



Comparative Study of Machine Learning Techniques in the Medical Field

Sharmila Gaikwad¹; Saarah Patel²; Ajinkya Shetty³

Department of Computer Engineering, MCT's Rajiv Gandhi Institute of Technology, Mumbai, India

¹sharmila.gaikwad@mctrgit.ac.in; ²sarahpatel786@gmail.com; ³ajinkya.shetty10@gmail.com

DOI: 10.47760/ijcsmc.2020.v09i12.008

Abstract— *In the ever-advancing field of technology, Artificial Intelligence (AI) has become an important part of our day to day lives. It has demonstrated to improve the efficiencies of working environments thus reducing human effort. In decision making-problems, AI plays a major role in providing useful outcomes but adopting one out of several methods for achieving better results is a rigorous task. The objective of this paper is to understand the various techniques that have contributed in the rising growth of studies using AI and its subfields like Machine Learning and Image Processing especially in the medical field. Machine Learning algorithms have shown impressive accuracies and sensitivity in the recognizable proof of imaging abnormalities. A study on different proposed methodologies involving various algorithms for the stages involved along with their preferences and downsides which can help in the determination and appropriation of the methods later on have been discussed.*

Keywords— *Artificial Intelligence, Machine Learning, Deep Learning, Image Processing, Medical field*

I. INTRODUCTION

Artificial Intelligence is a part of science and technology which helps machines discover answers for complex issues. Artificial intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs [23]. The recent years of statistics have witnessed an increased research interest in interaction and intelligent computing [22]. Over the years, Artificial Intelligence has been widely used in the different fields of Engineering, Stock Market, Medicine, Education, etc. Due to this, a lot of time and manpower has been saved. In a recent ad launched by Cadbury which is India's first hyper-personalized ad, AI used around 260+ different pin codes to detect the nearest local stores. The ad was made in such a way that every part of the country saw a different and personalized ad based on their location. This ad helped over 1800 local retailers from different cities to increase customer footfall. AI has now become an important topic globally because of its wide contribution in its subfield of Machine Learning, Image Processing, Natural Language Processing and Data Mining. Machine Learning is one of the most active areas in AI because the machine is trained and learns from its past experiences. The primary focus of ML is to develop various programs in the computer that can change when presented to extensive sets of data and are categorized as Supervised Learning, Unsupervised Learning & Reinforcement Learning. It focuses on algorithms that are worked through which input is taken and output value is predicted after statistical analysis. Machine learning is helping change the world in all segments including transport, entertainment, healthcare, education, housing and many more. Deep Learning, a subset of Machine Learning are multi-level representation-learning methods, obtained by making simple but non-linear modules that each change the representation at one level into one at a higher level and with its help, very complex functions can be learned. Deep learning is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for many years [24]. Another subfield of AI is

Digital Image processing which is a technique used to perform operations on an image to get an enhanced image or to extract some specific features from it. Image processing is one of the most rapidly growing technologies used for tasks like scaling, color conversion, image enhancement, segmentation, image sharpening, etc. The basic steps of image processing are as given below in figure 1.

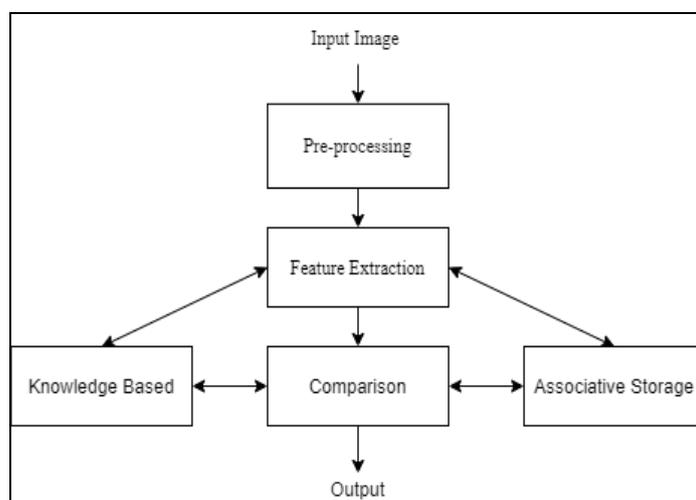


Figure 1. Digital image processing system

II. LITERATURE REVIEW

G. Gupta and V. Singh [1] proposed a strategy which was a combination of fuzzy C means (FCM) used for segmentation and support vector machine (SVM). Segmentation is a process of extracting suspicious areas from the image. SVM, which is a supervised learning technique depending on the decision planes which differentiates two classes, was used in the classification process. These classes were defined as $+1$ and -1 and in order to divide them, the maximum margin was obtained by minimizing the weights. The performance was calculated based on the formulae of true positive, true negative along with false positive & false negative. Before undergoing the segmentation process, the MRI images were improved by increasing the brightness, contrast stretching i.e. converting the RGB images into gray scale, mid-range stretching, where the center intensity of the images were stretched, they were mapped between the values 0 and 1 and by using a function they were converted to indexed images in order to enhance the images. After this, skull stripping technique was used where the methods, such as, double thresholding which converts image from gray scale to binary, Erosion where the unwanted pixels are removed from the image, region filling in which the holes generated due to erosion were filled back. After segmenting the images, feature extraction in which the related features are searched from the image by transforming the image into a compressed form was used. For this, a second level maximum frequency sub bands of the discrete wavelet decomposed picture was obtained using the gray level run length matrix (GLRM). After which, classification was done. However, this paper doesn't explain in depth about FCM clustering. Also, the mentioned results obtained on Linear and RBF kernels which are 91.77% and 90.01% respectively, doesn't justify the differences. Also, a smaller data set was used which consisted of just 124 images taken from different sources.

Z. Ahmad and S. Gul [2] proposed a system for classifying MRI images into tumorous and non-tumorous by evaluating different supervised learning techniques such as SVM, k-NN and ANN. This paper focuses more on pre-processing, morphological processing, segmentation and feature extraction. In order to remove noise from the images, the images were converted to gray scale and a Gaussian filter was applied along with Sobel edge mask and gradient magnitude was also calculated. After this, morphological operations which are used for obtaining flatten maxima inside each object by cleaning the images were used. In order to do image segmentation which identifies object boundaries and markers on the basis of color, texture and intensities, Watershed algorithm was used. Gray level co-occurrence matrix (GLCM) technique was utilized for feature extraction & stored in a separate txt file. The performance was calculated by considering the same as discussed in the previous paper [1]. The results obtained for SVM, k-NN and ANN were 85%, 88% and 93% respectively. However, this paper doesn't explain much about the classifiers used. Also, the dataset collected was of 3064 images out of which only 507 samples were used. The remaining images were removed due to poor segmentation

N. Vani, A. Sowmya and N. Jayamma [3], proposed a system that classifies MRI images into cancerous & non-cancerous using SVM classifier. On getting a labeled dataset, the SVM tries to compute a mapping function for all samples. This function was capable of realizing RBF and multi-layer perceptrons. The function is given as $D(z) = \text{sign} \left(\sum_{i=1}^N \alpha_i y_i K(z, s_i) + b \right)$ in which alpha coefficients, class labels of support vectors, support

vectors and input vectors are the variables utilized. It also specifies K as the kernel function which can be any of the different kernels available like linear, polynomial and RBF. In the system, the tumorous data was taken as input. For preprocessing of data, thresholding was utilized post which the images were labeled followed by feature extraction by using discrete wavelet transform. The DWT used is helpful in handling pictures since it can restrict the motions in time and scale which gives an absolute coefficient. To this coefficient, the feature vector generation was performed using the parameters like Euler number, height & width calculations, area, eccentricity and compactness and hence feature vectors for the image were generated. It was then fed to the SVM classifier for training and the obtained evaluation result was 82%. However, a very small dataset of 27 images was used in this system which was available in the DICOM format that had to be converted to jpeg format in MATLAB. The obtained accuracy was too less to be used in real world application.

T. Kumar, K. Rashmi, S. Ramadoss, L. Sandhya and T. Sangeetha [10] proposed a classification learner app which included two types of classifications that are SVM and k-NN. The app was utilized in order to train and classify the data with help of supervised learning approaches and also compare it using scattering plots along with confusion matrix. It consisted of two classifiers for training, manual- which classifies one at a time and parallel- which can train multiple at a time. The steps involved in this system were similar as mentioned in [2] where pre-processing, morphology, feature extraction, k-NN and SVM were concerned. However, this system differed in one step where the neural network was used for training after feature extraction and before morphology. With the help of plotting using the mean square error the training operation was validated. A signed distance map (SDF) was created for masking purpose and finally the classification was done by which efficiency of each classifier was found and compared with one another.

G. Birare and V. Chakkarwar [12] proposed a system that classifies tumorous MRI images as benign and malignant. The steps involved were pre-processing; used for improving different image parameters like noise removal, smoothing edges and removing unnecessary parts from background by applying adaptive contrast enhancement which is based on sigmoid function to get a clearer image. Segmentation; a process of capturing only the needed portion of the image by using k-means which is a method of assigning data points to a cluster such that the sum of the squared distance between the data points and the cluster's centroid is at the minimum and Otsu thresholding which converts grey scale images to binary were used. Feature extraction; a method of collecting useful data from an image such as color, shape, texture and contrast was based on grey level co-occurrence matrix (GLCM) method which used different statistical formulae like mean, standard deviation, entropy, skewness, kurtosis and energy. After this, classification was done using SVM. The results showed the calculated statistical features, textural based features and the classification accuracy using SVM. However, the dataset used consisted of only 60 MRI images (30 cancerous & 30 non-cancerous). Further this paper includes different GLCM formulae (as mentioned), but does not specify the details on textural features nor the reason for calculating all the attributes of the same. The paper mentions about using wavelet transform for decomposing images in the introduction section but the pre-processing and segmentation section does not clarify it. Since, a very small dataset is used, this approach fails to provide statistical guarantees.

A. Krizhevsky, I. Sutskever and G. Hinton [5] trained a large, deep convolutional neural network in order to classify the 1.2 million high-resolution images in the ImageNet contest. As ImageNet consisted of variable resolution images, they had to down-sample the images to a 256x256 resolution. The network architecture consisted of 5 convolutional and 3 fully-connected layers. They used Rectified Linear Units (ReLU) since deep CNN works are trained faster with great influence on the performance when using a large dataset. The training speed was quick using multiple GPU's non-saturating neurons. By using normalization the error rates were deducted. Some of the five convolutional layers were trailed by max-pooling layers. However in order to reduce overfitting two primary methods were adopted namely data augmentation and dropout. Data augmentation was done in two forms. In the first form, 224x224 patches were randomly extracted which resulted in increasing the dataset size. In the second form the intensities of the RGB channels were altered. The second method dropout which is, setting to zero the output of each hidden neuron with probability 0.5, roughly doubled the number of iterations that were required to converge and hence, this proved to be very effective. Equal learning rate was used throughout the training process for all the layers by manual adjustments. The network was trained for 5 to 6 days using two GPUs. This network successfully brought about top-1 and top-5 test set error rates of 37.5% and 17.05%. The best performance accomplished during the ILSVRC2010 competition was 47.1% and 28.2%, however, it was found that the performance of the network degraded on removing even one convolutional layer.

O. Ronneberger, P. Fischer and T. Brox [6] proposed a network and training methodology that depends on the solid utilization of data augmentation to utilize the accessible samples more effectively. The design consisted of a contracting way to capture context and a symmetric extending way that empowers exact localization which was based upon a more rich architecture, the supposed "completely convolutional network", which was changed and broadened with the end goal that it worked with not many training images and yielded more exact segmentations. The essential notion became to decorate a normal contracting community via way of means of revolutionary layers, wherein pooling operators had been changed via way of means of up-sampling

layers. To localize, excessive decision capabilities from the contracting manner had been joined with the up-sampled. One crucial change of their structure became withinside the up-sampling element wherein a big wide variety of characteristic channels had been used which allowed the community to propagate context records to better decision layers. Fully linked layers had been now no longer used yet, only a useful piece of each convolution, for example, the segmentation map which simplest contained the pixels, for which the entire context became withinside the enter image. This method approved the steady segmentation of big images. To are expecting the pixels withinside the outskirts locale of the image, the lacking placing became extrapolated via way of means of reflecting the enter image. This tiling method became crucial to be implemented to big images, in any other case the decision might be restricted via way of means of the GPU memory. The u-net (averaged over 7 circled variations of the enter data) accomplished a much less warping errors of 0.0003529 and a rand-errors of 0.0382 which proved fulfillment in the usage of convolutional networks on semantic segmentation tasks.

S. Geethapriya, N. Duraimurugan and S. Chokkalingam [7] proposed a system that detects objects based on linear regression by using the 'You Only Look Once' (YOLO) approach for which convolutional networks were used. Unlike other methods, in which only the necessary part was extracted from images, this approach predicted the classes and bounding boxes (from which one object can be identified by a grid) of the whole image at once. The input images were divided into 3x3 matrices and their classification loss (squared error of the class conditional probabilities for each class), localization loss (error between box locations and the sizes) and confidence loss (objectness of the box) functions were calculated. This algorithm predicted fewer false positives but resulted into some localization errors.

P. Afshar, A. Mohammadi and K. Plataniotis [11] proposed a new method for brain tumor classification using CapNets. CNN's require a large amount of training data for handling input values so CapNets were proposed in this paper to overcome the problems faced by CNN's. CNN's cannot handle smaller data sets efficiently, so CapNets solved this problem by using a property called 'routing by agreement'. It basically focused on using capsules rather than neurons for building the architecture. For the goal of tumor type classification, two types of images were fed as the input to the Capsule network. They were the whole brain tissue as the input, and type two was segmented tumor regions first and then using these regions as the input to the classification model. However, CapNets provided a good accuracy for segmented tumors rather than whole brain images. This system suffered from the problem of overfitting. Overfitting is observed when a model observes noise in training data such that it has a negative impact on the performance of the model. So finally CapNets overcomes a lot of issues but still has to improve its accuracy for brain images as compared to segmented tumors.

Havaei et al. [16] proposed automatic brain tumor segmentation using deep CNN. They built a cascade of two networks and performed two-stage training, by training with balanced classes and then refining it with proportions near originals. They studied various CNN models and their method predicted the class of the pixel. Training was done on a two phase procedure which helped them to train CNNs efficiently. The speed required for segmentation was found to be anywhere around 25 seconds to 3 minutes. Hence, these networks were much faster than the previous approaches to this problem, and their ability to transfer knowledge from other tasks were critical in improving their generalization capacity.

N. Abiwinanda, M. Hanif, S. Hesaputra, A. Handayani and T. Mengko [9] proposed a CNN based approach to classify the three most common types of brain tumor such as Glioma, Meningioma, and Pituitary. Their CNN architecture consisted of different parameters and features depending on the depth of the convolution layer and the fully connected network which didn't involve region based preprocessing stages. It comprised 2 layers of convolution namely activation (ReLU), and maxpool, followed by a hidden layer of 64 neurons. However, out of five proposed architectures consisting of the different layers, when the number of epochs increased, only one showed consistently decreasing pattern in the validation loss leading to the highest validation accuracy out of the rest. The training and validation accuracies of this architecture was found to be 98.51% and 84.19% respectively.

D. Zikic, Y. Loannou, M. Brown and A. Criminisi [20] studied the scope to directly use convolutional neural networks (CNN) for segmentation of brain tumor tissues. For the input data they used multi-channel intensity information from a small patch around every point to be marked. To account for scanner differences only standard intensity preprocessing was used on the input. Preprocessing was not used on the result of the CNN. Standard CNN implementation was applied for the segmentation task that is established on multi-channel 2D convolutions was used to modify it such that it functions on multichannel 3D data normally there for brain tumor segmentation task. Pre-processing inhomogeneity correction was applied on each channel. CNN framework was formed by the following layers; layer 0 had an input patch of size $19 \times 19 \times 4$, layer 1 had 64 filters of size $5 \times 5 \times 4$, layer 2 had maxpooling with kernel size 3 and stride of 3, layer 3 had 64 filters of size $3 \times 3 \times 64$, layer 4 was fully connected with 512 nodes, layer 5 comprised of soft-max with 5 output nodes. The assessment of this CNN technique was done with 2-fold validation in which the first fold comprised of the odd

test case IDs and the second fold consisted of the even ones. The result of one fold was found by the CNN that was trained on the other fold. Based on the results the CNN technique was found to show very promising results.

S. Pereira, A. Pinto, V. Alves and C. Silva [21] proposed an automated segmentation technique primarily based on Convolutional Neural Networks. Due to the use of small kernels, a more profound design was proposed for the problem of overfitting. Intensity normalization was also used in preprocessing along with data augmentation as it was found to be very efficacious for this task. The primary steps used in this were preprocessing, classification via CNN and post processing. In the first stage the images were modified by the bias field distortion which caused the intensity similar tissues to vary across the image. Intensity normalization was used on each sequence so that the contrast and intensity ranges become more similar. In this method, a certain number of intensity landmarks were being learnt for each sequence from the training set. To boost some features of the input the weights of the kernels were modified in the training phase by backpropagation. The same characteristic was found irrespective of the location as the same kernel was used over all the images. Assembling many convolutional layers, the features taken out became more abstract with the growing depth and some small clusters might be inaccurately classified as a tumor. As a solution to this, they applied volumetric constraints by getting rid of clusters in the segmentation acquired by CNN that were lesser in size when compared to the predefined threshold. LReLU was discovered to be more effective than ReLU in the training phase of the system.

R. Vasam and P. Nayak [8] proposed Instance segmentation using Mask R-CNN. Since segmentation is used for real world problems, it faces certain challenges, hence, Mask RCNN (a deep neural network) aimed to solve instance segmentation problems in machine learning or computer vision. In other words, it could separate different objects in an image or a video. When an image was taken as an input, it gave the object bounding boxes, classes and masks and therefore instance segmentation was used to overcome it, as it detects every unique object of interest according to pixel characteristics in the image. Mask R-CNN was preferred as it gave accurate detection of objects and a flexible framework for segmentation. Steps carried out were image processing, anchoring filtering, bounding box refinement, segmentation mask. Using this mechanism, the images were resized. The implementation of instance segmentation using Mask R-CNN on real time object detection got a higher accuracy compared to previous techniques of R-CNN. In order to get better results, Image pre-processing techniques and morphological transformations were employed to reduce the noise and increase pixel clarity.

R. Liu et al. [17] with the help of transfer learning, proposed a method of exploring deep features from brain tumor images. This paper proposed a novel image feature extraction method for predicting survival time from brain tumor magnetic resonance images using pre-trained deep neural networks meaning that it focused on applications with pre-trained CNNs. Using pre-trained CNNs is based on the idea of transfer learning. To train an entire CNN from the beginning is very complex. This is the concept in which training a network with one dataset and applying it to another can be helpful. In the dataset, each patient had 4 MRI modalities including T1-weighted (gadolinium enhanced), T2-weighted, Fluid-attenuated Inversion Recovery (FLAIR), and the Apparent Diffusion Map (ADM). By utilizing a pre-trained CNN network, their study overcomes the limitation requiring large-scale training data, which is a typical necessity for building a complex CNN. If knowledge that is learned is reused it saves time and also improves accuracy. The recent success of deep convolutional neural networks in computer vision suggests an alternative method to extract features using pre-trained convolutional neural networks. The results demonstrated deep features enabled classifiers to have comparable or better predictive power (95% accuracy) than conventional handcrafted feature extraction methods.

P. Krishnammal and S. Raja [18] mainly put their focus in utilizing Convolutional Neural Network which makes use of the component maps preprocessed in Curvelet domain to classify the MRI brain image datasets. In this paper the feature extraction applied was found to be much better in terms of accuracy than traditional wavelet transforms because of its multi-directional feature. The segmentation techniques to understand the localization of brain tumors and anatomical structures was taken care of and the performance of the Convolutional Neural Network was evaluated. The proposed strategy was based on the CNN architecture for cerebrum tumor classification. There were 4 steps in this process. First the MRI brain image dataset was acquired. In the second step features were extracted by applying FDCT and GLCM. In the third step classification was done with the use of CNN. The 4th step comprised of segmentation with the help of K-means technique. Also features were extracted by the use of curvelet transform which aims in overcoming the limitations of traditional DWTs. Another method used to extract the feature is Gray Level Co-occurrence (GLCM) that helps in computation of the GLCM and calculation of textual features. When comparing the three CNN models the model preferred was AlexNet because of its flexibility to be modified, its ability to lessen over fitting using drop outs and its capability to train faster. The CNN model was pre-trained from the MatConvNet toolbox; this model had 25 layers. The image was taken as input in the first layer, in between the Convolutional layers were the max pooling layers and ReLu activation function. The final layer used was the classification layer which had 1000 classes which helped in classifying the tumor. In the image dataset 70% was used for

training and the rest 30% was used for testing. The pre-trained CNN model was then trained for 100 epochs. The aim of this paper was classification and localization of the tumor accurately.

A. ARI and D. HANBAY [19] put forward a technique consisting of three steps. The first step was preprocessing in which denoising and normalization tasks were executed to prepare the images for the next step. The next step in this technique was the extreme learning machine local receptive fields (ELM-LRF) based tumor classification, and processing the image by region extraction. At the very start, nonlocal means and nearby smoothing techniques were used to get rid of possible noises. In the following steps, cranial magnetic resonance (MR) images were divided on the basis of benign or malignant with the use of ELM-LRF. In the third step, the segmentation took place. The implemented CNN model used for comparison mainly comprised of six layers. The first layer consisted of the input layer, following that was the convolution layer that consisted of six convolution filters. In the third layer i.e. pooling layer, half sampling was executed following the primary convolution layer. The fourth layer comprised of one more convolution layer in which 12 convolution filters were utilized. Following that was another pooling layer and the last layer that was a fully connected layer. The CNN model made use of the sigmoid activation function. Classification accuracy of 97.18% was obtained with the proposed method.

J. Seetha and S. Raja [14] used Deep Neural Network (DNN) and Support Vector Machine (SVM) for brain tumor classification. The CNN algorithm used had 5 stages. Initially, convolution filter was applied followed by reducing the sensitivity of the filter by subsampling. The signal transfers from one layer to another layer was controlled by the activation layer which was then improved using ReLu, then the neurons was connected to every neuron in subsequent layer and while training, loss function layer based on gradient descent was added at the end to give a to obtain a better accuracy through feedback. Classification using SVM was performed by segmentation based on FCM, texture and shape feature extraction. However, when both classification techniques were compared it was found that though the SVM model had less complexity, it underwent high computation time and low accuracy in tumor and non-tumor detection while CNN achieved an accuracy of 97.5%.

T. Hossain, F. Shishir, M. Ashraf, M. Al Nasim and F. Muhammad Shah [15] applied two different approaches for segmentation and detection of Brain tumor. First model segmented the tumor by FCM and classified it by traditional machine learning algorithms and the second model focused on deep learning for tumor detection. The Brain image segmentation system consists of seven stages. A Five-Layer Convolutional Neural Network approach was adapted for CNN and the loss was evaluated using binary cross-entropy. The accuracy was found out to be much higher in the CNN approach with a 97.87% accuracy when compared to the traditional algorithms that had an accuracy of only 88% to 92%.

E. Alberts *et al.* [4] proposed a DNA methylation-based approach that contained multi-modular clinical images utilized in the classification of glioblastomas tumors. 3D usage, for example, Histograms of Oriented Gradient (HOG), Local Binary Pattern (LBP) and Binary Robust Independent Elementary Features (BRIEF), was created for short nearby picture descriptors where tumor areas were identified by Bag-of-designs just as hand-made and auto-encoders deep features that were computed for segmentation masks in tumor diagnosing. However, the framework was validated on 116 brain tumor patients from the database. It was complex and obtained an accuracy of 83%.

H. Mohsen, E. El-Dahshan, E. El-Horbaty and A. Salem [13] proposed a methodology which combined the deep neural network (DNN) with discrete wavelet transform (DWT) to classify the brain MRIs into normal and 3 types of malignant brain tumors namely glioblastoma, sarcoma and metastatic bronchogenic carcinoma. Image segmentation into 5 sections was done using Fuzzy C-means clustering technique. For Feature extraction, DWT was used which provided localized time-frequency information of a signal using cascaded filter banks of high-pass and low-pass filters to extract features in a hierarchy manner followed by reduction using Principle component analysis (PCA) technique and the finally classification was done using Deep neural networks. Accuracy obtained from DNN was 94.67%. However, the dataset collected, consisted of only 66 real human brain MRIs with 22 normal and 44 abnormal images.

III.RESULT AND DISCUSSION

The figure below shows the different techniques adopted in the proposed system in stages where image processing, segmentation, feature extraction and classification was used.

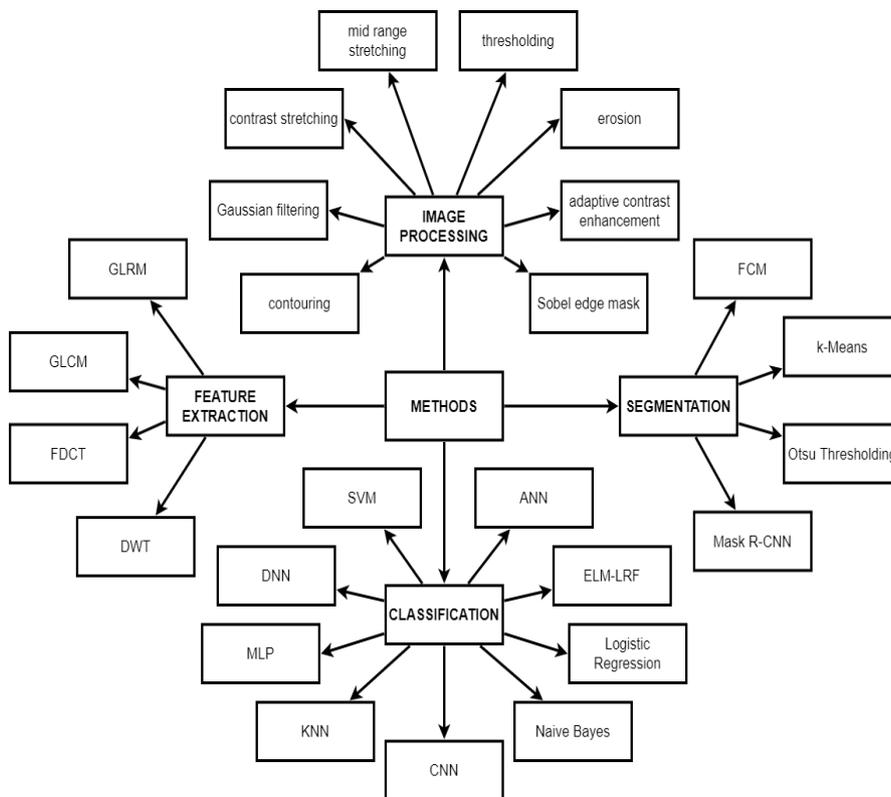


Figure 2. Different techniques from literature review

The table below shows the results obtained from some of different adopted methods in the recent years along with the methods used.

TABLE I
LITERATURE SURVEY

PAPER	YEAR	METHODS	ACCURACY
G. Gupta and V. Singh [1]	2017	SVM	91.77% Linear 90% RBF
Z. Ahmad and S. Gul [2]	2018	SVM, k-NN and ANN	85%, 88% and 93%
N. Vani, A. Sowmya and N. Jayamma [3]	2017	SVM	82%
E. Alberts et al. [4]	2017	LBP, BRIEF and HOG	83%
N. Abiwinanda, M. Hanif, S. Hesaputra, A. Handayani and T. Mengko [9]	2018	CNN	84.19%
G. Birare and V. Chakkarwar [12]	2018	SVM, k-means clustering and Otsu thresholding	98.38%
H. Mohsen, E. El-Dahshan, E. El-Horbaty and A. Salem [13]	2018	DNN, DWT, Principal Components Analysis (PCA)	94.67%
J. Seetha and S. Raja [14]	2018	CNN	97.5%

T. Hossain, F. Shishir, M. Ashraf, M. Al Nasim and F. Muhammad Shah [15]	2019	CNN	97.87%
R. Liu, L. Hall, D. Goldgof, M. Zhou, R. Gatenby and K. Ahmed [17]	2016	pre-trained CNN	90.91%
P. Krishnammal and S. Raja [18]	2019	CNN	100%
A. ARI and D. HANBAY [19]	2018	CNN, ELM-LRF	96.23% and 97.18%

IV. CONCLUSIONS

The approaches to the classification task by using traditional techniques were found to have various disadvantages as discussed in their sections of this paper, whereas some techniques indicated accomplishment in different papers and successfully outperformed the others. These techniques too faced drawbacks in its performance which were dealt with later. Thus, in this paper we have discussed the different methodologies that have contributed in the innovative advancements, especially in the medical field and attempted to integrate the study on various researches and proposed systems along with addressing the different steps involved with their advantages and drawbacks which can help in the selection and adoption of the techniques in the future. Although, good systems are created, but still there is a need to build more efficient, affordable, adoptive and advanced techniques.

REFERENCES

- [1] G. Gupta and V. Singh, "Brain Tumor segmentation and classification using Fcm and support vector machine", *Irjet.net*, 2017.
- [2] Z. Ahmad and S. Gul, "Brain Tumor Detection & Features Extraction From MR Images Using Segmentation, Image Optimization & Classification Techniques", *Ijert.org*, 2018.
- [3] N. Vani, A. Sowmya and N. Jayamma, "Brain Tumor Classification using Support Vector Machine", *Irjet.net*, 2017.
- [4] E. Alberts et al., "Multi-modal Image Classification Using Low-Dimensional Texture Features for Genomic Brain Tumor Recognition", *Graphs in Biomedical Image Analysis, Computational Anatomy and Imaging Genetics*, pp. 201-209, 2017.
- [5] A. Krizhevsky, I. Sutskever and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks", *Papers.nips.cc*, 2012.
- [6] O. Ronneberger, P. Fischer and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation", *Arxiv.org*, 2015.
- [7] S. Geethapriya, N. Duraimurugan and S. Chokkalingam, "Real-Time Object Detection with Yolo", *Ijeat.org*, 2019.
- [8] R. Vasam and P. Nayak, "Instance Segmentation on Real time Object Detection using Mask R-CNN", *Ijeat.org*, 2019.
- [9] N. Abiwinanda, M. Hanif, S. Hesaputra, A. Handayani and T. Mengko, "Brain Tumor Classification Using Convolutional Neural Network", *IFMBE Proceedings*, pp. 183-189, 2018.
- [10] T. Kumar, K. Rashmi, S. Ramadoss, L. Sandhya and T. Sangeetha, "Brain tumor detection using SVM classifier", *2017 Third International Conference on Sensing, Signal Processing and Security (ICSSS)*, 2017.
- [11] P. Afshar, A. Mohammadi and K. Plataniotis, "BRAIN TUMOR TYPE CLASSIFICATION VIA CAPSULE NETWORKS", *Arxiv.org*, 2018.
- [12] G. Birare and V. Chakkarwar, "Automated Detection of Brain Tumor Cells Using Support Vector Machine", *2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, 2018.
- [13] H. Mohsen, E. El-Dahshan, E. El-Horbaty and A. Salem, "Classification using deep learning neural networks for brain tumors", *Future Computing and Informatics Journal*, vol. 3, no. 1, pp. 68-71, 2018.
- [14] J. Seetha and S. Raja, "Brain Tumor Classification Using Convolutional Neural Networks", *Biomedical and Pharmacology Journal*, vol. 11, no. 3, pp. 1457-1461, 2018.
- [15] T. Hossain, F. Shishir, M. Ashraf, M. Al Nasim and F. Muhammad Shah, "Brain Tumor Detection Using Convolutional Neural Network", *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 2019.

- [16] Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, Pal C, Jodoin PM, Larochelle H, "Brain tumour segmentation with deep neural networks", Arxiv.org, 2018.
- [17] R. Liu, L. Hall, D. Goldgof, M. Zhou, R. Gatenby and K. Ahmed, "Exploring deep features from brain tumor magnetic resonance images via transfer learning", 2016 International Joint Conference on Neural Networks (IJCNN), 2016.
- [18] P. Krishnammal and S. Raja, "Convolutional Neural Network based Image Classification and Detection of Abnormalities in MRI Brain Images", 2019 International Conference on Communication and Signal Processing (ICCSP), 2019.
- [19] A. ARI and D. HANBAY, "Deep learning based brain tumor classification and detection system", TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES, vol. 26, no. 5, pp. 2275-2286, 2018.
- [20] D. Zikic, Y. Ioannou, M. Brown and A. Criminisi, "Segmentation of Brain Tumor Tissues with Convolutional Neural Networks", MICCAI Multimodal Brain Tumor Segmentation Challenge (BRATS), 2014.
- [21] S. Pereira, A. Pinto, V. Alves and C. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images", IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240-1251, 2016.
- [22] S. Gaikwad, A. Shetty, A. Satam, M. Rathod and P. Shah, "Recognition of American Sign Language using Image Processing and Machine Learning", International Journal of Computer Science and Mobile Computing, vol. 8, no. 3, pp. 352 – 357, 2019.
- [23] J. McCarthy, M. Minsky, N. Rochester and C. Shannon, "A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence", AI Magazine, no. 4, pp. 12-14, 1955.
- [24] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning", Nature, vol. 521, no. 7553, pp. 436-444, 2015.