Chapter 2

A REVIEW OF BACKGROUND KNOWLEDGE
2.1 INTRODUCTION

In the medical sciences the various sources are there for getting the medical images for the diagnosis purpose of the human being, mainly MR imaging technique is an advanced technology of getting medical pictures of the human being which gives important information about the human soft tissue anatomy. It has number of benefits over other imaging techniques allowing it to provide 3D data with high contrast amongst soft tissues. However, the amount of information or data is huge for manual analysis or manual interpretation, and this is the major difficulties in the active use of MRI. For this cause, automatic or semi-automatic methods of image analysis in the computer environment are very important tasks. Identifying and discriminating the gray matter, white matter and CSF in to different classes of tissue of MR images is a significant task.

Yongyue Zhang et.al., (2001) demonstrated that brain MR scans have several characteristics, particularly the following: Firstly, they are normally simple in the statistics : MR Images are hypothetically piecewise constant with a minor number of classes. Second, they can have relatively high contrast between different tissues. Contrasting to the various other medical image acquiring techniques, the contrast in an MR image based strongly upon the way the image is captured. By altering the parameters like radio-frequency and gradient pulses, and by sensibly selecting relaxation timings, it is conceivable to focus various components in the entity being pursued and generate images with high contrast. These two features enable segmentation. In the different manner, ultimate imaging conditions are never considered in actual implementation. The piecewise-constant feature is decreased noticeably by electronic noise, the bias field (intensity in-homogeneities in the RF field) and the partial-volume effect, all these properties are the key reason using what the classes fall to overlay in the image intensity histogram. Furthermore, MR scans are not always having the high contrast. Many -weighted and PD images have small contrast between Gray and White Matter. Hence, it is important to take the benefit of beneficial data whereas at the similar period overwhelming probable complications (7).
2.2 REVIEW OF BRAIN TUMOR SEGMENTATION TECHNIQUES

Yan Li and his research subordinates (2005) have given several typical MR scans identification means segmentation approaches, these are as follows:

1. Threshold techniques: In which classification of every pixel based on its own physical characteristics such as intensity and color information. These methods are effective when the histograms of objects and background are clearly detached.

2. Edge-based methods are used to deliberate on detecting contour. They never work when the image is blurry or too complex to classify a given border.

3. Segmentation based on Regions: It is the perception of mining characteristics (related texture, intensity stages, and sharpness) from a pixel and its nearby pixels is implemented to originate relevant information for every pixel.

4. Cooperative hierarchical approach: In which it uses specific structures to link the image features to an array of master nodes, choosing iteratively the point that average or link to a certain image value.

5. Statistical approaches: This kind of method associates pixels according to probability values, which are calculated depends on the intensity distribution of the image. With an appropriate hypothesis about the distribution, statistical techniques used to resolve the problem of predicting the associated class label, given only the intensity for each pixel. Such a prediction problem is inevitably expressed from a documented condition.

6. ANN image segmentation techniques: invented from clustering procedures and pattern identification approaches. They typical goal is to develop unsupervised segmentation algorithms.

Sometimes, the above techniques and methods are overlapped and can be combined (8).
### Table 2.1: Noticeable Scholars in the area of Brain cancer Segmentation

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Year</th>
<th>Researcher</th>
<th>Research</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2007</td>
<td>Xiao Xuan</td>
<td>MRI Brain Tumor Segmentation using SSA.</td>
</tr>
<tr>
<td>2</td>
<td>2005</td>
<td>Shan Shen</td>
<td>MRI FS of Brain Tissue Using NN Optimization</td>
</tr>
<tr>
<td>3</td>
<td>2009</td>
<td>Tao Wang</td>
<td>FVF and Applications in Tumor Segmentation.</td>
</tr>
<tr>
<td>4</td>
<td>2012</td>
<td>Andac Hamamci</td>
<td>Tumor-Cut: Segmentation of Brain Tumors on CE MR scans.</td>
</tr>
<tr>
<td>5</td>
<td>2011</td>
<td>Shaheen Ahmed</td>
<td>Efficiency of Texture, Shape, and Intensity Merging for Tumor Segmentation.</td>
</tr>
<tr>
<td>6</td>
<td>2001</td>
<td>Yongyue Zhang</td>
<td>HMM and the Expectation-Maximization Algorithm for MR scan Segmentation.</td>
</tr>
<tr>
<td>7</td>
<td>1997</td>
<td>Javad Alirezaie</td>
<td>NN based Segmentation of MRI of the Brain.</td>
</tr>
<tr>
<td>8</td>
<td>2007</td>
<td>Su ruan</td>
<td>Tumor Segmentation from MR scans by SVM classification.</td>
</tr>
<tr>
<td>9</td>
<td>2007</td>
<td>Herng-Hua Chang</td>
<td>Segmentation of Brain MR scans Using a CFM.</td>
</tr>
<tr>
<td>10</td>
<td>2000</td>
<td>Yutaka Hata</td>
<td>Automated Segmentation of MR scans Aided by FIG and FI.</td>
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Xiao Xuan and Qingmin Liao (2007) in their research paper entitled “Statistical Structure Analysis in MRI Brain Tumor Segmentation”, which emphases on the fundamental analysis of structure of both tumor affected and non tumor affected MR scans. They worked on 3 varieties of features; these features are based on intensity, symmetry and texture. These features are discovered from structural elements. Then for the classification purpose they used AdaBoost technique that learns by picking the best discriminative features that can classify the structural elements into not affected and affected tissues. They done the experiment on 140 tumors affected MR brain scans which gives segmentation average accuracy of 96.82% (9).

Shan Shen et.al. (2005) in their paper entitled “MRI Fuzzy Segmentation of Brain Tissue Using Neighborhood Attraction with Neural-Network Optimization”, in which they have demonstrated a robust technique of the segmentation which is the revision to the old fuzzy c means clustering algorithm. A nearby attraction of the pixels, which is constructed on the comparative position and characteristics of the nearby pixels, is revealed to upturn the performance of the segmentation. The grade of fascination is enhanced by a NN model. Virtual and practical brain MR scans with different noise levels are segmented to demonstrate the dominance of the projected technique matched to other FCM based methods. Currently this method used for the segmentation is one the most useful techniques in MR scans analysis (10).

Tao Wang et.al. (2009) in their research paper entitled “Fluid Vector Flow and Applications in Brain Tumor Segmentation”, they used fluid vector flow active contour model to report difficulties of insufficient capturing scope and low merging for concavities. With the capability to capture a big scope and extract concave shapes, FVF validates enhancements over techniques like gradient vector flow, boundary vector flow, and magneto static active contour on three types of the practical approach like: synthetic, pediatric head MR scans, and brain tumor MR scans from the Internet Brain Segmentation Repository (11).

Andac Hamamci et.al. (2012) in their research paper “Tumor-Cut: Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications”, they demonstrate a firm and strong practical tool for segmentation of dense tumors with low user interaction to support doctors and scholars in radiosurgery planning and valuation of the reply to the treatment. Mainly, Cellular-Automata constructed seeded
tumor segmentation technique on contrast improved T1 weighted MR scans, which regulates the volume of interest and seed choice is planned. First, they interconnected the CA constructed segmentation to the graph-theoretic technique to display that the iterative CA framework resolves the optimal route problem. In that respect, they change the state conversion function of the CA to calculate the exact optimal route solution. Additionally, a parameter entitled sensitivity is accessible to adjust to the varied tumor segmentation problematic, and an implicit level set surface is developed on a tumor likelihood map assembled from CA states to execute spatial smoothness. Adequate information to initiate the algorithm is collected from the operator simply by a drawing a line on the maximum diameter of the tumor, adjacent with the clinical practice (12).

**Shaheen ahamd et.al. (2011)** in their research paper titled “Efficiency of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI”, they carefully observe efficiency of numerous varied image features such as intensity, texture, and structure of level-set in segmentation of posterior-fossa abnormal tissue progression for patients. They explained the significance of using 4 different selection procedure for the features and 3 different methods for the segmentation, respectively, to discriminate the unusual area from ordinary tissue in multi-modal brain MRI. They did the additional revision for selective mixture of these individualities for the upgrading in PF tumor segmentation (13).

**Yongyue Zhang et.al. (2001)** in their research paper titled “Brain MR Image segmentation through a HMRFM and the Expectation-Maximization Algorithm”, in which they demonstrated a new model established on hidden Markov random field model, which is a probabilistic process formed by a MRF whose formal structure cannot be noticed directly but which can be indirectly evaluated through observations. Arithmetically, it can be presented that the FM model is a debased form of the HMRF model. The advantage of this model invents from the way in which the multidimensional data is prearranged through the joint effects of adjacent sites. Although MRF modeling has been active in MR scan segmentation by other researchers, most stated methods are insufficient to using MRF as a general prior in an FM typical based method. EM algorithm is used to initiate the HMRF model. They indicate that by joining HMRF model and the EM algorithm into a HMRF-EM frame, correct and healthy results can be achieved (14).
Alirezaie et al. (1997) in their research paper titled “Neural Network-Based Segmentation of Magnetic Resonance Images of the Brain”, they describe the study of inspecting the importance of artificial NN for the discrimination and segmenting MR scans of the brain of the human beings. In this research study, they demonstrate the use of a learning vector quantization (LVQ) ANN for the multi-spectral supervised discrimination of MR scans. They made some changes to the LVQ for better and more correct classification. They have compared the results using LVQ ANN versus back-propagation ANN. This valuation indicates that, conflicting back-propagation ANN, their method is unresponsive to the gray-level dissimilarity of MR scans between different scans. It expresses that segmenting tissue using LVQ ANN also does improved and quicker task than that using back-propagation neural network algorithms (15).

Su ruan et al. (2007) in their paper titled “Tumor Segmentation from a Multispectral MRI Images by using SVM classification”, they demonstrate a supervised system goaled at capturing the volume of the tumor part during a healing treatment from multi-spectral MRI volumes. They have used 4 different types of MRI in their study: PD, FLAIR, T1 and T2. For dropping the execution time, the said method implements a multi-scale pattern to recognize initially the irregular field and remove the abnormal region. SVM is used for both the phases. At the commencement of the treatment the training is conducted only on the initial MRI examination. The tracing process at the time-point t proceed the abnormal region got in the examination at t-1 as its initial phase. Only the other step is implemented for next examinations to remove the abnormal region. The output got show that the given system attains favorable results in relations with effectiveness and time consummating (16).

Herng-Hua Chang (2007) in their paper titled “Segmentation of Brain MR Images Using a Charged Fluid Model”, they developed a novel model, CFM that practices the replication of a charged-fluid to isolate anatomic structures in MR scans of the brain. Theoretically, the charged fluid acts similar to fluid such as it runs from side to side and around different hurdles. The replication progresses in two phases ruled by Poisson’s equation. In the first phase, it issues the components of the charged liquid within the circulating interface until an electrostatic equilibrium is attained. The second stage spreads the circulating front of the charged fluid such that it deforms into a new outline in reply to the image gradient. This approach don’t need the information
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of anatomic structures, it requires only one parameter that is sub-pixel precision in the region of interest. They demonstrated the importance of this novel procedure to segment the anatomic structures on replicated and factual brain MR scan of various matters. The investigational outputs in dissimilar types of MR scans specify that the CFM procedure attains good results of segmentation and is of prospective importance in brain image processing uses (17).

Yutaka Hata et.al. (2000) in their research paper titled “Automated Segmentation of Human Brain MR Images Aided by Fuzzy Information Granulation and Fuzzy Inference”, in which they recommends an automatic method for segmenting an MR scans of a human brain established on fuzzy logic. An MR volumetric image collected of many slices contains several parts: gray matter, white matter, cerebrospinal fluid, and others. Normally, the histogram contours of MR volumetric pictures are diverse from person to person. Fuzzy truths granulation of the histograms can proceed to a sequence of histogram crests. The intensity thresholds for segmenting the complete brain of a object are mechanically resolute by outcomes of the peaks of the intensity histogram got from the MR scans. After these thresholds are assessed by a process called region growing, the complete brain can be detected. The experiment was done on 50 human brain MR volumes. A statistical investigation presented that the automated segmented volumes were parallel to the volumes physically segmented by a physician (18).

2.3 REVIEW ON BRAIN TUMOR CLASSIFICATION TECHNIQUES

Brain tumor discrimination is very significant step in the medical sciences. The images gathered from various equipment’s such as CT, MR that should be tested by the surgeon for the advance action, but the physical discrimination of the MR scans is the stimulating and time unbearable task.
### Table 02.2: Noticeable Scholars in the area of MR Brain cancer Discrimination

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Year</th>
<th>Researcher</th>
<th>Research</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>2013</td>
<td>Marlene Huml</td>
<td>Brain Tumor discrimination Using AFM &amp; DM Methods.</td>
</tr>
<tr>
<td>2</td>
<td>2013</td>
<td>A. Jayachandran</td>
<td>Tumor identification and discrimination of MR scans Using Texture Features &amp; FSVM.</td>
</tr>
<tr>
<td>3</td>
<td>2012</td>
<td>Paulene John</td>
<td>Tumor discrimination Using Wavelet and Texture Based NN.</td>
</tr>
<tr>
<td>5</td>
<td>2011</td>
<td>Yi-hui Liu et.al.</td>
<td>Classification cancer scans Based on GWA.</td>
</tr>
<tr>
<td>6</td>
<td>2008</td>
<td>Simon Duchesne</td>
<td>MRI-Based Automatic system discrimination of Likely AD Against Usual Controls.</td>
</tr>
<tr>
<td>8</td>
<td>2013</td>
<td>Behnood Gholami</td>
<td>Tumor-Type Credentials in Surgical Neuropathology Using Tissue Mass Spectrometry Imaging.</td>
</tr>
<tr>
<td>10</td>
<td>2011</td>
<td>M. G. Kounelakis</td>
<td>Strengths and Weaknesses of 1.5T and 3T MRS Data in Glioma Classification.</td>
</tr>
<tr>
<td>11</td>
<td>2011</td>
<td>A. Padma</td>
<td>Automatic discrimination of Brain Cancer in CT scans using Gray level Run length Features.</td>
</tr>
</tbody>
</table>
Marlene Huml et al. (2013), in their research paper titled “Brain Tumor Classification Using AFM in Combination with Data Mining Techniques”, they have projected a procedure established on AFM resulting pictures made from histopathological examples in mixture with the data mining methods. By associating AFM pictures with matching light microscopy pictures of the similar area, the advanced development of hollows due to cell necrosis was recognized as a distinctive morphological marker for a computer-assisted study. Using genetic software design as a tool for feature study, a finest method was formed that attained 94.74% discrimination accurateness in discriminating grade II tumors from grade IV. Whereas operating recent image analysis methods, AFM may happened as an significant apparatus in astrocytic tumor identification. By this way patients getting pain from grade II tumors are recognized unmistakably, having a less danger for malignant alteration. They would help from early adjuvant therapies (19).

A. Jayachndran et al. (2013), in their research paper titled “Brain Tumor Detection and Classification of MR Images Using Texture Features and Fuzzy SVM Classifier”, they have given a merging procedure for finding brain tumor in MR scans using statistical features and FSVM classifier. Tumors are not detected early and healed properly so they will become the reason for perpetual brain damage or death to patients. Tumor location and dimension are significant for effective treatment. The projected method contains of 4 steps namely, Noise decrement, Feature removal, Feature decrease and discrimination. In the first step by using anisotropic filter the MR scans are made ready for removing the features. In the second step, obtains the texture characteristics related to MR scans. In the third step, the features of MR scans have been reduced using principles component analysis to the most essential features. At the last stage, the Superior classifier based FSVM has been used to discriminate subjects as normal and abnormal brain MR scans. It classifies this with accuracy 95.80% .The output shows that the projected method is robust and effective compared with other recent works (20).

A. Pdma et al. (2011), in their research paper titled “Automatic Classification and Segmentation of Brain Tumor in CT Images using Optimal Dominant Gray level Run length Texture Features”, they explained about the projected method in which SVM
is used for the discrimination purpose from the CT scans using the appropriate segmentation procedure. The main intention of their work is to distinguish amongst various feature extractions techniques like dominant grey level run length method, wavelet based texture technique and SGLDM technique. ROI in the image from where the dominant gray level run length textural features are taken. Genetic Algorithm is utilized to select the appropriate textural features. The particular ideal run length texture features are feed to the SVM classifier to discriminate and segmenting abnormal area from brain CT images. The regular exactness for the segmenting and the discrimination in the given technique is 97.0% (21).

AmirEhsan Lashkari (2010) in his research paper titled “A Neural Network-Based Method for Brain Abnormality Detection in MR Images Using Zernike Moments and Geometric Moments”, he has presented instinctive brain abnormal part identification technique to upturn the accurateness and reduce the analysis time. The objective is discriminating the tissues into two types of the class, first is normal and another is abnormal. MR scans that have been utilized at this juncture are MR scans from normal and abnormal brain tissues. Here, it is practiced to specify clear information from brain tissues using Zernike Moments, and some other basic statistical features such as mean, median, variance and correlation, values of maximum and minimum intensity. Feature selection method are also used to reduce the scope of the features. This method uses NN for the discrimination purpose. The purpose of this project is to discriminate the brain tissues to normal and abnormal classes mechanically, that saves the time and increases the performance of the diagnosis (22).

Pauline John (2012) in his research paper entitled “Brain Tumor Classification Using Wavelet and Texture Based Neural Network”, he introduces an effectual method for the brain tumor discrimination, where, the actual MR scans are discriminated into normal, non cancerous (benign) brain tumor and cancerous (malignant) brain tumor. The projected method considers three steps, [1] wavelet decomposition, [2] texture feature removal and [3] classification. To decompose the MR scan into various stages of fairly accurate and complete coefficient, discrete wavelet transform is first implemented and then the gray level co-occurrence matrix is created, from which the textural statistics such as energy, contrast, correlation, homogeneity and entropy are got. The outputs of co-occurrence matrices are then used to train the neural network for further discrimination and tumor identification.
The projected method has been applied on real MR scans, and got the best accuracy of classification using probabilistic neural network (23).

Yi-hu Liu et.al. (2011), in their research paper entitled “Classification of MR Tumor Images Based on Gabor Wavelet Analysis”, they experimented the feature extraction using Gabor wavelet of MR cancerous images to distinguish amongst primary central nervous system lymphoma (PCNSL) and glioblastoma multiforme (GBM). Gabor wavelet transform with 8 orientations and numerous frequencies is accomplished on contrast-enhanced T1-weighted MR scans to retrieve the classified features, including tumor outline information. A discrimination model is designed rest on the retrieved features. Investigational effort shows that the projected hybrid technique, which applies wavelet analysis, Gabor wavelet analysis, SVM, and LDA, can separate diverse diagnosis types of cancerous images (24).

Simon Duchsne et.al. (2008), in their research paper entitled “MRI-Based Automated Computer Classification of Probable AD Versus Normal Controls”, in which the accurateness of their ACC practice is measured when offered with actual lifetime, unsatisfactory data, i.e., cohorts of MR scan with various gathering parameters and imaging superiority. The relative technique uses the Jacobian determinants came from dense deformation fields and scaled grey-level intensity from a chosen volume of interest centered on the clinical chronological part. The ACC performance is measured in a sequence of leave-one-out experimentations intended at isolating 75 probable AD and 75 age-matched normal controls. The actual output accurateness is 92% using a SVM based on least squares optimization. Lastly, it is presented that determinants and scaled grey-level intensity are noticeably healthier to changing factors in validation studies using replicated data, when associated to raw volumes. The capability of cross-sectional MRI at perceiving probable AD with high accurateness could have thoughtful inferences in the managing suspected AD contenders (25).

Omar Al-Kadi et.al. (2008), in their research paper entitled “Texture Analysis of Aggressive and Nonaggressive Lung Tumor CE CT Images”, they presented prospective for fractal study of time series contrast-enhanced computed tomography images to distinguish amongst violent and nonviolent malignant lung cancer. The objective is to improve CT tumor enactment forecast accurateness through realizing
malignant aggressiveness of lung tumors. As splitting of blood vessels can be calculated by a fractal process, the investigation inspects vascularized cancer areas that display tough fractal features. The study is done after introducing 15 patients with a contrast agent and converting at least 11 time sequence CE CT pictures from every patient to the fractal dimension and defining matching lacunarity. The fractal textural characteristics were counted over the cancer area and quantitative discrimination given up to 83.3% accurateness in difference amongst violent and early-stage (nonviolent) malignant cancers. Also, it presented solid correlation with matching lung cancer phase and consistent cancer uptake value of fluorodeoxyglucose as resolute by PET. These outcomes specify that analysis of time series CE CT images of lung cancers could deliver additional data about likely cancer aggression that could possibly add the influence on decisions in choosing the appropriate treatment procedure (26).

Leena Gorelik *et al.* (2013), in their research paper entitled “Prostate Histopathology: Learning Tissue Component Histograms for Cancer Detection and Classification”, they describe and evaluate their scheme for involuntary prostate tumor identification and grading on eosin-stained flesh pictures. Their method is envisioned to express the double encounters of large data size and the essential for high-level tissue data about the localities and grades of cancers. Their scheme uses 2 phases of AdaBoost-based discrimination. The first gives high-level tissue component category of a super-pixel image division. The second uses the tissue component category to give a discrimination of cancer versus non-cancer, and low versus high grade cancer. They calculated their method using 991 scans mined from digital pathology scans of 50 tissue parts from 15 prostatectomy patients. They calculated accuracies of 90% and 85% for the tumor versus non-tumor and high versus low-grade discrimination tasks, respectively (27).

M. G. Kouneliks *et al.* (2011), in their research paper entitled “Strengths and Weaknesses of 1.5T and 3T MRS Data in Brain Glioma Classification”, they developed the technique in which main three steps they have included, in the first step they have used the scanners of 1.5T & 3T for the retrieving the finding information of the treatment in consideration with the glioma cancer classification. In the second step and final step they calculated the public known distinguishing markers of the metabolic ratio that is retrieved from these two scanners to discriminate the low, high
and intermediate glioma cancer, which is a very tedious job. Their experimental outcomes demonstrate that the information they are getting from the 3T MRS scanners gives the better result for the discrimination purpose. Features like pulse-sequence and the spectroscopic data retrieving methods can impact the judgment efficacy (28).

Behnod Gholmi et.al. (2013), in their research paper entitled “a Statistical Modeling Approach for Tumor-Type Identification in Surgical Neuropathology Using Tissue Mass Spectrometry Imaging”, in which they have given a technique for histopathological computer assisted assessment using mass spectrometry imaging. Specifically, this imaging technique can be utilized to gather the chemical structure of a tissue section and, hence, provides a outline to focus the molecular structure of the sample while preserving the morphological characteristics in the tissue. The projected discrimination structure applies statistical modeling to recognize the cancer type related with a given object. In addition, if the cancer type for a given tissue object is unidentified or there is a inordinate grade of doubt related with conveying the cancer type to one of the known cancer models, then the procedure refuse the provided object without discrimination. In line for to the modular nature of the projected structure, new cancer replicas can be included without keeping all existing models (29).

D. Judee Hemnth et.al. (2010), in their research paper entitled “Application of Neuro-Fuzzy Model for MR Brain Tumor Image Classification”, they presented the technique which completely based on the fuzzy inference system namely adaptive neuro-fuzzy inference system for the MR scan cancer discrimination. Cancer affected MR scans are divided in four different classes such as metastase, meningioma, glioma and astrocytoma are used for the experimental work. The perfect characters set and the fuzzy-based rules are chosen for the discriminating the abnormal area of the specific type. The actual result of the experiment demonstrates the outstanding results in consideration with the discrimination accurateness. A comparison is done with the existing ANN and fuzzy systems to express the powerful nature of ANFIS systems (30).
2.4 ANN APPROACHES FOR CLASSIFICATION PROBLEM

2.4.1 Introduction

Neural networks were discovered fifty years ago. Their early capabilities were overstated, molding misgivings on the field, as a entire there is a new transformed attention in the field, however, because of new methods and a improved hypothetical thoughts of their abilities (31).

The replication of man intellect using machineries was and is continuously a challenge to inventiveness. In the century mid an innovative discipline describing itself Artificial Intelligence (AI) arised. The meaning for the term AI is very unclear; this has its main reason in the point that there can not be usually conventional meaning for 'intelligence'. The most complete description for AI includes all research aimed to put on brainy actions.

Notwithstanding the obtainability of huge computational control the outcomes of present investigation are far from the objectives projected in the eagerness of the 1950's and 60's. Nonetheless methods constructed to pretend intellect in a limited domain, such as expert systems in medication or predicting applications are already positively applied (31, 32).

ANN can be utilized in the following fields:

- Signal processing: overwhelm line sound, with adaptive echo canceling, separation of the blind source.
- Control: e.g. engineering mechanism for controlling mechanical machines.
- NN for process automation in basic industries, e.g., in continuing mill controller controls more than 100 NN do their task, 24 hours a day.
- Robotics - direction finding, visualization recognition.
- Pattern recognition- i.e. all applications related to the biometric authentication.
- Medicine, i.e. keeping medicinal chronicles grounded on instance facts
- Medical Image Analysis.
- Speech reproduction: reading text aloud.
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- Speech recognition.
- Visualization: facial expression identification, outline detection, and graphic search engines.

2.4.2 Artificial neuron Model

ANN, inspired by human biological neural system, is a immensely similar structure self-possessed of many working components, called as neurons, associated with one another through weights. The processing nodes used in neural net models are nonlinear, typically analog, and may be slow compared to modern digital circuitry. The simplest non-fuzzy node that adds n weighted inputs and transfer the result through nonlinearity as illustrated in the below Figure 2.1. The nodes are characterized by an internal threshold \( T \) and by the kind of non-linearity (33).

Two basic kinds of non-linearity’s used with computational node are; hard limiters and sigmoidal non-linearity’s. Other complicated nodes may contain different time realizing and more confusing arithmetic’s than simple addition. The result of the neuron is presented by the next equation.

\[
o = f^1 \left( \sum_{i=1}^{n} w_i x_i \right)
\]

(2.1)

\[
o = f^1 W^T X
\]

(2.2)

Where \( w \) is the weight vector defined as \( w=[w_1, w_2, \ldots w_n]^T \) and \( x \) is the input vector defined as \( x=[x_1, x_2, \ldots x_n]^T \), and \( f^1(\cdot) \) is some non-linear activation function. The maximum extensively utilized is sigmoidal equation given by:

\[
f^1(\text{net}) = \frac{1 - e^{-g \text{net}}}{1 + e^{-g \text{net}}}
\]

(2.3)
Where $g_1$ is the parameter which controls the slope of the sigmoidal function and the variable $\text{net}$ is defined as the scalar product of the weight and the input vector as $\text{net} = w^T x$.

The threshold value is not explicitly used in (2.1). It is assumed that the modeled neuron has $n-1$ actual inputs that come from actual variable inputs $x_1, x_2, \ldots, x_{n-1}$. The study has also assumed that $x_n = -1$ and $w_n = T$, where $T$ is a threshold.

2.4.3 Learning scheme: Adapting the knowledge base

Neural network arrangements experience a training process accordingly the related weights are familiarized. The procedures for changing these connection powers are called as learning rules (34). The main intention of learning rule built on the applications. For example, the objective in object analysis is to discriminate sample data and estimate effectively on new data. In pattern recognition, each sequence of presentation of all sample patterns is usually referred as learning epoch. However, no generalization as to how NN can be adapted. The DFD for the learning algorithms implemented in diverse neural arrangements to adapt synaptic weights is given in Figure. 2.2. As given in the figure, the learning algorithms may be approximately considered as error-based and output based (35).
Figure 2.2: A flow diagram of learning algorithms

Error-based which is also predicted as supervised learning implements an exterior orientation signal and produce an error signal by associating the orientation with the obtained reply. Based on error signal, neural network adapts its synaptic links to recover the system valuation. In this learning it is expected that anticipated response is recognized a priori. The error-based learning procedure is schematically given in Figure 2.3. A general equation for the error-based learning algorithm is

\[ w_i(t + 1) = w_i(t) + \Delta w_i(t) \]  \hspace{1cm} (2.4)

Where

\[ \Delta w_i(t) = \mu x_i(t) [o_d(t) - o(t)] \]  \hspace{1cm} (2.5)

and \( w_i(t) \) is the synaptic weight conforming to the input \( x_i(t) \). The parameter \( \Delta w_i(t) \) is the alteration in synaptic connection \( w_i(t) \) over an instant in time, \( \mu \) is the learning degree, \( o_d(t) \) is the desired neural output and \( o(t) \) is the actual neural response.

The proper selection of \( \mu \) is of acute reputation in these learning rules. A very small value of \( \mu \) will result in extremely slow learning. Besides this, a large value of \( \mu \) will make learning faster, but it may also result in oscillations or make the system unstable.
In reverse, learning algorithms which are having the outputs, do not include a orientation signal and usually contain self-organization ideologies that depend on only upon local facts and interior control procedures in direction to identify developing shared belongings. The 2 maximum important types of output-based learning are Hebbian and competitive learning. A Hebbian learning given in Figure. 2.4 contains the modification of the synaptic weight rendering to correlation of the input \( x_i(t) \) with the neuron’s output reply \( o(t) \). A simple Hebbian learning rule applied is

\[
\Delta w_i(t) = \mu x_i(t) o(t) \tag{2.6}
\]

Where \( \Delta w_i(t) \) signifies the chronological alteration of the synaptic weight \( w_i(t) \) and \( \mu \) is the learning degree. We can spread these fundamentals learning rules to fuzzy neuron also.
NN representations are detailed by the net structure, nodule characteristics, and learning procedures. These procedures express an earlier set of weights and specify how weights should be adjusted while training to recover performance. Nomenclature of six significant NN that can be used for discrimination of statistical patterns (36, 37, 38).

2.4.4 Linear Separability and Non-linear Separability

![Figure 2.4: An output-based (unsupervised) learning scheme](image)

![Figure 2.5: (a) Linear Separability (b) Non-Linear Separability](image)
The 2 types are therefore parted by the ‘decision' line as given in the figure 2.5 (a) which is expressed by placing the activation equivalent to the threshold. It goes out that it is likely to simplify this effect to TLUs with n inputs in 3-D the 2 types are separated by a decision-plane. In n-D this becomes a decision-hyperplane. The contrast of this is that, any TLU is expressed by some hyper-plane in its pattern space and any function that cannot be understood in this way cannot be understood by a TLU. Since the essential equation for the hyper plane is linear, the TLU is a linear discriminator. Applying some ideas about vectors, it is likely to prove these outcomes. The 2 layer network was initially presented in the context of discriminating more than 2 classes. Deliberate now, the subsequent state in pattern space. The 2 classes A and B cannot be detached by a single hyper-plane. In overall we need an arbitrarily shaped decision surface. In the figure, the study has approached this surface by two planes. We may now built a two layer net to solve this problem. Each plane is resolute by one of a pair of hidden nodes. Supposing each of these nodes trained to signal a ‘1’ for class A. The output node can currently discriminate A as a ‘1’ if it trains the OR function.