optimized for example enhanced joint hybrid CNN BiLSTM (EJH-CNN-BiLSTM); Ensemble – in this model, the output of several base models are combined; and Transfer learning (TL) –in this model, DL model trained on one type of problem is used for the same type of problem. Popular CNN models which are used as TL models are VGG (e.g., VGG16 or VGG19), Google Net (e.g., InceptionV3), Inception Network (Inception-v4), Residual neural Network (e.g. ResNet50), AlexNet. Joint AB based DL combines two types of pooling to obtain optimal features: max pooling, and attentive pooling.

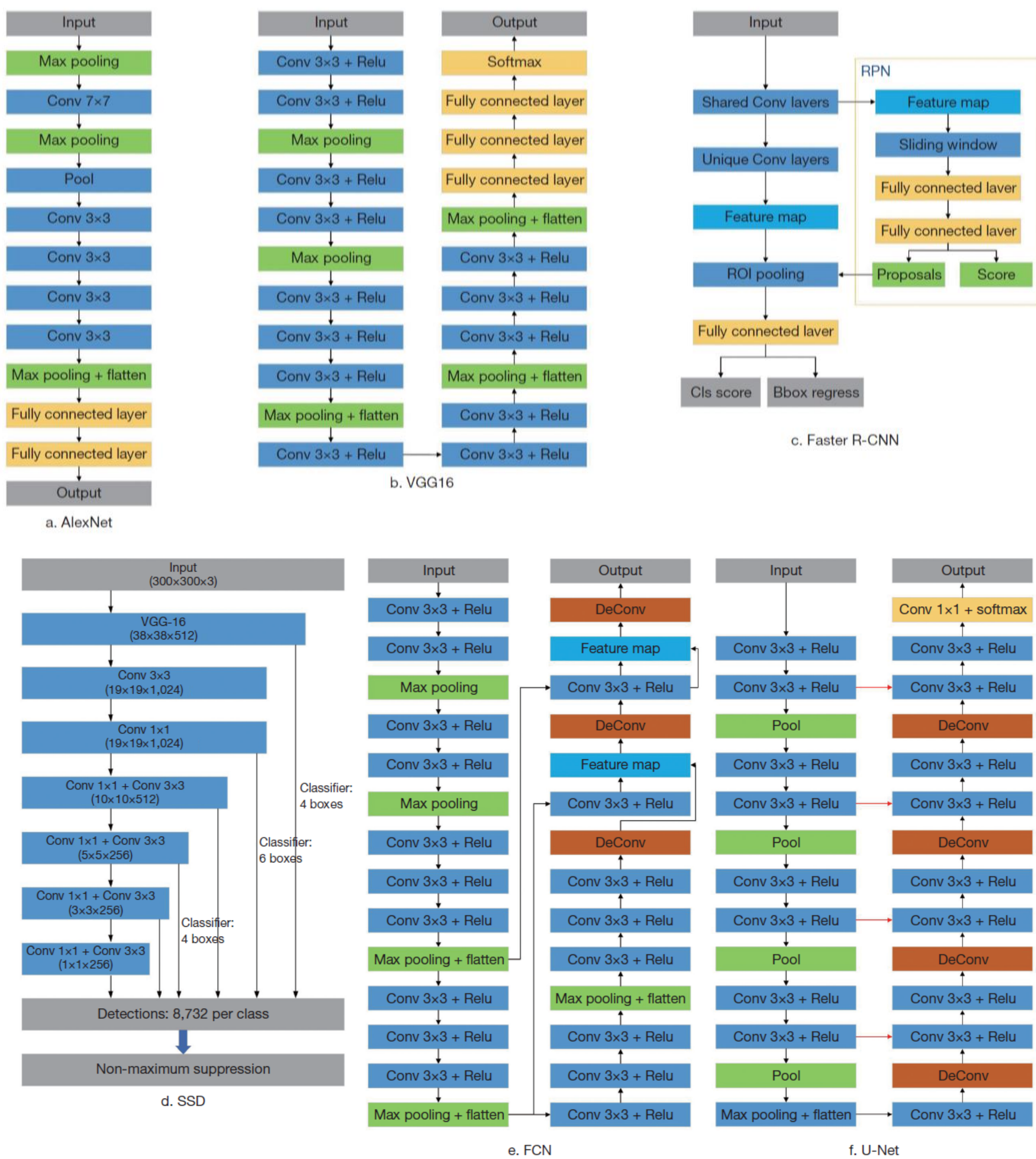

Fig 10. The typical network structures of the deep learning .

6. Image classification in medical field:

Medical images classification is a supervised method which is based on probability distribution models that could be parametric or non- parametric such as Euclidean classifier, k-nearest neighbour, minimum distance, and decision tree etc. Although, in supervised classification one is provided with a collection of labelled (pre-classified) images and the problem is to label newly encountered, unlabeled images. In general, the prearranged labelled (usually called training set) images are used to do the machine learning of the class (group) description which in turn is used for unknown image[18] .

The images must be understood for the accurate detection of anomalies or the diagnosis of functional abnormalities. If an abnormality is detected, then its exact location, size and shape must be determined. These tasks are traditionally performed by the trained physicians based on their judgment and experience. Intelligent healthcare systems aim to perform these tasks using intelligent medical image understanding. Medical image classification, segmentation, detection and localization are the important tasks in medical image understanding.[5]

There are several medical imaging modalities that involve ionizing radiation, nuclear medicine, magnetic resonance, ultrasound, and optical methods as a modality media. Each modality media has a special characteristic and differences response to human body structure and organs tissue [50].

There are four imaging modalities [51]:

- **Projectional Imaging**
  X-rays are a form of electromagnetic radiation (EM), which has a wavelength range between 0.1-10 nm. They are translated into photons with energy levels, 12-125 keV. The x-ray imaging projection used almost at the same time with the need to use laboratory testing as a medical diagnostic tool. Image formation process is divided into three main steps: Image pre read, Image main read, Image processing.

- **Computed Tomography (CT)**
  The conventional x-ray imaging projection sometimes fails in achieving good results because of tiny differences in attenuation (less than 5%). CT improves the subject contrast using discrimination less than 1%. The application for cancer screening such as lung and virtual colonoscopy often uses CT. There are several variations of CT imaging, namely: Positron emission tomography (PET) / CT, CT perfusion, CT angiography, Dual source and dual energy CT.

- **Magnetic Resonance (MR)**
  A powerful magnetic field is used in Magnetic Resonance Imaging method (MR) for the nuclear magnetization alignment of hydrogen atoms in water molecules. MR became the standard of cross-sectional imaging modalities that useful to visualize soft tissues (such as muscle, brain), fat and bone (especially marrow bone).

- **Ultrasound Imaging**
  The high- sound waves with the frequency range from 1- 20 MHz that can be applied to produce cross-sectional images of the human body. The strength of the echo ultrasound

return depends on the characteristics of biological tissue which they pass through.

7. Challenges in medical imaging

Deep learning in MI suffers many issues. We summarize some of the potential issues associated with deep learning. there are some challenges in medical image classification, as follows:

1- How can we extract effective features from a small medical image dataset? In general, medical image datasets are so small that we cannot obtain sufficient information to extract discriminative features. Without regard to the size of the image dataset, even if the proposed method can gain very good classification accuracy, the actual application value is extremely limited, a new data augmentation method is proposed to avoid small datasets leading to acquiring non valid features. then, they used an extension dataset to gain good performance of their model. therefore, it is meaningful to find a method that can extract discriminative features from a small dataset.[38]

2- How to fuse different types of features quickly and efficiently from different models? It appears easy to formulate the idea of directly combining the feature vectors into a larger feature vector and determining one proportion parameter between different features. However, this method usually requires trial experiments to train the parameters and cannot obtain a better outcome. If we could design a more favorable fusion approach, then it would gain better accuracy performance than any of these methods. therefore, there is a great demand to effectively fuse the features.

3- Low resolution images and reconstruction overhead: Low resolution images have attracted researcher's attention in the health domain because of their easy acquisition method and small computational cost [52] but their classification is a challenging task due to their noisy representation and limited information [53]. Researchers deployed conventional linear interpolation methods to generate high-resolution images from low-resolution images but these methods suffer from artifacts such as aliasing, blur, and halo around the edges[54].

The reason why deep learning can develop so rapidly in the medical field is inseparable from many clinical practices. How to better apply deep learning to all stages of medical treatment becomes a more challenging task. It depends on two aspects: one is the constantly updated iteration of technology, and the other is the continuous accumulation of medical experience.[55]

8. Related work:

This section provides a brief overview of the research papers involving different classification methods to classify abnormalities in medical images.
there are many methods that have been proposed to solve these challenging problems on image classification, which can be categorized into two types of methods: traditional methods and deep model methods. Traditional methods include color and texture[56],[57],[58], random forests[58], and support vector machines[59],[60]. Studies on deep models to classify medical images include[61],[62].

In Reference [58],the authors have addressed two systems for the detection of melanomas in dermoscopy images using texture and color features. One system uses global features to classify skin lesions, and another system employs local features. the results were demonstrated on a dataset of 176 dermoscopy images from Hospital Pedro Hispano.

Iyatomi et al [56],proposed an Internet-based melanoma screening system based on shape, color, and texture features. this system gained a sensitivity (SE) of 86% and a specificity (SP) of 86% on 1200 dermoscopy images.

Stoecker et al. [57]analyzed the areas of granularity between melanoma and similar areas in nonmelanoma skin lesions with a combination of color and texture features. their paper used the receiver operating characteristic (ROC) curve to display the systems best separation performance on a dataset with 88 melanomas and 200 nonmelanoma lesions.

Riaz et al. [63]first deployed a novel region-based texture and color descriptors to identify cancer in images. In their model, texture features are based on Gabor filters, and they use homomorphic filtering to obtain color features, which can address the problem of different rotations, scaling, and illumination.

Ramirez et al. [64]proposed a variant of random forests on single photon emission computed tomography (SPECT) image classification to help diagnose Alzheimer's disease (AD). First, they extracted score features using partial least squares from the image datasets to structure the random forests. Using this system as a classifier helped to classify all of the images. the specific process is to classify the image to the closest centroid recessively until reaching a leaf of a single tree, which is the classification of the image. the most important characteristic of this algorithm is that it can extend from the previous model, a process referred as to incremental learning, without retraining the images from scratch.

In Reference [60], the authors proposed a classifier that is based on a fractional Fourier transform and nonparallel support vector machine to classify magnetic resonance brain images into pathological brain image and healthy brain image categories . thus, it was a binary classification task. For a given image, the system first used a weighted-type fractional Fourier transform to extract the spectrum features, and then, it utilized principal component analysis to reduce the dimensionality of the spectrum features. Finally, its incorporated spectrum features were fed into support vector machines. However, in this paper, the dataset that contains 90 T2-weighted MR brain images is relatively small. Although it has obtained good performance, it is not adapted to a larger dataset.

Li et al. [61] trained a customized convolutional neural network (CNN) to classify lung image patches. In this model, the system contained only one convolutional layer to extract the deep features, to overcome the overfitting problem, and it obtained the best classification performance compared with scale-invariant feature transform (SIFT) features, rotation-invariant local binary pattern (LBP) features, and unsupervised feature learning using the restricted Boltzmann machine (RBM).

In Reference [65], the authors first proposed simple deep learning architecture called principal component analysis network (PCANet) that had been used by [65] combined with the spatial distribution information of color images to achieve the state-of-the-art classification accuracy in various databases.

In Reference [62], the authors employed a CNN trained by ImageNet to identify different types of pathologies in chest X-ray images. they achieved the best accuracy performance by combining the features extracted from a CNN and handcrafted features. Shin et al. [66]discussed why transfer

learning can be useful to address medical images. Additionally, they proved their results on thoracoabdominal lymph node (LN) detection and interstitial lung disease (ILD) classification.
Rakotomamonjy et al. [67]employed scattering transform which first proposed by [68] to extract features combined with local binary patterns (LBP) and local quinary patterns (LQP) for lung cancer detection which proved to be robust to small deformations in the images. And they verified the performances and effectiveness on the 2D-Hela dataset and Pap smear dataset.
Cruzroa et al. [69]presented a deep learning approach for automatic detection of invasive ductal carcinoma (IDC) tissue regions in whole slide images (WSI) of breast cancer (BCa) which verified through a dataset from 162 patients diagnosed with IDC achieving balanced accuracy 84.23%.
Ahn et al. [70] proposed a method that combined domain-transferred convolutional neural networks (DTCNNS) with a sparse spatial pyramid (SSP) to classify X-ray images. In this paper, they used VGG19 (19 layers CNN) proposed by [71] as the transferred network, which could ignore the medical image characteristics. However, this approach provided a new train of thought to solve this problem.
In Reference[72],the authors first proposed multiscale high-level feature representations for face verification, which they termed Deep hidden Identity features (DeepID). the multiscale features fuse the features extracted from the third and fourth layers of the CNN model.

Sabuni et al. [73] has proposed a deep learning model that defines the neural structure for the prediction of brain tumour using backward propagation. The efficiency and accuracy of proposed model was measured and compared to current models, producing high sensitivity, specificity, accuracy and precision.

Noreen et al. [74] has proposed strategy focused on concatenation of characteristics using pre-trained variety of deep learning with convolution neural network approaches to detect of tumour, models outperformed.

Mahanty et al. [75] has proposed a work that requires a neural network method by considering the MRI as "TUMOUR IDENTIFIED" or "TUMOUR NOT IDENTIFIED," a CNN dependent approach is used. A mean accuracy value 96.08% and 98.3f score is captured by the model.

[76],[77] by suggesting an updated CapsNets system, that also calls the borders of the tumor throughout its key BTC pathway, they illustrated upon that issue. Overall value of people in America with neural tumors in 2019 is rated at approximately 0.8 million. There were 0.86 million cases found. Of these patients, 60,800 were verified to benign and 26,170 were verified too malignant.

[78],[79] has tried to resolve the key two CNNs concerns towards BTC topic, with the score for vast quantities and learning owing to the downstream of substantial transition handling capabilities. Capsule Networks (CapsNets) were analyzed against multiple key goals, i.e., ensuring higher precision with BTC, investigating their over-fitting queries, the adequacy of CapsNets tumour areas only or MRI images, then visualizing the training images of MRI for better comprehension.

[80]has proposed a block-wise fine-tuning methodology towards classification of brain tumour classification has been adopted, which would be more difficult than that of the classification problem.

[81]has proposed the functionaries to identify brain tumors using a pre-trained googleNet [82] framework across three distinct groups, i.e., glioma, meningitis and pituitary tumors.

[83] Strategy of content-based extraction for acquires related brain tumor portraits employing VGG-19 functionaries including shuttered-form proportional processing for estimation of similarities.
in a study by Xie et al., Inception-V3 achieved a 96.84% level of accuracy using the BreaKHis database, with the total number of 7,909 imbalanced types of breast cancer histopathological images [84].

Jannesari et al. [85] combined BreaKHis and TMA databases with different resolutions. The number of types and subtypes were then balanced with data augmentation techniques. The total number of input images in this study was 16,846. They also employed pre-processing techniques, such as normalization, and color-distortion before examining all the layers in the model with _ne-tuning techniques. In the same study, several experiments on ResNet models, including ResNet-152, ResNet-101, and ResNet-50 were conducted, obtaining 98.70%, 98.40%, and 97.80% scores of accuracies, respectively. By using the same techniques and databases, this study illustrated the importance of the deep layers in which ResNet-152 achieved the highest accuracy among all ResNet models.

In another study, Inception-V4 and Inception-V3 were examined by Jannesari et al. [85] using images from TMA and BreaKHis. Inception-V4 gained a lower accuracy score (77.70%) than Inception-V3 (82.20 %). By comparison, the accuracy scores gained by Inception-V3 for the BreakHis database were 96.2 and 98% in a study by Xie et al. [84] and Lim et al. [86], respectively. Thus, this model gained better accuracy scores when investigating the BreakHis database in comparison with the database collected from TMA and BreaKHis.

Vang et al. [87] applied Inception-V3 with the dual-path network (DPN) to separate the class of in-situ
carcinoma from invasive carcinoma. Two other studies also employed Inception-V3 and shared the same data augmentation and transfer learning methods [88], [87]. Thus, a decent pre-processing method was more important than ever because these two studies were different in terms of the pre-processing methods.

In another study, ResNeXt-50 was examined by using the combination of BACH and BISQUE databases [89]. As the BISQUE database consists of few but precious images. This model gained the lowest accuracy score (81%) among all the studies.

In another study, the SDG optimizer was applied together with momentum but without the regularization method [88]. The SDG optimizer was also utilized with dropout regularization by researchers in another two studies [89],[90].
the experiment done by Xie et al. [84]with Inception-ResNet-V2 achieved the highest accuracy of 97.63% for the eight classifications. In this experiment, the data augmentation techniques were applied to increase the number of images of each subtype besides balancing them, improving the accuracy from 92.07% to 97.63%. After increasing the number of images by the augmentation technique, the input images for benign tumors subtypes included adenosis (1,335), _broadenoma

(3,045), phyllodes-tumor (1,362), and tubular-adenoma (1,710). As for malignant tumor subtypes, the input images included ductal carcinoma (3,451), lobular carcinoma (1,881), mucinous-carcinoma (2,379), and papillary-carcinoma (1,683). Furthermore, pre-processing techniques such as normalization, cutting border, and saturation adjustment were used in this study.

Cruz-Roa et al. [1]suggested the segmentation of chest X-ray using convolutional neural network. In their work, they introduced image segmentation into bone tissue and non-bone tissue. The aim of their work was to develop an automatic or an intelligent segmentation system for chest X-rays. The system was established to have the capability to segment bone tissues from the rest of the image. This model considers the limited features only for the classification process.

In another recent research, Patil and Kuchanur [91] presented the application of some image processing techniques in the classification of patients chest X-rays into whether cancer is present or not (benign or malignant). In this work, it was shown that by extracting some geometric features that are essential to the classification of the images such area, perimeter, diameter, and irregularity; an automatic classification system was developed.

Li et al. [61] suggest an overview of the dimension reduction based on data. An adaptive classification method is used to check the input data level. Eigen matrix and Eigen vector for dimensional reduction are found in the proposed PCA-based method. Due to the methodology suggested, redundant information from the original data input reduces the size of the data collection.

Shin et al. [66]suggested a hybrid approach to KNN and genetic algorithms to boost the precision of the classification of the data set on heart disease. The proposed method used genetic search to prune redundant or obsolete attributes and to find classification attributes. The least graded attributes are excluded, and classification is conducted according to high classification.

In 2018, Yutong Xie et al. [92] recommended an algorithm for lung nodule classification that circuits the Texture, Shape and Deep model-learned data (Fuse-TSD) at the choice level. This algorithm utilizes a GLCM-based surface descriptor, a Fourier-shape descriptor to portray the heterogeneity of nodules and a DCNN to train the features of nodes.

Hiba Chougrad et al. [93] investigated a CAD framework based on CNN to classify the breast cancer. Deep learning generally requires expansive datasets to prepare systems while transfer learning method uses a little dataset of medical images. The CNNs optimally trained with the help of transfer learning method. The CNN accomplished the best outcomes in terms of accuracy i.e., 98.94%.

Heba Mohsen et al. [80]demonstrated the DNN classifier for brain tumor classification where the DNN is combined with wavelet transform and principal component analysis.

In 2015, Alok Sharma et al. [94] proposed a method of regularized linear discriminant analysis, in which the regularization parameter computed traditional cross-validation algorithm. To investigate the medical data for prediction of disease needs a proper set of features. There have been many evolutionary algorithms has been applied to obtain the optimal selection of features. Recently, gravitational search algorithm and Elephant Herd optimizations are utilized for the selection of optimal features [95][96].

Kuruvilla, J. and Gunavathi, K (2014) developed an ANN based cancer classification for CT images. The statistical used for the classification model developed. The paper claimed that feed forward back propagation network provides better accuracy compared to feed forward networks. Also, the skewness feature has more significance in enhancement of classifier accuracy [97].

Abbass developed a system with pareto-differential evaluation algorithm with local search scheme, called memetic pareto-artificial neural network (MPANN) [98]. MPANN analyzes the data effectively than other models. The method achieved 98.1% accuracy on random split.

Tuba and Tulay proposed the statistical neural network-based breast cancer diagnosis system [99]. In the diagnosis system, they used RBF, general regression neural network (GRNN), and statistical neural network structures on WDBC dataset. The system obtained 98.8% on 50–50 partitioning split.

Paulin and Santhakumaran [100] developed a system with back-propagation neural network (BPNN) and obtained 99.28% accuracy with Levenberg–Marquardt algorithm. They used median filter for preprocessing and normalized the data using min–max technique. None of the features are eliminated from the dataset. The
accurate result attained from 80:20 partition scheme.

Karabatak and Ince [101]developed an expert system for breast cancer detection. Association rules (AR) are used to reduce the dimensions of the dataset. In the system, AR1 and AR2 are developed to reduce the features. AR1 reduces one feature from 9, and AR2 reduces 5 features out of 9. The conventional neural network is used for classification in both AR1 and AR2. The method attained 95.6% accuracy on AR1, 97.4% on AR2, and 95.2% on all 9 features with threefold cross-validation scheme.

Mert et al. [102] used radial basis function neural network (RBFNN) for medical data classification and independent component analysis for feature selection. The method selects the one feature vector randomly from 30 features. The method obtained the accuracy in the average of 86%.

Bhattacherjee et al. [103] used BPNN for classification. The method achieved 99.27% accuracy. An intelligent medical decision model was developed based on evolutionary strategy [104]. They validated the performance of the method by testing on different datasets. Neural network (NN), genetic algorithm (GA), support vector machine (SVM), K-nearest neighbor (KNN), multilayer perceptron (MLP), radial basis function (RBF), probabilistic neural network (PNN), self-organizing map (SOM), and Naive Bayes (nB) are used as classifiers. Crossover and mutation techniques are applied between different algorithms. The method proves that the SVM classifier on WBC dataset attained better recognition rate than other classifiers.

Schmidhuber [105] provides an overview of deep learning in neural networks. The method proves that the deep learning algorithms reduced the error rate and increase the accuracy with respect to training of algorithm.

Abdel and Eldeib [106] applied deep belief network (DBN) for WBC dataset and achieved 99.68% accuracy. The dataset was divided into train-test split of 54.945.1%. DBN follows unsupervised path and back-propagation network to follow supervised path. This system was constructed by BPNN with Levenberg–Marquardt learning function. Here, the weights are initialized with DBN path. This system provides the promising result and outperforms than other classifiers. This motivated to use deep learning concepts for medical data classification. Deep learning reduces the error rate, and it will improve the accuracy rate.

Conclusions:

This paper provides a complete scanning to image classification based on deep learning. Different categorization has been investigated and discussed. The procedures required for image classification have been discussed based on different techniques. The paper proves that the whole techniques used for image classification is trused in some advantages and have some weakness.

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