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# An Empirical Research on the Use of Machine Learning Algorithm for Medical Image Classification

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**Abstract**

Medical imaging can benefit from the pattern recognition method known as machine learning. It is a powerful tool that can help with medical diagnosis, but it can also be misused. Computing the picture attributes deemed to be essential for creating the intended prediction or diagnosis is frequently the initial step in machine learning. The system then concludes how these image properties ought to be organized ideally for classifying the image or creating some measurement for the assigned image district utilizing machine learning strategies. There are various strategies that can be utilized, and each has advantages and disadvantages. Additionally, deep learning, which belongs to a larger family of machine learning techniques, has the ability to effectively examine a lot of data. The goal of this study is to aid researchers in properly comprehending machine learning and its uses in the healthcare industry.

Machine learning and deep learning approaches are gradually becoming more prevalent in the dynamic field of medical imaging research. Presently a ton of work is being finished to upgrade medical imaging applications by utilizing these algorithms to recognize mistakes in sickness discovery systems that could bring about very questionable medical therapies. Profound learning and machine learning algorithms are utilized in medical imaging to help anticipate early ailment side effects.Convolutional networks in particular, which are a part of deep learning approaches, have quickly developed a way of their own for analysing medical images. It makes predictions using supervised or unsupervised algorithms using a particular standard dataset. We examine medical imaging principles such as picture categorization, object detection, pattern recognition, reasoning, etc. These are used to increase accuracy in medical imaging by extracting the pertinent patterns for the particular condition. This paper's main goal is to illustrate machine learning techniques for categorising medical images.

**Keywords:** Medical imaging, Machine learning algorithms, Image enhancement, Medical disciplines.

## 1. Introduction

Machine learning strategies are regularly utilized in the field of medical imaging research as proficient classifier and gathering algorithms. The best classifiers utilized now are support vector machines and grouping strategies like k-closest neighbour (kNN).A group of methods known as medical image processing are used to extract data from various imaging modalities that is clinically relevant, usually for diagnosis or prognosis. The majority of modalities are in vivo. According to the demands of the patient, the information/data that was retrieved could be used further to enhance diagnosis and prognosis (A. Karpathy, 2020).

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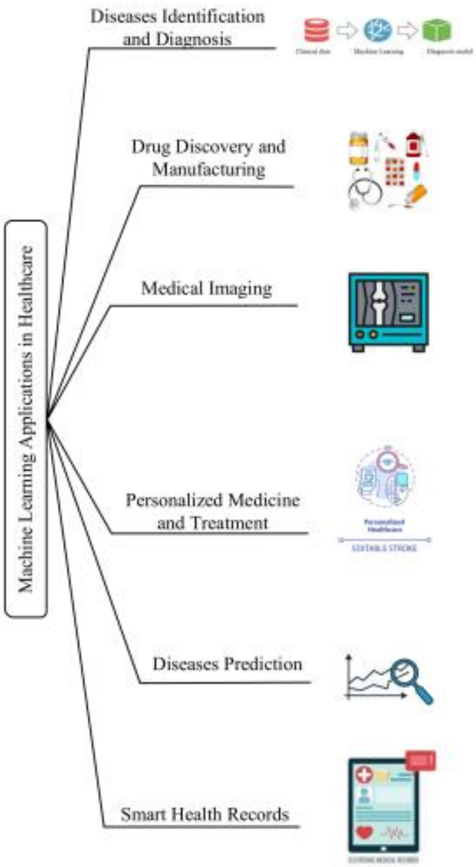
The main contrast between machine learning with feature input and machine learning with image input, including "deep learning," is the direct usage of pixel values with machine learning models. By being deeply incorporated into a variety of medical sectors, from drug research to clinical decision making, machine learning algorithms have the potential to significantly alter how medicine is practised. Machine learning methods are currently successful in computer vision applications, which is in line with the rapid digitalization of medical data. This makes medical image analysis a perfect application for an automated, precise, and powerful machine learning method.

Machine learning methods assume a huge part in the change of the PC framework into a specialist that can be utilized for expectation and navigation.Computers can learn without explicit programming thanks to the field of machine learning.The rapidly expanding field of medical imaging is used to identify diseases early enough to treat them. The role of image processing in the healthcare industry is connected to the expanding use of medical imaging. Based on certain estimates, digital image processing has a substantial impact on the decision-making process (Bernal, 2021). Better accuracy and feature extraction are provided. Functional assessment is a difficult process that involves several unique qualities. The methods of digital image processing are integrated into a wide range of computer systems. The adoption of certain procedures that have an impact on the performance of these systems requires the authentication of image processing approaches. As a result, decisions and actions are influenced by imaging techniques in medicine. It offers a vast array of simple and complex image analysis and visualisation tools. The primary field used to show human intellect in a machine is artificial intelligence (AI). Artificial intelligence is created using both deep learning and machine learning. Several processes are applied to medical photographs before the output is noticed. The medical image is first given as contribution to the machine learning and profound learning algorithms. The image is then separated into various segments with the goal that you can zero in on a specific region. The highlights are thusly removed from these sections utilizing data recovery procedures.

A diagnosis is a method of categorising medications that is essential to how a medication plays its role in society. The medical system depends on it. It organises disease by identifying treatment options, predicting outcomes, and providing an educational process. A detailed diagnosis is typically required for appropriate and efficient treatment. The overall diagnostic procedure has undoubtedly been improved by the corresponding advancements in imaging and diagnostic testing (Çiçek, 2020). But even in this period of rapid technological change, the human technique of scientific judgement leading to accurate diagnosis remains crucial for high quality and healthy medical services. The patient-harming diagnostic error does, however, occur regularly.

Using methods like fuzzy logic or machine learning (ML), these diagnostic errors might be reduced, which would enhance healthcare services. The kind of analytics a doctor may acquire using ML can give them greater information and, as a result, better care while treating a patient. The question of how to design systems that continuously learn from experience is addressed by ML. It is perceived as one of the specialized fields with the fastest current development since it sits at the nexus of figuring and investigation and at the underpinning of both computerized reasoning (AI) and information science. The 21st century flood in the formation of huge information, ML, and information science has principally helped the business sectors that have had the option to get such information and enroll the faculty important to make an interpretation of their items into a benefit up to this second (D. Shen, 2021).The algorithms developed in and around these marketplaces offer significant promise for advancing medical and clinical research, especially if practitioners use electronic health records often (EHR). Two areas that benefit from the application of ML approaches in the healthcare industry are diagnosis and outcome estimation. ML can test the expectation force of each doable blend of components for deciding analytic and prognostic parts as well as dealing with different crude information mixes and applying setting weighting.

**Figure: 1. Various ML applications in healthcare**




## 2. Literature Review

For both commercial and scientific purposes, a number of content-based medical picture systems have been created in multimedia applications. The first commercially available content-based medical image system is called Query By Image Content (QBIC). The colour histogram, average RGB, Tamura features, circularity, shape area, eccentricity, and moment invariants have all been used in this approach to extract features. In order to speed up retrieval, a multidimensional indexing structure called the R * tree is used. The colour set and wavelet-based texture characteristics are employed in the Smith & Chang visual feature search engine known as Visual SEEK. In order to expedite retrieval, this system used indexing methods based on binary trees. Pentland et al. created the photo book, which used appearance, 2D shape, and textural features as its search criteria. They searched the photographs using colour and textures in segmented 7 image regions, employing images of

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humans, texture swatches, fish, etc. Netra was employed. The free freeware GNU Image Finding Tool (GIFT) uses the relevant feedback method to enhance the search results. However, receiving Relevance response requires the user to wait until he is pleased before receiving the photographs, which takes time. The aforementioned systems are primarily used for searching for people, finding objects in nature, and other general-purpose image searches. The approaches chosen for colour, texture, or shape when these general purpose content based medical image-systems are employed to extract the medical images render ineffective results. The researchers have also created and evaluated a number of CBMIR systems (De Vos, 2020).

A content-based medical image retrieval system was proposed by Ramamurthy and Chandran (2012) employing Euclidean Distance as the similarity metric, GLCM as texture features, K means method, and classification. The experimental findings indicated that classification could not be applied to features with non-continuous values and performed badly on overlapping regions. The classification of the photos also makes use of machine learning methods. The two most frequently utilized machine learning strategies are Support Vector Machine (SVM) and Relevance Vector Machine (RVM).

Using an image, Mohanaiah et al. suggested a method for extracting textural information. For extracting textural information, they used the Gray Level Co-occurrence Matrix technique (GLCM). An important step in classifying images in image analysis is the textural analysis. So it is feasible to extract textural information from grayscale photos using GLCM. In medical applications, these characteristics are crucial for categorising diseases as normal or abnormal. This statistical technique for feature extraction is helpful (F. Milletari, 2021). This matrix technique was employed by the author to assess the characteristics of picture movements. From MRI scans, they calculated characteristics like Angular Second Moment (energy), Correlation, and Entropy, among others. Comparing this method to the discrete wavelet transform, it takes less time.

A article on the technique for extracting features from colour images was provided by Dong ping Tian et al.. In grayscale images, texture is measured from a group of pixels, but in RGB colour photos, colour is a feature of a pixel. The pixel statistic or pixel structure in the image and its domain serve as the foundation for the textural elements. In this study, local features and global features are the two main categories of features extracted. This paper uses LBP, Gabor wavelet, and histogram to extract colour image features. The histogram technique is used to extract global information from an image whereas Gabor wavelet and Sobel shape detector are efficient at extracting local features. The image representation has been done using these features.

### 2.1. Objectives of the study

- To investigate the application of machine learning techniques for categorising medical photographs.
- To understand more about how machine learning methods are used in medical imaging.

## 3. Machine Learning In Medical Imaging

To investigate explicit sicknesses, medical imaging utilizes machine learning algorithms very well. In medical image handling, different kinds of elements, like sores and organs, can be excessively convoluted to be loyally addressed by a basic numerical arrangement. Using

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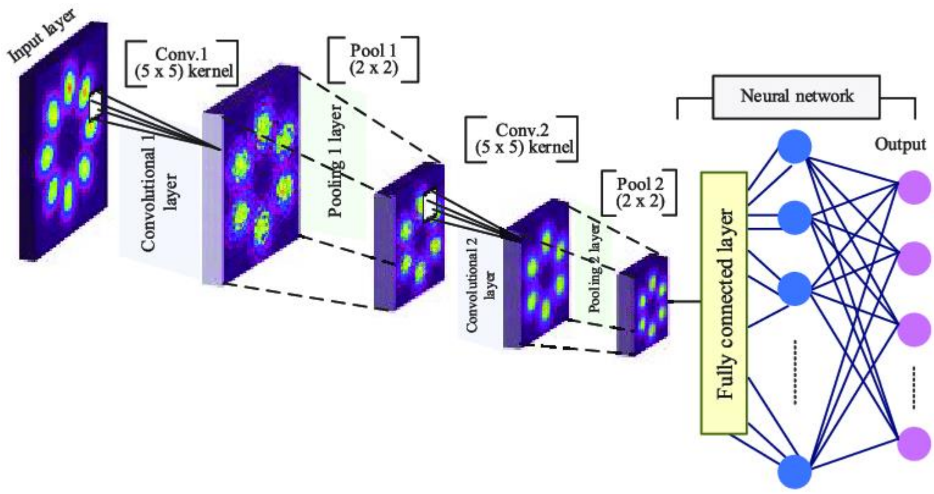
pixel-based analysis, the author of looked for problems in medical images. With the advent of medical image processing, pixel analysis was created, which uses individual values from images as input data rather than features deduced from chunks. The use of this methodology might be more successful than straightforward element based classifiers for explicit issues. Low differentiation images are trying to examine regarding their attributes. As opposed to traditional classifiers, which can keep away from botches welcomed on by inaccurate division and component computation, highlight estimation and division are not needed for pixel-based machine learning. The gigantic dimensionality of the info requires significant preparation for the pixel examination (countless pixel in an image). The creator of focused his examination on the medical images with unfortunate difference. The second best method for improving difference is histogram evening out (HE). The creators proposed a method named "Changed Histogram-Based Contrast Enhancement Using Homomorphic Filtering" (MHFIL). Its two-work dealing with process remembers histogram alteration for the initial step to work on generally contrast (G. Eli, 2021). Expectations for second stage homomorphic sifting for picture honing are likewise included. Ten low-contrast chest X-beam images from medical records are analyzed in the examination. The MH-FIL has negligible qualities in every one of the 10 photos when contrasted with different strategies. The vital obligations of radiologists incorporate the examination and production of more excellent images as well as the explanation of medical images. PC supported plan, now and then known as CAD, has extended over the long run.

Medical images are used to examine a variety of machine learning techniques, such as support vector machines, decision trees, and linear discriminant analysis. The author employed machine learning techniques for the evaluation of medical images. They utilised local binary patterns, which were heavily considered among texture descriptors, in particular. A report on recent experiments utilising a number of low binary pattern descriptors of biomedical photos is also included. Neonatal face image data set for classifying pain syndromes starting with facial descriptions. Results on the meticulously planned 2D-HeLa dataset are particularly noteworthy, as the suggested descriptor achieves the widest adoption among the different texture descriptors. On the 2D-HeLa dataset and the PAP dataset, a linear support vector machine classifier is employed. The accuracy obtained, 92.4%, is the greatest value of any other descriptor on the dataset in question. Medical photos are examined for illness features using the neural network technique (G. Litjens, 2020). For the purpose of discovering cancer, the neural network groupings are kept. It is used to criticise situations where a cell is assumed to be normal with an overly high degree of certainty and each individual network only has two possible outcomes: normal cells or cancer cells. The expectations made by the organization of these phones are consolidated utilizing a typical democratic technique called majority casting a ballot. The outcomes showed that the brain network for the most part had a high precision rate and a low worth of misleading negative examination.

The machine learning master frameworks' devices can create premises thanks to the use of patient information. Various standards are mined from the mastery of experts to develop an expert framework. A deliberate portrayal of clinical highlights that unequivocally describe the clinical circumstances for the assortment of clinical issues that might be used as models in shrewd frameworks can be created utilizing machine learning procedures. Thusly, data can be communicated as an assortment of straightforward principles or — all the more much of the time — a choice tree. The ECG interpretation program KARDIO is a notable illustration of this kind of approach. In medical image examination, a factual examination fills in as a helpful benchmark for evaluating picture credits. The channelized Hoteling onlooker (CHO) is oftentimes utilized in atomic medication imaging. The channels are energized by the possibility of amiable subjects in the human visual structure (Ghodrati, 2020). This strategy is utilized to assess the nature of the images, and the CHO impacts medical imaging. The accompanying calculation is known as a channelized SVM (CSVM). Two medical physicists surveyed the six-point certainty level of a sore's attendance right now and the perceptibility of deficiencies in 100 loud pictures.Then, 60 more pictures were utilised in a training session.The human observers successfully completed this task for six different flattening filter selections and two different OS-EM rebuilding algorithm repetition number selections.

**Figure: 2. A schematic illustration of the convolutional neural network (CNN) architecture.**




### 3.1. Types of Medical Imaging

There are many different imaging modalities, and their use is becoming more common. 30.9 million imaging tests were examined between 1996 and 2010 by Smith-Bindman et al. across six sizable integrated healthcare systems in the United States. During the duration of the study, the use of CT, MRI, and PET increased by 7.8%, 10%, and 57%, respectively. Various imaging modalities, including ultrasound, X-beam, processed tomography, attractive reverberation imaging (MRI), positron outflow tomography (PET), retinal photography, histology slides, and dermoscopy images, can be utilized to make advanced medical images. A portion of these strategies (like CT and MRI) focus on various organs, though others are organ-explicit (retinal photography, dermoscopy) (Hagan MT, 2020). The amount of information that each study produces differs. Rather than a histology slide's couple of megabytes, a solitary MRI sweep might be a few hundred megabytes enormous. This has specialized repercussions for the pre-handling of the information as well as the engineering plan of a calculation because of processor and memory limits.

### 3.2. History of medical image analysis

Initially, a rule-based system with a single task limitation was created by gradually implementing low level pixel processing and mathematical modelling for the interpretation of medical images. In a similar vein, there were undoubtedly rules governing GOFAI (Good Old

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Fashioned Artificial Intelligence) agents. In the field of medical image analysis, supervised techniques—in which models are built using training data—were becoming more and more well-liked at the end of the 1990s. The dynamic shape model and the atlas technique are two examples. Pattern recognition and machine learning are gaining traction thanks to the advent of various cutting-edge ideas. As a result, systems that were developed by people have given way to those that were taught by computers using examples from the data.

Machine learning also entails creating data-driven models to address research-related problems. Supervised learning and unsupervised learning are two subcategories of machine learning. Each example in the training set in supervised learning consists of a set of training instances, each of which consists of an input item and a desired output value.In order to assist future judgments, supervised machine learning systems give learning algorithms access to known quantities. We use input data with matching labels to train the models (J. Chen, 2020). The model is both a prediction model that is verified using test data that hasn't yet been seen by the user and a mathematical model that can link input data with the matching labels. A type of machine learning techniques called unsupervised learning is used to identify patterns in data. Since the input variables (X) for the unsupervised algorithm are not labelled, there are no matching output variables provided.

The ANN statistical technique was inspired by brain mechanisms seen in neuroscience. A typical neuron is the fundamental building block of the crucial brain system. An electrically excitable cell known as a neuron receives signals from other neurons, processes the information it receives, and then sends electrical signals to other neurons. For a specific neuron to be activated and continue transmitting a signal, the input signal must be stronger than a predetermined threshold. The neurons are linked to one another and form a network that works together to control the brain's process (J. Ker, 2021). A network of interconnected neurons with layers of nodes is an abstraction known as an artificial neural network (ANN). It has three layers: an output layer, a hidden layer used for training, and an input layer that gathers input signals from other connected neurons. Each node computes the activation function using a variety of weights before transmitting the results to the nodes in the subsequent layer. The activation function closely resembles the intricate operation of a real neuron, which controls the potency of the neural output in a non-linear way. The following equation can be used to illustrate the mathematical operations carried out in a node:

$$\mathbf{Output} = \boldsymbol{\varphi}(\mathbf{W^T x} + \mathbf{b})$$

### 3.3. Applications in Medical Image Analysis

CNNs have been scrutinized in image examination for characterization, restriction, discovery, division, and enlistment. As per concentrates on machine learning, restriction — which involves drawing a bouncing box around a lone item in the image — and identification — which involves drawing jumping boxes around various articles, some of which might have a place with unmistakable classes — are two separate cycles.Target objects are marked with outlines around their boundaries during segmentation (semantic segmentation). Registration is the process of overlaying one image, which could be two or three dimensional. This work division is upheld below and is based on various machine learning approaches. The authors contend that a viable machine learning system will join some or every one of the positions

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into one framework on the grounds that the doctor doesn't put a lot of significance on the differentiation between the undertakings (K. Kamnitsas, 2020). It would be magnificent to have a solitary work process that could perceive a lung growth on a CT chest examine, pinpoint it, separate it from neighboring solid tissue, and gauge a few treatment choices, such chemotherapy or medical procedure. A few of these obligations really do cover in the distributions we've covered.

### 3.3.1. Classification

#### 1) Image classification

Deep learning's primary purpose is the classification of medical images in order to look for clinically relevant disorders and treat patients as soon as possible. An exemplary classification might yield one demonstrative changeable, or it might require countless photos as information (sickness yes or no). In these cases, each demonstrative test is a model, and dataset sizes are much of the time more modest than in PC vision. The fine change achieved 57.6% precision rather than 53.4% exactness in the multiclass score assessment of knee osteoarthritis. Notwithstanding, the uncovered that CNN highlight recovery accomplished tweaking in cytopathology picture order precision with 70.5% versus 69.1%.

#### 2) Object classification

The discrete interest region of the medical image are the focal point of the article order. These pieces might be projected into at least two classes. For further developed precision, taking into account both the neighborhood data of these pieces and the overall calculated information is fundamental. In, the creator fixed the image at three different article scales utilizing three CNNs profound learning methods.Finally, the outcomes of these three methods mirrored the characteristics matrix of the general image qualities.

### 3.3.2. Detection: Organ and region

The phase that follows categorization is object detection and localisation. It is a crucial stage in segmentation where we may determine the significance of each object, concentrate exclusively on the objects that interest us, and ignore the noise. Deep learning techniques are utilised in a 3D data processing strategy to address this problem. Three separate groupings of 2D and 3D MRI chunks were used by the author. It is utilised to pinpoint the locations of several linked things that concentrate on certain disorders including heart, aortic arch, and descending aorta.

### 3.3.3. Segmentation

The medical images' organs and supporting components are processed using the segmentation technique. It is used to analyse clinical aspects quantitatively. Additionally, it does duties in CAD. The object of interest is made up of distinct pixels, which can be identified. The U-net combines the layer architectures of up sampling and down sampling. It combined the layer samples' convolution and de-convolution connections.

### 3.3.4. Registration

The registration process unifies various data sources into a single coordinate system. In order to offer comparison or integration of the data received from various viewpoints, times, depths, sensors, etc., it is an essential step in medical pictures. This is the iterative procedure we use to settle on a certain set of parameters as the gold standard. Using deep learning techniques, it is utilised to determine the parameters of two photos' similarity. The registration is utilised in medicine, namely with NMR and CT data. This is very useful for gathering patient data, monitoring tumour growth, confirming a cure, and comparing the patient's data with anatomical atlases. In contrast to, which is employed on breast MR pictures, mutual information collected in utilising Powell's and Brent's method to register MR, CT images is different.

#### 3.3.5. Localization

The localisation of normal anatomy may be helpful for anatomy training, but it is less likely to be of relevance to the practising clinician. Localization, on the other hand, may be helpful in fully automated end-to-end applications where the radiological image is analysed and reported without human participation. Yan et al. built a two-stage CNN from transverse CT image slices to outperform a standard CNN. Local patches were found in the first stage, which was followed by their distinction by various body organs in the second stage. Depending on the organ, hierarchical features trained across the spatial and temporal domains provided detection accuracies ranging from 62% to 79%.

## 4. Machine Learning Architectures

- **Supervised learning models**

### 4.1. Convolutional neural networks

#### A. Convolution Layer:

An operation on two functions is referred to as a convolution. In image analysis, there are two functions: a filter (kernel) and input values (such as pixel values) at specific locations in the image. Each of these functions can be represented as an array of numbers.

Convolution suggests fundamental principles for sparse connection and parameter sharing machine learning that is computationally efficient. As opposed to not many brain organizations, where each information neuron is associated with each result neuron in the following layer, CNN neurons have meager associations, showing that main a predetermined number of data sources are associated with the prevailing next layer.

The * symbol indicates that the operation is a convolution. When input 1(t) is convolved with a filter or kernel K(a), an output s(t) is defined below.

$$\mathbf{s(t) = (I * K)(t)} \quad \textbf{(1)}$$

Now, discretized convolution can be represented as follows if t can only take integer values:

$$\mathbf{s(t) = \sum I(a) \cdot K(t-a)} \quad \textbf{(2)}$$

The convolutional operation in equation (2) is one-dimensional.

With input I (m, n) and a kernel K (a, b), a two-dimensional convolution operation is expressed as:

$$\mathbf{s(t) = \sum_a \sum_b I(a, b) \cdot K(m-a, n-b)} \quad \textbf{(3)}$$

After flipping the kernel, the previous equation can be expressed as,

$$\mathbf{s(t) = \sum_a \sum_b I(m-a, n-b) \cdot K(a, b)} \quad \textbf{(4)}$$

Cross-correlation is another function that neural networks implement; it is similar to convolution but does not flip the kernel.

$$\mathbf{s(t) = \sum_a \sum_b I(m+a, n+b) \cdot K(a, b)} \quad \textbf{(5)}$$

#### B. Rectified Linear Unit (RELU) Layer:

The most well known enactment capability in profound learning models is the Rectified Linear Unit. Any regrettable information makes the capability return 0, yet any sure worth x makes it return that worth.

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Thus, it may be expressed as

$$\mathbf{f}(\mathbf{x}) = \mathbf{max}(\mathbf{0}, \mathbf{x}) \qquad \textbf{(6)}$$

Where x is the neuron's input. The leaky RELUs, sigmoid, and tanh RELUs are further activation mechanisms.

It's amazing how well your model can account for non-linearity and interactions using such a basic function (and one made up of two linear components). However, the RELU function is quite popular because it performs well in the majority of situations.

**C. Pooling Layer:**

Neighborhood or worldwide pooling layers in convolutional organizations can mix the results of neuron groups at one layer into a solitary neuron in the accompanying layer[9]. A crucial concept in CNNs is pooling, a sort of nonlinear downsampling. A variety of non-linear functions, including max pooling, can be used to implement pooling. The maximum is produced for each of the non-overlapping rectangles that are created by dividing the input image into smaller sections. The pooling layer, which also resizes the input spatially, separately processes each depth slice of the input.

In order to decrease the number of parameters that must be calculated as well as the size of the image, the Pooling layer is introduced between the Convolution and RELU layers.

**D. Fully Connected Layer:**

Through completely associated layers, each neuron in one layer can speak with each neuron in each and every other layer. It is identical to the conventional multi-facet perceptron brain network on a fundamental level. After a few convolutional and max pooling layers, the significant level thinking of the brain network utilizes completely associated layers. A completely associated layer in a customary (non-convolutional) counterfeit brain network has associations with each enactment in the layer above it. Accordingly, their enactments can be determined as a relative interpretation, network increase, and inclination offset.

### 4.2. Recurrent neural networks (RNNs)

A feed forward neural network that can handle a variable-length sequence input is a feed forward neural network extension known as a recurrent neural network (RNN). By having a recurrent hidden state whose activation at each iteration is reliant on that at the previous iteration, it manages the variable-length sequence.

Due of their ability to create text, RNNs have been utilized in text examination applications, for example, machine interpretation, discourse acknowledgment, language demonstrating, text expectation, and image subtitle blend.The general rule is that a layer can store context in "memory" by adding its output to the input that comes after it and handing it back (K. Suzuki, 2020).

In this way, to beat the issues related with disappearing angles while back spreading through time, customary RNNs have advanced into Long Short Term Memory (LSTM) organizations and Gated Recurrent Units (GRUs). These are upgrades to RNNs that empower them to neglect or dispose of a portion of the assembled input while putting away long haul reliance.

In medical image analysis, RNNs have primarily been used for segmentation. CNN and RNN have been used to distinguish between fungal and neural structures in three-dimensional electron microscope images.

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## 5. Conclusion

In recent years, machine learning expertise has increased. Machine learning techniques are currently incredibly adaptable to real-world situations, and the structures actually benefit from the learning process. It has previously been relevant to the practise of medical imaging, and it may develop quickly in the near future. Machine learning in medical imaging has significant implications for the treatment. The fact that this field of study guarantees better patient care is highly important. The capabilities of machine learning tools are crucial to demonstrating that they are used in the most effective manner. Deep learning techniques aid in categorising, classifying, and enumerating illness patterns from image processing in medical image analysis. Additionally, it enables the expansion of analytical objectives and produces patient treatment prediction models. Researchers studying medical imaging are taking these issues into account (Sasikanth, 2021). Deep learning in the field of health care research is also being considered. Like many other applications of deep learning outside of healthcare, it is advancing quickly. Machine learning techniques have demonstrated impressive performance in non-medical regular imaging research compared to standard machine learning techniques, thus medical image processing will greatly benefit from them. We have provided a brief overview of the transition from classical machine learning to deep learning in this article. We have also highlighted some deep learning applications in medical imaging and come to a conclusion with some disadvantages and future expectations for deep learning in this field.

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