AUTOMATED DETECTION OF BRAIN TUMOR USING DEEP LEARNING AND MAGNETIC RESONANCE IMAGINING (MRI) FOR CLASSIFICATION

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By

SERAG MOHAMED AKILA

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Biomedical Engineering

NICOSIA, 2020

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Approval of Director of Graduate School of

Applied Science

Prof. Dr. Nadire CAVUS

We certify this thesis is satisfactory for the award of the degree of Masters of Science in Biomedical Engineering

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are original to this work.

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Date: **23/07/2020**

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To my Family…

ABSTRACT

Advents in technology has over the years pave ways in the field of Oncology. The use of Artificial Intelligence (AI), has promised great possibilities. Deep learning neural network and MRI has been very useful in the staging of cancer. However, the aim of this study was to conduct a quantitative study on the staging of brain tumor using deep learning algorithm and MRI. The objectives of this study involved analyzing the impact of deep learning algorithm in the diagnosis of brain tumor, acquisition of brain tumor dataset for the analysis of deep learning, the implementation of ResNet and GoogLeNet for the training and testing of the dataset, and the interpretation and analysis of results as well as comparisons of our study with related studies. The dataset utilized in this study was obtained from Harvard Medical School. The methodology involved the use of deep learning as well as two networks (ResNet and GoogLeNet). Results obtained from the study indicated that ResNet had a better accuracy (99.8%) than GoogLeNet (98.7%). Hence, it can be observed that due to the high level of accuracy, deep learning convolutional neural network is a very effective technique for cancer detection.

Key words: Artificial Intelligence (AI), Deep learning, ResNet, GoogLeNet, Brain tumor

Özet

Teknolojideki ilerlemeler Onkoloji bölümündeki gelişmelere zemin hazırlamıştır Yapay Zeka (YZ) kullanımı, büyük olanaklar yaratmayı vaat etmiştir. Derin öğrenme, sinir ağı ve MRI, kanserin evrelemesinde çok faydalı olmuştur. Bununla birlikte, bu çalışmanın amacı, derin öğrenme algoritması ve MRI kullanılarak beyin tümörünün evrelendirilmesi üzerine kantitatif bir çalışma yapılmasıdır. Bu çalışmanın amaçları, derin öğrenme algoritmasının beyin tümörü teşhisinde etkisini, derin öğrenme analizi için beyin tümör veri kümesinin elde edilmesini, veri kümesinin eğitimi ve testi için ResNet ve GoogLeNet'in uygulanmasını, sonuçların yorumlanması ve analizi ile çalışmamızın ilgili çalışmalarla karşılaştırılmasını içermektedir . Bu çalışmada kullanılan veri kümesi Harvard Tıp Okulu'ndan alınmıştır. Çalışmanın yöntemi, iki ağın (ResNet ve GoogLeNet) kullanımının yanı sıra derin öğrenmenin kullanımını içermektedir. Çalışmadan elde edilen sonuçlar, ResNet'in (% 99.8) GoogLeNet'ten (% 98.7) daha iyi bir doğruluk seviyesine sahip olduğunu göstermiştir. Bu nedenle, yüksek doğruluk düzeyi nedeniyle, derin öğrenme evrişimli sinir ağının, kanser teşhis için çok etkili bir yöntem olduğu görülebilir.

Anahtar Kelimeler: Yapay zeka (YZ), Derin öğrenme, ResNet, GoogLeNet, Beyin tümörü

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LIST OF ABBREVIATIONS

ACC: Accuracy

AI: Artificial Intelligence

CNN: Convolutional Neural Network

FP: False Positive

FN: False Negative

MRI: Magnetic Resonance Imaging

MSE: Mean Square Error

SP: Specificity

SE: Sensitivity

TP: True Positive

TN: True Negative

CHAPTER 1
INTRODUCTION

1.1 Background on Deep Learning and Brain Tumor

Advents in convolutional neural network has been very effective in diverse fields of studies, especially in the medical sector. The use of deep learning algorithm has made it easier to identify different kinds of medical defections, using an adequate amount of medical data images (Muhammed et al., 2019). However, medical images used for deep learning analysis can be collected in different forms, such as the use of Magnetic Resonance Imaging (MRI). The use of MRI is non-invasive, and it can be used in detecting neural brain activities and, it can provide different imagery information's on the genetics, physiology, hemodynamics and abnormalities (Mabray & Cha, 2016). The use of MR scans has been very effective in the detection diverse brain abnormalities, hence making a preprocessing that can help with the classification of normal and abnormal (Gudigar et al., 2019).

Moreover, deep learning technique as a detective algorithm has been one of the most widely used machine learning methods in the detection of different medical problems (Plawiak, 2018; Yildirim & Baloglu, 2017). With the aid of deep learning algorithm, several data can go through different layers of processing, with little dependency on engineering features (Bengio & Lee, 2015). The use of deep learning has been so effective as a result of the complexities in computing using MRI (McBee et al., 2018). One of the major techniques used in improving the performance of deep learning is by pre-training the network. In eradicating problems associated with deep learning, the use of transfer learning is usually adopted. Hence, a pre-trained network can be used in training another model with knowledge obtained from the pre-trained model. Moreover, this is usually effective when training a small dataset, knowledge obtained from the pre-trained larger dataset can help in an optimal processing of the data's (Muhammed et al., 2019).

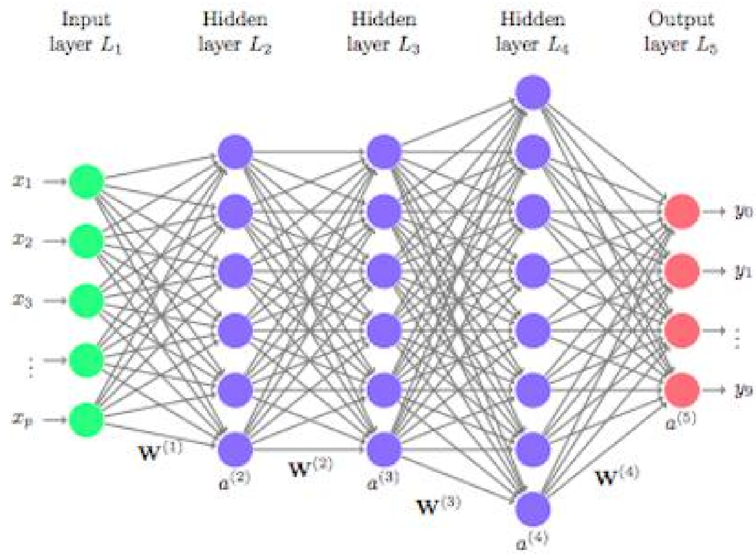

Figure 1.1: Deep Learning Algorithm

Brain tumor is a mass of abnormal cell growth in the brain, which can be either malignant or benign. The mortality rates of patients diagnosed with brain tumor has increased over the years. An early detection of these tumors that could be cancerous can reduce the mortality rate in most patients. The use of a more effective measure in detection such as deep learning has over the years yielded a more effective and accurate result compared to the use of MRI (Nida et al., 2016). Several symptoms are associated with headaches, memory loss, vomiting, nausea and other forms of behavioral changes. The use of manual detection techniques for brain tumor has always been subjected to human errors, which may endanger the lives of several patients. However, in this study the use of a smarter and better technique for the detection of brain cancer, using deep learning.

1.2 Aim of the Study

The aim of this study was to conduct a quantitative study on the staging of brain tumor using deep learning algorithm and MRI. Datasets were used in getting images that helped in the analysis of this study.

1.3 Objectives of the Study

The objectives of this study were outlined as:

i) Analyzing the impact of deep learning algorithm in the diagnosis of brain tumor.
ii) Acquisition of brain tumor dataset for the analysis of deep learning.
iii) The implementation of ResNet and GoogLeNet for the training and testing of the dataset.
iv) The interpretation and analysis of results as well as comparisons of our study with related studies.

1.4 Significance of Study and Contribution to Knowledge

The use of deep learning algorithm has been very effective in several medical diagnosis over the years. The mortality rates recorded as a result of carcinogenic diagnosis has increased in recent times, hence the need of identifying better diagnostic measures that can help with the detection of brain tumor.

The acquisition of findings from related studies as well as a perfectly structured methodology proposed in this study, the issue of an accurate brain tumor diagnosis will be an historic event and hence will create great promise and solutions in the medical sector. Moreover, findings from this study will be a base and a reference point for more scholars to carry out future research related to brain tumor using a deep learning algorithm.

1.5 Research Questions

Several research questions were raised during the course of this study:

i) What are the factors responsible for low accuracy in the staging of brain tumor using a deep learning algorithm?
ii) What is the best convolutional algorithm to be used in the diagnosis of brain tumor?
iii) How does the data training of a dataset help in getting a very high accuracy during the testing of data's?
iv) Is the use of a pre-processing network needed in deep learning analysis?
v) How effective is the use of MR imaging and the use of a deep learning neural network algorithm?

1.6 Organization of the Study

Chapter I: This section consists of the background of the study, the aims and objectives of the study, significance of study and contribution to knowledge, the problem statement as well as the structural organization of the study.

Chapter II: Related studies on brain tumor using deep learning and MRI were reviewed in this study. The findings from the review acted as a base to understand the extent of research in this area and how to develop on the study.

Chapter III: The methodology and the dataset used in this study was explained in this chapter. A guide of how the ratio of data trained and tested was described as well as the numbers of datasets, classification networks used.

Chapter IV: Interpretations, comparisons and several other analyses on the results of this findings were discussed in this section.

Chapter V: Conclusions, future recommendations and the limitations of the study was discussed in this section.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

In these modern times, the incidence of brain is consistently on the rise. Notable of these are brain tumors in which the growth is in the brain. This in some cases makes effective treatment challenging. Tumors can be categorized based on several factors as either primary or secondary. If benign, it is classed primary but if malignant, is classed secondary.

In the sphere of medicine, the mostly utilized technique for obtaining brain images is the MRI technique. The advantage of this technique is as a result of its increased resolution properties. It provides much knowledge on the construct of the brain as well as exposes brain cell deformities (Mohsen et al., 2018). Several sophisticated Machine Learning and Deep Learning techniques exist that find applications in image procession. Other techniques like the Support Vector Machine (SVM), Neural Network, C4.5, Multilayer Perception and other similar tools are used for categorization. Each of these has their benefits as well as pitfalls.

For the categorization of depictions, Deep Learning Techniques are commonly utilized. This technique has increasingly gained popularity over the past couple of years. A technique commonly utilized in identifying pictures is the Convolutional Neural Network (CNN). It composes of neurons with the ability to learn weights as well as discrepancies. It finds applications in accomplishing precision in classifying pictures with exemption of prior preparation steps. It also can recognize complications on pictures through automatic means (Hao et al., 2017).

One of the prominent libraries widely used in this field is TensorFlow. Constructed by Google, it is compatible with CNN, RNN as well a host of other neural networks. It is widely used in identifying graphics, identification of articulation as well as many Deep Learning patterns. Published by Google in 2015, TensorFlow finds applications in design, construction as well as tutorship. It depicts processed information as a chart. The margins of the chart account for the information that is relayed from one intersection to another.

2.2 A Brief Review of Previous Works

A number of studies have been conducted with respect to the identification of growths in the brain from MRI graphics.

One study involved the application of throbs in conjunction with neural networks for improving MRI graphics of the brain. It also involved reverse transmission network for categorizing MRI graphics of the brain. Their investigation proved that this application of throbs coupled with neural networks together with reverse transmission network led to better graphic resolution as well as categorization in the identification of tumors in the brain from the MRI graphic (Subashini et al., 2013).

Another study conducted by Shashank and colleagues involved the application of Naïve Bayes as well as a results diagram technique for forecasting the growth in the brain. This depends on the source of the growth, clinical presentation, therapy as well as frequency of the growth. From the outcome of the investigation, it was deduced that the use of these decision diagrams called decision trees are user friendly and easy in forecasting the therapy of the growth in the brain than it is using the Naïve Bayes technique (Shashank et al., 2018).

A novel proposed technique involved the classification of growths identified from MRI graphics with the use of Hellinger decision technique HD tree as well as HD forest techniques. In this technique, 97 MRI brain graphics were utilized to categorize MRI graphics on the basis of various characteristics such as the clinical presentation of the growth, centroid and the structural appearance. It was found out that the operation of the HD forest with an accuracy of 96.50% outperformed that of the LA SVM with an accuracy of 96% (Singh et al., 2018).

Another method proposed by Sankari and colleagues involved brain growth categorization dependent on CNN. It involves the implementation of a non-linear activating task that is a Leaky Rectifier Linear Unit (LReLU). The emphasis was on fundamental characteristics like entropy, average as well as standard of deviation of the graphics. The deduction from this study revealed that CNN yields better operational results with respect to representation of complicated characteristics of cerebral tissues affected by tumors (Sankari et al., 2017).

Another method involved the utilization of MRI graphics of cerebral tumors for obtaining vital data on the classification of cerebral tumors as well as their segmentation. For this investigation, CNN techniques were utilized for developing a classification pattern for cerebral growths. From this investigation, it was deduced that the operation of CNN on the basis of accuracy as well as precision was enhanced by 18% as opposed to that obtained with the use of Artificial Neural Network (ANN) (Yuehao et al., 2015).

Another proposed study involved the use of artificial neural network ANN, which is on the basis of setting in place a system of the early identification of cerebral tumors. This technique makes use of the neuro fuzzy logic in identification of cerebral growths. From the results of this study, it was seen that the period of identification of cerebral tumors as well as the sensitivity was enhanced by about 50 to 60 % in comparison to the already established neuro category (Kumar et al., 2010).

Another proposed technique involved the use of Multilayer perceptron technique which was found to yield better results than the C4.5 classifiers. This suggested technique involves the joint utilization of C4.5 and the Multilayer perceptron on the basis of the stretches of both the main and minor axes, Euler number and characteristic of growth. This suggested technique was investigated with one hundred and seventy-four MRI graphics of cerebral growths. From the results, it was observed that the Multilayer perceptron categorization accuracy was 95.2% whereas the C4.5 categorization accuracy was 91.1% (Nadir et al., 2015).

An approach based on neuro fuzzy logic for the categorization of cerebral growths on MRI graphics has also been investigated. This method of categorization is based on the structure and extent of the cerebral growth. This suggested technique utilizes various categorization techniques with use of k-method as well as CBIR classification means. From the outcomes of this study, it was seen that the operation of Tree augmented naïve Bayes nearest neighbor (TANNN) technique proved more efficacious as opposed to other techniques. Also, it was observed that the extent of the categorization period of the k-nearest neighbor is minimal in comparison to other categorization techniques (Ali et al., 2015).

Another investigation was conducted based on support vector machine categorization for cerebral growth tissues. In this investigation, an efficacious technique for categorizing cerebral growths in tissues was suggested with the use of gene-based algorithm as well as SVM categorizer. This gene-based technique for categorizing cerebral growths was utilized for characteristic extraction as well as SVM for categorization. This approach identifies cerebral growths on the basis of average, mode as well as median numbers of the area of growth. From these, the nature of the tumor is categorized (Bangare et al., 2017).

A proposed approach for the identification of cerebral growths with the use of CNN categorizer as well as local binary patterns (LBP) extraction technique. In this case, Relu activation application is utilized in the CNN technique. This method was experimented with a hundred samples and it depicted 86% sensitivity (Mehekare et al., 2017).

An automated cerebral growth identification technique with the utilization of CNN categorizing technique for classifying as either cerebral growths or non-cerebral growths. The sensitivity of this technique was observed to be 97.5% on CNN. It proved to yield much better accuracy than SVM and DNN categorization techniques (Seetha et al., 2018).

From a host of similar studies, it was seen that the use of Convoluted Neural network yielded best results in the categorization of cerebral growths from MRI graphics.

Cerebral tumors are one of the most life-threatening ills in modern times. Cerebral tumor is the localized sprouting of carcinogenic or non-carcinogenic diseased cells of the brain. Cerebral tumors account for several deaths in recent times. Magnetic Resonance imaging is a technique widely used for depicting the medical condition of the cerebral tumor for further investigation.

The brain is one of the most vital and complex organ structures of the human body. The bony skull which protects the brain prevents direct studies on the function and properties of this organ. It also makes the diagnosis of infections and diseases a difficult feat (Khan 2013). Though not vulnerable to infections like the other body organs, it is nonetheless likely to experience a spark that could lead to an abnormality in the growth of brain cells. This growth of diseased cells can change the structure and function of the brain. This abnormality signifies the presence of a brain tumor. A technique commonly used to identify such tumors is the Magnetic Resonance Imaging technique.

Technological advances have provided for the opportunity of conducting research to classify these tumors (Iftekharrudin et al., 2005). The main factor in such classification of MRI images involves the clumping characteristically similar vectors. Hence, this necessitates isolation of significant characteristics as the fundamental requirement for properly classifying MRI graphics. The challenge however in isolation is due to the complexity of the different tissues of the brain (Wang 2001). The classification of the MRI image is a notable feature for investigations concerning brain tumors. This is so because of the rate of classification of brain growths could exclude features from other cerebral structures hence yielding much better sensitivity in the sub-categorization of cerebral growths. This thus provides insight on prognosis as well as efficaciously observe growth, resurgence or contraction of the tumors.

The approaches of classifying graphics can be categorized on the basis of area or surface growth, marginal identification, categorizers, quantification or characteristic clumping of vectors. This approach of quantification of vectors is efficacious for the categorization (Chen eta la., 1990). This approach segregates the n dimensional vector zones to M sectors for the optimization of criteria functionality. This quantification of vector is concerned with two procedures of directing and inscription. Directing determines the library (codebook) vector system based on the probability of the given information whereas inscription determines the assigned vectors available in the codebook. The categorization of graphics for uses like the recognition of deformities, deciding for a surgery as well as patient monitoring following a surgical procedure is a relevant factor in the sector of human medicine. Several techniques have been developed for such categorization.

Studies conducted in 2005 investigated the efficiency of two separate characteristic qualities together with the implementation of numerous modal magnetic resonance graphics for the segmentation and classification of child cerebral growths. The fractal characteristic of the quality is gotten with the use of Piecewise triangular prism surface area (PTPSA) technique. The other quality sorting out utilizes the differential Brownian motion technique. Via s self-organizing map (SOP), the joining of both characteristics is achieved. The outcome of the investigation showed that the joining of the strength as well as fractal application of the numerous modes of magnetic resonance graphics yielded finer outcomes as opposed to those with those with just one mode (Iftekharuddin 2005).

In 2012, a study was conducted by developing and introducing an efficient technique for the identification of cerebral growths. The classification was on the basis of ‘thresh-holding coupled with water-shed approaches. Graphics obtained of the brain from magnetic resonance imaging found applications in the classification procedure. The drawback of this technique however is the fact that the uses of this technique does not include the classification of three-dimensional graphics (Mustaqeem et al, 2012).

Research conducted by Padole and Chaudhari in 2012 involved the development of a technique for the identification of cerebral growths from graphics of magnetic resonance imaging via the evaluation of constituents. Such an approach has the possibility of identifying, through automated means the expanse of the cerebral growth. It is a technique which involves the use of both the Normalized cut (Ncut) technique and the shift technique (Chaudhari et al., 2012). Another approach developed by Roy and colleagues involves the identification and measurement of cerebral growths from magnetic resonance graphics with the use of symmetrical evaluations. The condition of the abnormality is detected through the engagement of quantitatively evaluations (Roy et al., 2012).

A number of differential and categorization approaches were re-evaluated by El-Dahshan and colleagues. From their studies, it was deduced that prognosis based on computer assisted programs is the main aspect of the magnetic resonance imaging technique of the brain. Therefore, artificial intelligence was developed for the automated identification of human cerebral growths from graphics of magnetic resonance imaging. The differentiation of the graphics is achieved through neural networks in combination to responsive throb. Categorization of the graphic as either normal or abnormal is made possible through the assistance of a signaling neural network along with reverse flow. These analyses were carried out on one hundred and one graphics of magnetic resonance imaging, of which eighty-seven constituted defective graphics while fourteen constituted healthy graphics. From the results, it was observed that the sensitivity of the technique was 99% (El-Dahshan et al., 2014).

A technique for the differentiation of magnetic resonance imaging graphics which incorporates the K-means clumping as well as blurry C-means technique. Precise detection of cerebral growths was obtained from the phases of thresh-holding as well as differentiation on an established point. The amount of time for calculations was reduced as a result of the use of K-means clumping. The use of blurry C-means improved the sensitivity.

The assessment of the quality of operation of this approach was achieved by measuring it with current methods based on operation, time frame of the process as well as sensitivity. The outcomes of this study demonstrated its efficiency at handling large quantities of tasks concerned with differentiation. It accomplishes this through the enhancement in the grade of differentiation as well as sensitivity within the least time frame (Abdel-Maksoud et al., 2015). The results of Multimodal Brain Tumor Image Segmentation Benchmark were described by Menze and colleagues. In these studies, a batch of sixty-five multi contrast magnetic resonance imaging graphics of many suffering from cerebral growths were utilized as a sample for about 29 differentiation techniques for the detection of brain growths. From the outcomes of this investigation, different techniques were useful for different sections of the growth. No sole technique was suitable for all sections (Menze et al., 1993).

A method for the detection of cerebral growth with the use of Particle Swarm Optimization (PSO) was developed. This method constitutes four phases. These are phases in charge of converting, implementing, selecting as well as extracting. This PSO technique aids in the determination of the expanse of the magnetic resonance imaging graphics of the brain (Mahalakshmi et al., 2015).

A novel technique for the differentiation of glioblastoma growths based on three dimensional Convolutional Neural Networks. This suggested technique involves the broad engagement of CNN to achieve three dimensional sieves for enhancing strength as well as for the conservation of statistics. This proposed CNN construct equally helps expand the efficient scope of information as well as achieve decrease in the variance of the built pattern. The sensitivity for this technique was found to be 89% (Planque et al., 2016).

CNN was again utilized by a further automatic approach that involved the exploration of minute 3 by3 nuclei. The utilization of these permitted for in depth outline of the construct. It generated a satisfactory outcome against over-fitting. A pre-initial requirement involved using the strength normalization coupled with amplification of the statistical information showed efficiency of the differentiation for magnetic resonance imaging graphics. The authentication of this approach is achieved with the use of the BRATS 2013 library. The major glitch with this study was the enhancement of sensitivity. This improvement of accuracy can be achieved by the utilization of an optimization approach involving the use of WCA (Pereira et al., 2016).

Dong and colleagues developed a fully automated approach for the differentiation of cerebral growths which engaged the utilization of Convolutional Neural Networks on the basis of U-Net. These studies were conducted on BRATS 2015 statistical sets which comprises LGG and HGG clients. The outcomes gotten from the study reveals this suggested approach to be efficient. This approach was authenticated with the utilization of 5-fold cross authentication. With this approach, a pattern for differentiating the growth graphics for particular clients could be gotten without manual engagement (Dong et al., 2017).

An automated method for the differentiation of brain tumors with the use of increased magnitude, resilient Deep Neural Network (DNN) was put forth by Havaei and colleagues. This approach engages the entire and localized properties simultaneously. The challenge involved with this approach is the disparity in the identification of the growths. But this imbalance is gotten rid of by making use of a process that constitutes 2 stages (Havaei et al., 2015).

Cerebral growths if left unnoticed and at prolonged periods of exposure is fatal. Therefore, early identification is of utmost importance for proper therapy for the betterment of the living condition of the sufferer and hence improving on their life expectancy. Magnetic resonance imaging techniques are broadly utilized in recent times for the identification of cerebral growths. This application of magnetic resonance imaging techniques is very useful particularly as it may involve the differentiation of large numbers of three-dimensional graphics which could be a cumbersome task if performed by manual means. Hence, automated differentiation will decrease the workload as well as enhance the prognosis of identifying growths.

The presentation of IT as well as electronic health applications into the field of medicine enables medical professionals supply enhanced medical care to sufferers. Cerebral tumors have been categorized as either benign or malignant. Benign growths develop slowly and are less detrimental to health unlike malignant tumors which are ferocious in growth. Several clinical techniques exist which provide graphics of the internal organs for the detection of infection which do not require invasive procedures. Some of these techniques include MRI, CT scan, ultrasound, SPECT, PET, X-ray (Borole et al., 2015). In comparison to all these techniques, the Magnetic Resonance Imaging technique is widely utilized. This is because, it gives much better contrast graphics of cerebral and cancer infected tissues. Hence identifying cerebral growths can be conveniently performed with the use of Magnetic Resonance Imaging (Bahadure et al., 2017). Prompt identification of cerebral growths is vital for proper and effective therapy. With the suspicion of a cerebral growth, scan images are gotten for an analysis of its position, expanse as well as its effect on neighboring tissues. Based on the data obtained, the most adequate treatment procedure is decided upon. If the growth be identified at its initial phase, this drastically improves the sufferer's opportunities for surviving (Huang et al., 2013). This explains why the investigation of cerebral growths with the use of such imaging techniques like the magnetic resonance imaging is widely popular in radiology.

An approach which utilizes the FCM technique for isolating the matter from the Region Of Interest (ROI) was suggested by Saleck and colleagues. This suggested method attempts to exclude the challenge of having to estimate the quantity of clusters in FCM. It does this by choosing the group of pixels which give the data needed for carrying out mass categorization through the fixing of 2 clusters. The isolation of the texture characteristics for the purpose of obtaining maximum threshold that sets the demarcation between the chosen groups from other pixel groups which has an effect on the sensitivity of the matter borders. The efficiency of this method is assessed by its precision, specificity and sensitivity (Saleck et al., 2017).

With comparison to the current methods, Bhima and colleagues brought forth a much-advanced diagnostic technique of cerebral growths. The drawback however of this technique involves the fact that it is restricted solely to the detection of cerebral growths. It doesn't encompass the broad investigation of the inner condition of the brain. This is especially a limitation as knowledge of the general internal environment of the brain is vital for proper therapy (Bhima et al., 2016).

In 2011, Vrii and colleagues enhanced the detection of brain tumor detection following a manual categorization technique as well as two dimensional and three-dimensional imaging of organizing surgery and evaluating the nature of the growth. Recognition of the growth and analyses had been performed for possible utilization of Magnetic Resonance Imaging statistics for enhancing the prediction of the size of the cerebral growth.

In the phases concerned with the preprocessing and processing, the graphic is transformed into a conventional graphic. Segmenting this graphic classifies this graphic to generate the sectors which compose it (Vrii et al., 2011).

The Magnetic Resonance Image was analyzed by Rashid and colleagues and developed an approach for adequately detecting the specific localization of the cerebral growth. The input for the procedure is the abnormal Magnetic Resonance Image, anisotropic noise filters for removing noise, SVM categorizer for categorization. Fundamental to this technique is obtaining clean graphics of the Magnetic resonance imaging process. the categorization of this obtained MRI graphic points out the cerebral growth (Rashid et al., 2018).

A 2015 study conducted by Sudharani presents a suggestion on categorizing and identifying several cerebral growths by utilizing k-NN technique which is on the basis of the training of k. The space of the categorizer is executed and computed by Manhattan metric. This technique can also be executed with the use of Lab View (Sadharani et al., 2015).

In 2013, a formulated pattern was suggested. This model is concerned with the identification of the section of concern with the utilization of joint outcomes of threshold categorization as well as operations involving morphology. At the early stages, the diseased cerebral Magnetic resonance image undergoes some processing with Otsu threshold-based categorization as well as operations of morphology such as abrasion. Subsequently, the categorized graphic which results from the initial processes are joint to the actual magnetic resonance image to conserve the initial setting and hence correctly identifying the section of the brain with the growth (Mittal et al., 2013).

In 2015, Li and colleagues suggested a method which involves the utilization of Local Binary Patterns, LBP for the isolation of characteristics like boundaries, edges as well as marks. Blending occurs at two stages: feature-stage blending and decision stage blending. Both of these are introduced to the isolated local binary patterns together with Gabor pieces and actual spectral traits. The feature stage blending is concerned with the sequencing of a variety of traits prior to the stage of categorization. Decision stage blending operates on the possibility outcomes of every single categorized channel. The principle of soft decision blending is about merging outcomes from the categorizer (Li et al., 2015).

In a 2012 investigation, Dhanaseely introduced 2 varied structures. These include the Cascade Neural Network (CASNN) as well as Feed Forward Neural Network (FFNN). Isolation is achieved by the utilization of Principal Component Analysis (PCA). This assists in decreasing the load of calculation.

From a library, the traits are isolated with the use of PCA. An example of a library used is the Olivetti Research Lab (ORL). These isolated traits are split into training and assessment groups. The group involved with training finds applications in training the neural network structures. They are then assessed with the use of the assessment set (Dhanaseely et al., 2012).

In 2013, Liu and Liu suggested a technique for the isolation of human viruses' graphic traits as well as identification with the utilization of Grey Level Co-occurrence Matrix GLCM. This was to enable the efficient isolation of characteristic data of human viruses' graphics. Initially, twenty microscopic graphics of sections of human viruses are gotten with the use of Grey Level Co-occurrence Matrix. Followed by this is the isolation of the four factors involved with texture which are entropy, energy inertia moment as well as correlation. These are all isolated with the use of Grey Level Co-occurrence Matrix. Following this step is the identification of the human virus graphic (Liu at al., 2013).

Singh and colleagues in 2015 suggested a novel blend approach on the Support Vector Machine SVM as well as Fuzzy C-means for the categorization of cerebral growths (Singh et al 2015).

This suggested technique combines the Support Vector Machine and the Fuzzy C-means to generate a joint or blended approach for the identification of cerebral growths. For this approach, the graphic is improved with the utilization of improvement approaches like the improving the contrast, mid-limits extension and so on. For the purpose of striping the skull, a two-times thresh-holding as well as processes involving morphology are utilized. Fuzzy C-means FCM, clumping is utilized for the categorization of the graphic to identify the section of the Magnetic Resonance Image of the brain that is considered suspicious of being diseased.

The isolation of the trait from the magnetic resonance image of the brain is performed by utilizing the Grey Level Run Length Matrix (GLRLM). Following this process is the SVM procedure for the classification of cerebral Magnetic Resonance Imaging graphics. This sequence of techniques yields precise and efficient outcomes for the categorization of cerebral Magnetic resonance imaging pictures (Singh et al., 2015). Ersoy and team in 2011 suggested a group categorizer in an effort to enhance the precision as well as the duration of processing. The precision of categorization and the duration of processing are vital aspects in selecting techniques for categorization.

They utilized twelve varied group categorization techniques and eleven lone categorizers. These were contrasted based on their precision as well as test processing duration across thirty-six data groups. The outcomes from the investigation depict that the greatest precision was with Rotation Forest. Nonetheless, precision and duration of processing, if taken together, Random Forest as well as Random Committees rank the best (Ersoy et Al., 2011).

As previously mention, cerebral growth is a collection of tissues characterized by a gradual multiplication of abnormal cells. It is responsible for numerous deaths around the world. It is of chief concern among all other forms of cancers. Detecting these abnormal cells is quite challenging and therefore requires the use of Magnetic Resonance Imaging technique for therapy. Simple scanning procedures may not adequately reveal the exact nature of the brain tumor. Group methodologies amongst other methodologies ranked top in developing Data mining as well as machine learning in the past couple of years.

These methodologies blend several patterns to generate much precise results than the results generated by individual constituents. These group methodologies blend the techniques of neural network, Extreme Learning Machine (ELM) as well as Support Vector Machine categorizers. This suggested technique constitutes a variety of stages. These are the pre-process, segmentation, trait isolation as well as categorization stages.

The preprocess stage was carried out by the utilization of the filtration technique. Segmenting was carried out by utilizing clumping technique. Trait isolation was conducted by using the Grey Level Co-occurrence Matrix (GLCM). The categorization stage is performed with the utilization of group categorization. This stage categorizes cerebral graphics into diseased (tumor) and healthy (normal or non-tumor). It utilizes the Feed Forward Artificial Neural Network categorizer. This study showed that this approach proved quicker and sensitive (Kumar et al., 2019).

The point of origin of all benign tumors is the brain whereas that for metastatic tumors could be from any other part of the body. Metastatic tumors otherwise known as cancers disseminate swiftly to affect other parts of the brain as well as spinal cord. Tumors can be further classified into four different stages. The higher stages reflect the severity of the tumor. For grown-ups, the general form of tumors that affect them are generally called gliomas (Wen et al., 2008).

The classification of tumors from I to IV is done according to the prescription of the World Health Organization (Reifenberger et al., 2016). The Grade I tumor cells appear benign as they do not really look different from normal cells. But as the grade increases to II, some form of cellular irregularities begins to manifest. From grade III, the cells are undoubtedly cancerous in nature. The metastatic cells which disseminate swiftly are purely considered grade IV.

Tumors are named depending on the part of the brain affected. Meningioma tumors or growths affect the layers of the meninges. Those that affect the pituitary gland are referred to as pituitary tumors. These constitute close to 14 % of brain tumors. A possible cause for this is hereditary effects while another likely cause is the continuous mutations of these cells (Ezzat et al., 2013).

Therefore, early diagnosis of the tumor is a significant factor for effective therapy and recovery of the sufferer (Kelly 2010). An MRI scan of the brain is always recommended for patients suffering from symptoms of a brain tumor. The detection of brain tumor from the MRI scan subjects the patient to a cerebral biopsy. Apart from biopsy however, a number of novel approaches have been developed in recent years. The distinguishing of low class from high class tumors with the use of perfusion Magnetic Resonance Imaging has tackled some challenges involved with biopsies. This computer assisted application aids in the detection of tumors. At earlier phases of the cerebral tumor, an effective and automated structure for the classification of the tumor assists medical practitioners to make sense out of the graphic as well as guides prognosis.

A number of investigations have been performed on the categorization of tumors, most of which are centered around implementing Magnetic Resonance Imaging as the central tool coupled with classification techniques such as evolutionary algorithms, MR cerebral graphics, Artificial Neural Networks, Support Vector Machine as well as a host of blended techniques (Wang et al., 2012). These classification techniques distinguish normal from diseased cells from the graphics gotten from Magnetic Resonance Imaging of the brain.

For instance, in a 2009 study conducted, Zacharaki and colleague employed the Support Vector Machine as the tool to classify the MRI graphic of the brain (Zacharaki et al., 2009). The section of interest is first of all reported in detail. This then followed by aspects like the structure of the tumor and its dimensions as shown from the MRI graphic. SVM was implemented in this investigation for the prevention of repeated aspects so as to enable accurate pinpointing of the exact feature. The projected approach of binary categorization as well as the monitoring of outcomes ensured the achievement of improved accurate results. The setback in this study was observed with the categorization of multiple grades which showed decreased sensitivity.

Landman and colleagues in 2016 utilized the Convolutional Neural Network (CNN) classification technique together with its linked prototypes. A variety of CNN system operations were contrasted as well as Relative Shallow Network with 2-max pooling sheets, 2 fully connected sheets as well as 2 Convolutional sheets were engaged in the categorization. For an enhanced sensitivity with respect to categorization, the Vanilla pre-processing technique yielded more effective outcomes (Landman et al., 2016).

Another investigation for the classification of cell and differentiating them into normal and abnormal cells as well as the distinguishing between low class and high-class glioma growths was conducted in 2017. This experiment utilized a modified form of AlexNet. This procedure required intense endeavors for patterning an automated as well as Real-time approach for cerebral Magnetic Resonance Imaging categorization (Khawaldeh et al., 2017).

In the course of fixing the challenging aspects involved with machine intelligence, convolutional neural networks have contributed much accomplishments and at present are considered the superior technique with respect to the interpretation of Magnetic Resonance Imaging graphics (LeCun et al., 2015). Regardless of quantity of matrices, they can be utilized in great quantities of network sheets. This presents a solution to the concerns with Convolutional networks which have increased calculation worth. It also has some significance from the fact that the information library in Magnetic Resonance Imaging engages several different grades and types. Another advantage is the automated isolation of characteristics of the graphic especially if compared to superficial ML approaches. This study engaged a technique for the isolation of characteristics and for the decreasing of dimension. Convolutional neural networks have been widely engaged in clinical graphics like cerebral tumors, categorization of tumors and segmenting (Mohan et al., 2018; Pinto et al., 2016; LeCun et al., 2015).

In 2019, a study conducted for classifying brain tumors utilized a convolutional neural network technique for the Magnetic Resonance Imaging graphic. Due to the challenges in selecting a convenient construct for Deep Neural Network, for a operation that is conducted with the use of a generalized frame, the convolutional neural network frame was obtained with the utilization of Particle Swarm Optimization (PSO) technique. The system which comprises multiple layers and features are analyzed via Particle Swarm Optimization. To achieve more processing, the system with the superior operation was selected.

Authentication of this experiment was with the engagement of 2 case studies. For the establishment of the approach in later studies, a number of different types of growths from other Magnetic Resonance Imaging libraries were used as data toward computational neural network to confirm the ultimate prognosis of the operation. With respect to guiding medical practitioners in earlier identification, the results of this investigation verify that this approach suits many different kinds of data sets of cerebral Magnetic Resonance Imaging (Rajini 2019).

Common types of cerebral growths include meningioma, glioma and pituitary tumors. Meningiomas originate from the meninges that surround the brain and spinal cord and are generally benign in nature. Gliomas on the other hand are an aggregation of growths within the brain matter and quite often are found alongside normal cells (Mahsa et al., 2016). With increase in dimension of gliomas, they result to brevity of life. Pituitary tumors originate in the pituitary gland of the brain. Some of these tumors lead to uncontrollable rise of the hormones which regulate vital body activities. As a result of their innate nature, pituitary tumors can pop up anywhere from the brain. They are shapeless, of varying dimensions and contrasting features.

Segmenting cerebral growths are paramount in the detection of tumors. The utilization of mechanical intelligence otherwise known as machine learning techniques which study the sequence of cerebral growths, it evades the demanding and time-consuming task of laborious segmenting and hence avoids the problems relating to human flaws. Generally, the segmentation of graphics is the procedure of automatic or semi-automatic identification of limits of a two dimensional or three-dimensional picture (Kadkhodaei et al., 2016).

The normal cerebral tissue comprises three sections namely the gray matter, white matter and the cerebrospinal fluid. Segmenting is helpful to point out the sections affected by the tumors. This segmenting distinguishes the tumor affected tissue from the dead tissue. It also helps to identify the inflammation surrounding the tumor. This is primarily accomplished by the identification of diseased sections when contrasted to normal sections (Havaei et al., 2017; Nyoma et al., 2019; Parihar et al., 2017).

Most automated cerebral growths segmenting techniques utilize handmade characteristics like corners, boundaries, texture, gradient histogram, Local Binary Pattern and much more (Bjoern et al., 2015). The above techniques have laid emphasis on implementing a classic mechanically intelligent channel. The aspects of interest are isolated and then introduced for classification by a classifier. The working principle of this classifier is independent of the type of aspect (Havaei et al., 2017).

Convolutional Neural Networks don't utilize handmade aspects. They have been implicated in segmenting Magnetic Resonance Images with satisfactory outcomes.

A 2019 study conducted by Zahra and colleagues in 2019 proposed an automated segmenting approach for cerebral growths dependent on Convolutional Neural Network. 3 perspectives of the MRI brain graphics were utilized. The advantage of the MRI scan to the CT scan is the fact that it presents less harm to the patient and generates greater accuracy.

In recent times, deep learning has gained popularity in computer assisted applications. One of these is in reducing human reliance in the prognosis of infection. Of particular interest of this application is in the detection of brain tumor infections which require an extreme degree of sensitivity, wherein minimal faults could have devastating effects. Thus, segmenting of cerebral growths is of paramount concern in the field of medicine. A number of approaches have been developed but are plagued with low inaccuracies. In the 2019 study conducted by Zahra and colleagues, Deep Learning technique was utilized. Various perspectives of the Magnetic Resonance Image were investigated. This was then subject to varied systems for segmenting. The impact of utilizing distinct network systems for segmenting Magnetic Resonance Images was analyzed by contrasting the outcomes to hat of a single network system. The outcome of this investigation shows that the Dice yield of 0.73 is accomplished for a lone system and the Dice yield of 0.79 is achieved for numerous systems (Zahra et al., 2019).

The proportion of deaths which result from cerebral tumors are greatest in Asia (International Agency for Research on Cancer; November 2018). Signs associated with brain tumors include diminished co-ordination, constant headaches, impediment in speech, inability to focus, fits and degenerative memory. Tumors of the brain are classed depending on their type, source, extent of progression, and phase (Brain Tumor Diagnosis; November 2018).

With respect to the extent of proliferation, the World Health Organization grades tumors into four stages (Lynch et al., 2016). Cerebral growths are further differentiated into levels with respect to their phase of development. These stages are 0, 1, 2, 3 and 4.

Phase 0 depicts diseased cells as tumors.

Phases 1 to 3 depict diseased cells which disseminate.

Phase 4 denotes abnormal cancerous cells which spread all over the body.

The rate of fatality of cancer can be avoided provided the cancer is detected at an early phase.

The prognosis of cerebral tumors could either be invasive or non-invasive. Invasive techniques involve making an incision of the brain to collect a sample of brain tissue for microscopic evaluation. The non-invasive technique involves the physical examination of the brain with the utilization of computer graphics. Some of these imaging techniques are Computed Tomography scans and Magnetic Resonance Imaging. These are faster, cost effective and safer than the gold standard technique of obtaining biopsies.

Such non-invasive approaches assist medical practitioners ascertain the existence of cerebral diseases as well the phase at which it is in. this goes a long way to help strategize the most appropriate form of therapy (Mahaley et al., 1989).

The interpretation of such images however is a heavily dependent on the experience and skill of the practitioner as it (Hayward et al., 2008).

A number of computer aided applications are now implemented in the detection of brain tumors. More research is performed on the possibility of improving these computer-aided applications for use among medical practitioners to ensure a level of consistency in their prognostic results.

2.3 Pathophysiology of Brain Tumors

2.3.1 Cellular Construct

The cell is the fundamental unit of structure and function of the human body. It determines the role of every structure in the human body like the flow of gases, of blood, as well as waste and end products of metabolism. Every cell has a main regulating structure called the nucleus. This nucleus bears twenty-three pairs of chromosomes which comprise several million genes. Guidelines for these genes are housed in deoxyribonucleic acid (DNA) (Griffiths et al., 2005). DNA is a form of pattern for genes. It determines their outcome. Gene protein acts like a conveyor of information between cells or genes. The information relayed depends on its three-dimensional architecture (Shinoura et al., 1996).

Genes regulate the life cycle of cells as well as apoptosis of diseased cells. The unregulated growth of diseased cells characterizes cancers. This is thus due to a mutation at the level of the genes which throw this DNA sequence off balance and hence leads to the irregular behavior of the genes. A handful of elements are implicated in gene DNA alterations. These elements could be environmental, way of living as well as diet.

Cancer-causing genes are known as oncogenic genes and are of three types.

The first types are those involved with regulating the cell death cycle known as apoptosis. These genes. These genes are called tumor suppressors (Evan et al., 2001). Two action paths are implicated by these cells in their actions. The first involves the cell being regulated to kill itself. The second involves the cell being directed by neighboring cell signals to kill itself. A gene alteration in any one of these courses leads to decreased apoptotic effects. In the situation where both pathways are affected by such gene alterations, there is a complete cessation of apoptosis (Burch 2012). Some suppressor genes include RBI, PTEN (Song et al., 2012).

The second types are involved with the repairing of faulty DNA. Some of these include MGMT as well as p53 protein.

The third category are called proto-oncogenes. These are implicated in the manufacture of protein factors in charge of cell replication and restricting apoptosis (Filmus et al., 1995).

The replication of normal cells is regulated by proto-oncogenes through protein triggers which originate from the cells. These signals flow through a signal transduction cascade. This involves a series of proteins which convey this signal from plasma membrane through cytoplasm to cell nucleus. At the nucleus, genes responsible for transcription are activated. An example of such is the RAS which is responsible for controlling the activation/deactivation process of the transcription process (Greenberg et al., 1985).

An alteration of this gene transforms it into an oncogene. As an oncogene, it loses its ability to deactivate the cell replication trigger which thus leads to uncontrollable replication.

Such cancers which originate from the above means is known as primary, but if originates from blood vessels, is known as secondary (Sneed et al., 2002). As with all living systems, these abnormal cells also require a supply of oxygen and nutrients. Genes responsible for this requirement commence setting up a blood supply network to meet this need. This is referred to as angiogenesis and is largely responsible for more growth of the cancerous cells (Bertram 2000).

2.3.2 Significance Between Brain Tumor and Oncogenes

As previously seen, gene mutations could lead to cancers. From a variety of investigations, it is proven that the extent of gene mutation is connected to the type of brain tumor experienced. Tp53 is implicated in DNA reconstruction as well as the commencement of cell death process. In advanced cases of gliomas, this protein is in high quantities and has been reported in over eighty percent of such tumors (Mabray et al., 2015). The RB1 (retinoblastoma) gene is involved with the repression of growths. It is implicated in about seventy-five percent of cerebral growths. It is especially common in glioblastomas (Mabray et al., 2015).

EGFR is a cross membrane receiver of the tyrosine kinase group. Alterations in it causes uncontrolled mutations as well as increases the tumor's cells resistance, hence improves their ability to survive. It is associated with glioblastomas which contain about forty percent of the alterations that led to the cause of these tumors (Hegi et al., 2006).

The PTEN is also a growth repressor gene. It is implicated in about fifteen to forty percent cases of primary glioblastomas. It has also been reported as constituting about eighty percent of ordinary glioblastomas (Hegi et al., 2006). A group of enzyme chemicals which regulate the tricarboxylic acid cycle are the IDH1 and IDH2. Alterations in these genes restrict the action of their respective enzymes. Only small proportions of about five percent of IDH1 are implicated in cases of primary glioblastomas. This proportion is however higher with glioblastomas where they constitute over seventy percent. Alterations in IDH2 are typical with oligodendrglial growths (Yan et al., 2008).

The expungement of chromosomes 1p as well as 19q signify a history of oligodendroglial. This is typical with about twenty to thirty percent cases of anaplastic oligoastrocytomas, thirty to fifty percent cases of oligoastrocytomas, sixty percent cases of oligodendrogliomas and finally up to eighty percent cases of oligodendrogliomas. The 1p and 19q genes provide guidance in the diagnosis and evaluation of therapy (Hu et al., 2016). Another chemical involved with the fixing up of DNA is the MGMT. It is implicated in about thirty-five to seventy-five percent cases of glioblastomas (Lee et al., 2018).

This is seen in the table below:

Table 2.1: Significance Between brain tumor and oncogenes

Gene type	Function	Effect of Mutation	Significance to Brain Tumor	Reference
TP53 (p53)	DNA repair Initiation of cell death	Genetic instability Decrease in apoptosis Angiogenesis	Relevant to HGG Causes 80% brain tumors	Mabray et al., 2015
RBI	Tumor suppression	Inhibits progress of cell division Unchecks cell division progress	Relevant to GBM Causes 75% brain tumors	Mabray et al., 2015
EGER	Transmembrane receptor	Increased growth Increases survival of cell tumor	Primary GBM (40%)	Hegi et al., 2006
PTEN	Tumor suppression	Increased cell division Reduction in cell death	Primary GBM (15 – 40%) 80% GBM	Hegi et al., 2006
IDH1 and IDH2	Regulates citric acid cycle	Inhibit enzyme function	IDH1 5% primary GBM 70 to 80% primary GBM class II to III IDH2 Significant to oligodendroglial tumors	Yan et al., 2009

Table 2.1: Significance Between brain tumor and oncogenes (Continued)

1p and 19q	Disease diagnosis and evaluation of therapy	Poor diagnosis	80% oligodendrogliomas 60% anaplastic oligodendrogliaomas 30 to 50% oligoastrocytomas 20 to 30% oilgoastrocytomas	Hu et al., 2016
MGMT	DNA repair Prognosticate survival	Cell division	35 to 75% GBM	Lee et al., 2018
BRAF	Proto-oncogene	Cell division Cell death	65 to 80% pilocyticastrocytomas 25% pleomorphic xanthoastrocytomas and ganglioglimas	Mabray et al., 2015
ATRX	Deposits genomic repeats	Genital abnormalities	Significant to oligodendroglial	Mabray et al., 2015

A proto carcinogen called BRAF protein is engaged in the mitotic division of cells, apoptotic effect on cells as well as the evaluation of therapy. BRAF proteins are implicated in about sixty-five to eighty percent cases of pilocyticastrocytomas, about eighty percent cases of pleomorphic xanthoastrocytomas and finally about twenty-five cases of gangliogliomas (Mabray et al., 2015).

The A-TRX gene fully known as the A-Thalassemia mental retardation syndrome X-associated gene codes for a chemical and is implicated with TP53 as well as IDH1 alterations. It is commonly helpful for diagnosis of tumors with IDH1 alterations. It also helps differentiate oligodendroglial growths of various causes (Mabray et al., 2015).

2.4 Imaging Techniques

Imaging techniques in clinical practice enables physicians, scientists and medical practitioners see the interior aspects of the human body as well as evaluate the interior events without having to carry out surgical procedures. The prognosis of cancer, its categorization, diagnosis of the sufferer as well as organizing a surgical procedure are the major hurdles to obtaining an efficient therapy for cancer.

A host of clinical imaging procedures exist. These can be divided into two major groups; structural and functional imaging techniques (Pope et al., 2018).

The structural imaging techniques involve the variety of aspects concerned with cerebral structure, tumor site, bruises as well as a variety of related brain abnormalities.

Functional imaging techniques involve aspects concerned with the detection of metabolic irregularities, microscopic bruises as well as the sighting of cerebral processes. The possibility of this sighting is as a result of variations in metabolism in some areas of the brain as depicted on cerebral scans. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) techniques are utilized in capturing various views of the brain without surgical procedures (Morris et al., 2009).

2.4.1 Magnetic Resonance Imaging

In medicine, the technique of Magnetic Resonance Imaging is widely utilized for the identification and therapy of cerebral tumors. The graphics are usually obtained from 3 different fronts known as the sagittal, axial and coronal fronts. These are shown in the figure below:

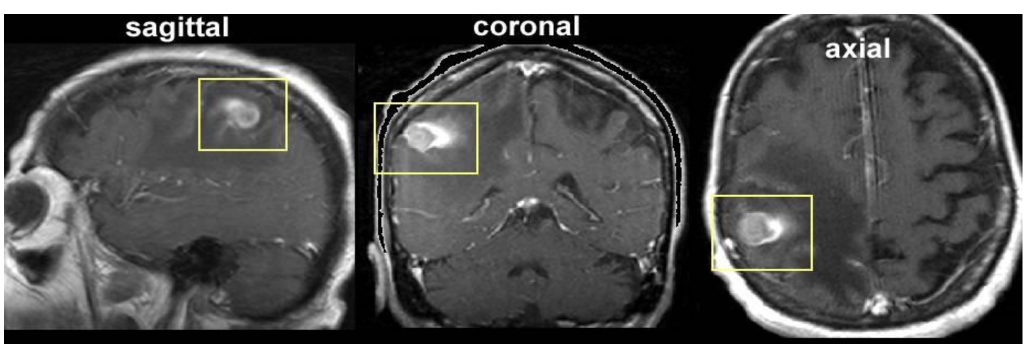

Figure 2.1: MRI of brain scan with single cerebral metastasis

This is a brain scanning technique which is void of the use of radiation and thus safer than the CT technique. More so, it generates much finer graphics with better details of the spinal cord, brain and the vascular supply as a result of its much superior contrast. The fundamental view planes of the magnetic resonance imaging technique are the axial, sagittal and coronal planes. The sequences generally employed by this technique are the T1 weighted, T2 weighted and FLAIR (Dong et al., 2004).

The contrast of grey and white matter is provided by T1 weighted examination. The T2 weighted examination is responsive to hydration. Hence, is most suitable for cerebral infections characterized by an accumulation of water in cerebral tissues. Both weighted examinations find usefulness in distinguishing cerebrospinal fluid. This CSF has no color and is located in the central nervous system. With T1 weighted graphics, it appears dark whereas with T2 weighted graphics, it appears bright.

Fluid Attenuation Inversion Recovery (FLAIR) is the third of these sequences. It shares much similarities with T2 weighted graphics safe for the procedure involved with obtaining it. It finds implementation in medicine as a distinguishing factor for cerebral irregularities and cerebrospinal fluid. Through the repression of free water indicators, FLAIR can site a section with an edema from cerebrospinal fluid. Therefore, it makes easily visible, graphics depicting injuries of periventricular hyper intensity.

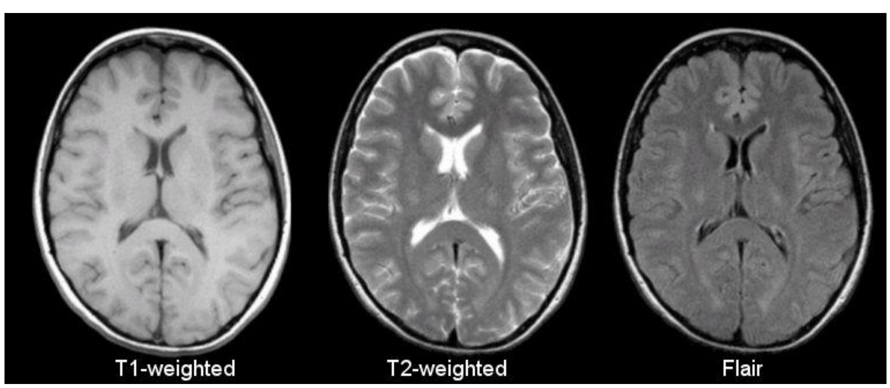

Figure 2.2: A comparison between the three sequences

Diffusion-weighted imaging (DWI) is also an MRI sequence. It finds implementation in identification of flowing water molecules in the brain (Khoo et al., 2011). With increased prohibition to the flow of these water particles, a bright indication reflects on the diffusion-weighted imaging. This sequence finds uses in the detection of acute stroke.

Perfusion-weighted imaging (PWI) is an MRI sequence which depicts the main sections of the brain where blood supply has been cut off or distorted.

Diffusion tensor imaging (DTMRI) is an MRI sequencing technique which identifies the movement of water molecules in tissues via a microscopic graphic. This helps guide physicians during a surgical incision of brain tumors.

Functional MRI (fMRI) is a sequencing technique utilized for the analyses of variations in blood oxygen concentrations as a means for interpreting neural activities. This is seen in the situation where increased activity in a particular section of the brain places more than usual demand of oxygen and blood. Hence this sequence imaging technique monitors brain activity by relating the mental activity and site (Savoy et al., 1999).

Despite the obvious beneficial results with MRI compared to other techniques like CT scan, it also has a variety of setbacks compared to the CT scan. For instance, the effect of movement artefact is of lesser quality in MRI. Though it aids in the detection of cerebral hemorrhage as well as cerebral lesions, it also necessitates much time acquiring it compared to the other approaches.

2.5 Imaging Tests

Techniques such as Computed Tomography, Magnetic Resonance Imaging, PET as well as SPECT are among the commonest cerebral imaging approaches for the confirmation of the presence of growths without having to perform a surgical procedure. Of the above-mentioned modalities, Magnetic Resonance Imaging is the most used. It is chiefly implicated with the identification of neural abnormalities as a result of its superior contrast with various tissues as well as the absence of the use of radiation. A number of factors make the automated identification of cerebral growths as well as their classification a hurdle. Some of these include the strengths which overlap, variations in physical structure, dimensions and planar configuration, noise as well as inferior contrast of the graphics (Sasikala et al., 2008). Some of these are shown in the table below:

Table 2.2: A summary of hurdles involved with the analysis of brain scans

Challenge	Aim	Modality
BRaTS 2012	Brain tumor segmenting	MRI
BRaTS 2013	Brain tumor segmenting	MRI
BRaTS 2014	Brain tumor segmenting	MRI
BRaTS 2015	Brain tumor segmenting	MRI
BRaTS 2016	Quantification of longitudinal variations; investigating the sensitivities of the volumetric variations between two periodic locations	MRI
BRaTS 2017	Segmenting gliomas in pre-operative graphics. Predict patient survival from these graphics	MRI
BRaTS 2018	Segmenting gliomas in pre-operative MRI graphics. Predict patient survival from these graphics.	MRI
MICCAI 2018	Segment gray matter, white matter, CSF	MRI
HC-18	Come up with a technique for automatic analysis of the circumference of fetal head from a two dimensional ultrasound graphic	Ultrasound

2.6 Methods of Classification

Machine learning is a condition in which a machine receives a duty and its operation on it gets better with frequency (Haykin 2009). There are two kinds of machine learning techniques namely; supervised and unsupervised learning (Wernick et al., 2010).

For supervised learning, the machine learning technique acquires skill from existing identified information. Whereas in unsupervised type, the machine learning technique attempts to acquire skill from inter-data connection with unidentified information. With regards to the examination of graphics from cerebral scans, machine learning has found uses in the characterization of cerebral tumors (Erickson et al., 2017).

The internal operations of machine learning techniques comprise two phases; the isolation phase and the implementation of machine learning technique for classification phase. The model of the procedure is shown in the figure below.

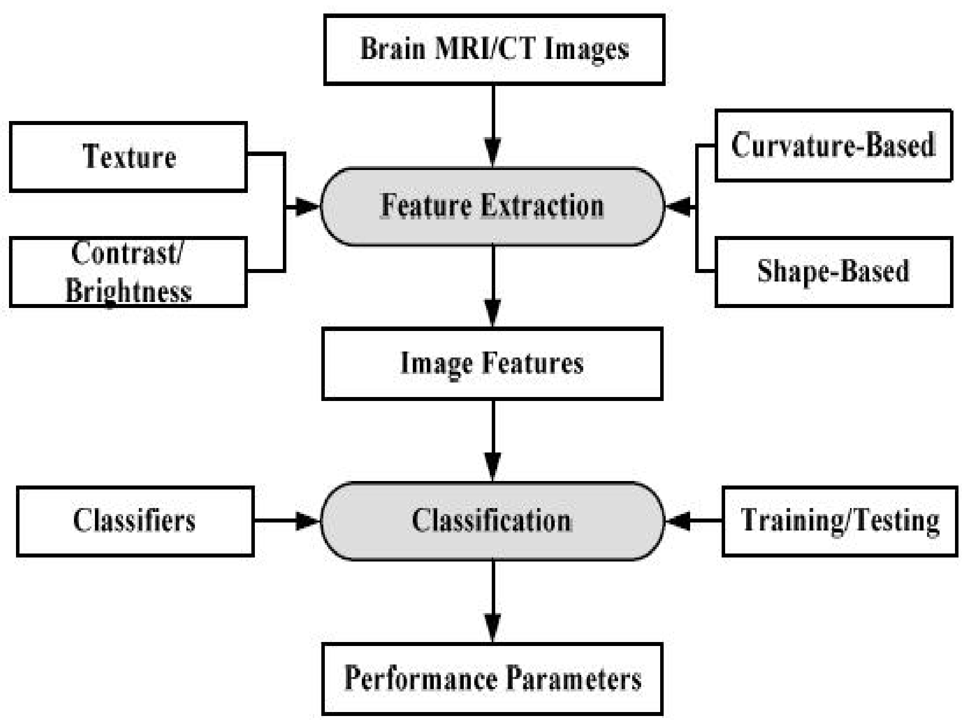

Figure 2.3: Process model of machine learning techniques

The isolation techniques are computational patterns dependent on a variety of graphic characteristics like texture, clearness and contrast. In some cases, a number of properties from various isolation patterns are joined together to enhance the bias strength of machine learning techniques (Vasantha et al., 2010). A few of the popular techniques for classifying and categorization are;

- K-Nearest Neighbors (KNN)
- Support Vector Machines (SVM)
- Artificial Neural Networks (ANN) (Yegnanarayana 2006)

The KNN classifying approach is dependent on the principle that characteristics of similar class clump together. It allocates an unidentified case the popular identification among its KNNs (Altman 1992). The SVM engages two techniques for characterizing: initially, it makes an attempt to situate the greatest distinctive hyper-plane among two groups. Next, if the properties can't be distinguished uni-dimensionally, these properties are charted to greater levels wherein they are rectilinearly distinguished with the use of the kernel technique (Cortes et al., 1995). ANN generates a categorical connection of mathematical intersections with the ability of learning from properties. They are grouped into various kinds based on construct, quantity of concealed levels, link weight upgrading techniques etc. the commonest of these ANN patterns are Extreme Learning Machines (ELMs) (Huang et al., 2006), Recurrent Neural Networks (RNN) (Grossberg 2013), Restricted Boltzmann Machine (RBN) (Hinton et al., 2012).

ELM is a monolayer Feed-Forward Neural Network (SLFFNN). RNN applies response systems in the network associations. RBN neural network has a random probability distribution. The emergence of better performing computer systems and decreased hardware prices have generated into the yield of patterns with many abstracting layers. It has also led to the emergence of multitudes of mathematical nodes which have permitted for classification with superior accuracies. These patterns are known in one collective term as Deep Learning methods (LeCun et al., 2015). The commonest of such DL techniques are Convolution Neural Networks (CNN) (Krizhevsky et al., 2012), auto-encoders (Hinton et al., 2006) as well as Deep Belief Networks (DBN) (Hinton et al., 2009).

2.7 Deep Learning

It is commonly utilized for the evaluation of cerebral graphics in a variety of functions like the classifying of cerebral growths as either normal or irregular, segmenting (swollen, enhanced as well non-enhanced tumor section), segmenting of stroke injuries, prognosis of Alzheimer's disease and much more.

2.7.1 The Convolutional Neural Network

The Convolutional Neural Network is utilized for understanding the manner in which graphics can be segmented. This technique isolates characteristics straight from the pixel graphics with little prior processing. The 2019 investigation conducted by Zahra and colleagues utilized the LinkNet network. It is a Deep Neural Network structure patterned for conducting semantic segmenting. The advantage of this network over the SegNet network is its speed and accuracy (Abhishek et al., 2017). This LinkNet structure is made of blocks of encoder and decoder. They crumble the graphic and reconstruct it prior to sequencing it via a series of convolutional sheets. An example of a LinkNet system is shown below:

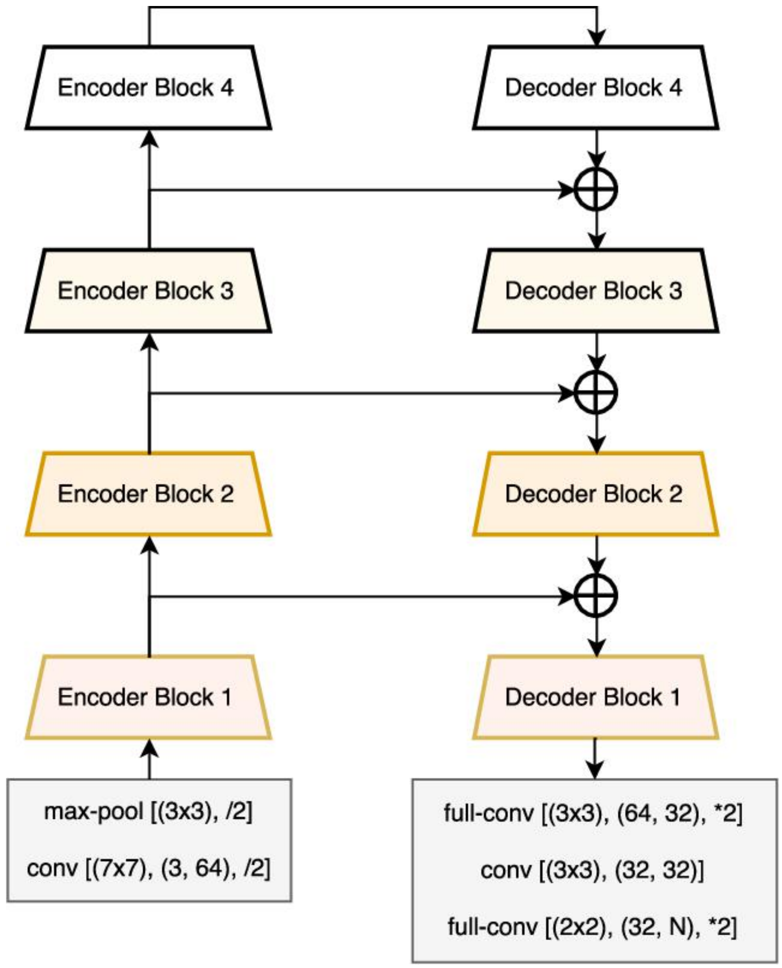

Figure 2.4: LinkNet Structure

The left of the network ıs the Encoder and on the rıght ıs the Decoder. This structure commences with the Initial block. This block engages a convolution application with 7×7 grain dimension as well as max pooling with step two. Addition of the output to the Decoder improves the operation of the LinkNet. This is so because it enables the Decoder in enhanced information recuperation of the layers of the Encoder blocks (Abhishek et al., 2017). Details of both blocks are shown on Fig 3 below.

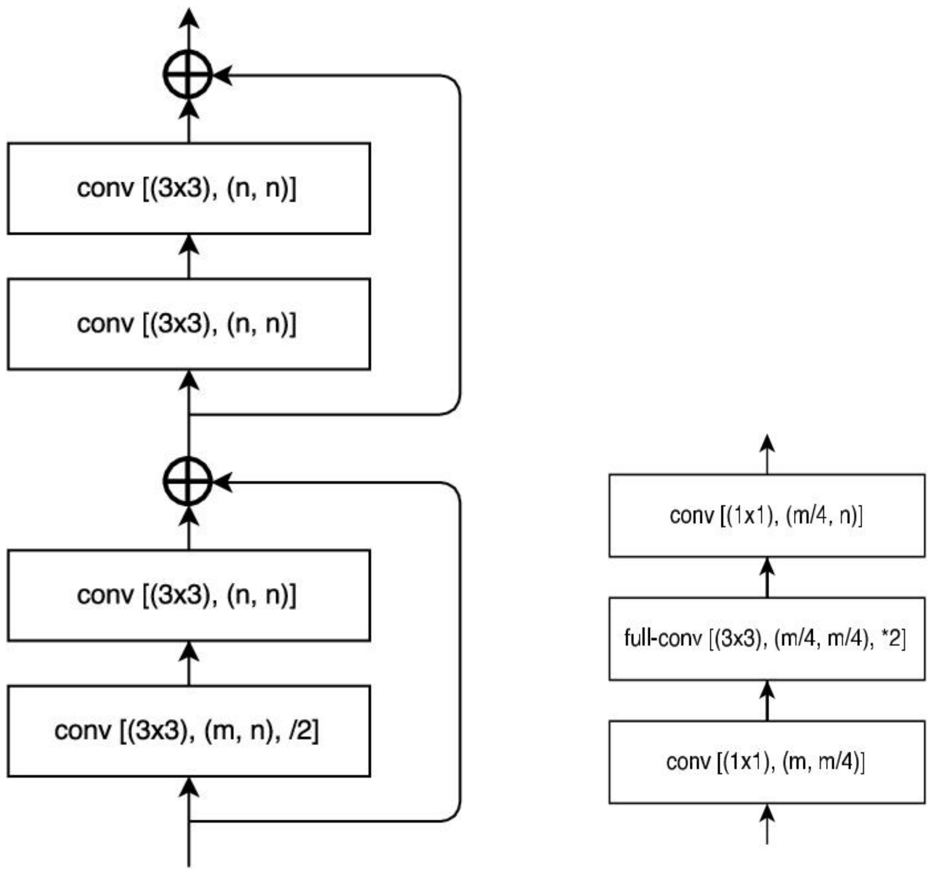

Figure 2.5: a. Convolutional modules in encoder block b. Convolutional modules in decoder block

Of the variety of techniques implemented in this, the Convolution Neural Network (CNN) is the commonest Deep Learning pattern grossly utilized for classifying as well as segmenting clinical graphics. CNN technique acquires skill on the dimensional connection between pixels in a categorical way. Such is achieved by convolving the graphics with the utilization of acquired strains for constructing a category of characteristic charts. Such convolving application is performed in many levels. This enables the properties acquired do not vary translationally and in configuration. This yields a superior level of accuracy. The fundamental layers of the Convolution Neural Network are given below:

2.7.2 Input Image Format

This input graphic is regarded as a display of pixel points. These pixel points are determined by the resolution and the dimension of the graphic. For instance, a colored input graphic is denoted as 3×m×n display of numerals. 3 represents the colors red, green and blue points in a situation of color pictures. The pixel points for every color ranges from 0 to 255; m and n represent the dimensions of the graphic.

In a situation of a grey graphic, the dimension of the graphic is represented by a two-dimensional display m × n. in this case, the strength of the pixels equally ranges from 0 to 255.

2.7.3 Convolution Layer

This is the primary of layers of the CNN construct. It isolates significant properties from the input graphic with the use of the convolution sieves. This sieve is a square display of numerical values that are weights or tools. They can be likened to neurons in the ANN or the kernel. The primary location of this sieve correlates to the top left section of the graphic in the convolution process. this process is defined from the equation:

$$f(x,y) = R(x,y) \otimes S(p,q) = \sum_{p=-m/2}^{m/2} \sum_{q=-m/2}^{m/2} R(x+p, y+q) \times S(p,q)$$

It depicts an instance of the convolving of a graphic R, with kernel S. The symbol $\otimes$ denotes the convolving function.

In essence, the function can be considered a sequence of computations of the graphic pixel grid followed by an addition of these computations. Noteworthy from the expression above is the fact that the dimension of the kernel size is m × m as well as the function is conducted at the center pixel (x, y), as well as close by; p and q represent the dummy variants.

The procedure repeats by moving the sieve to the right. The quantity of moves to the right for every stage describes the stride. The CNN acquires skills and upgrades of kernel points in the course of learning. The CNN construct is demonstrated in the figure below.

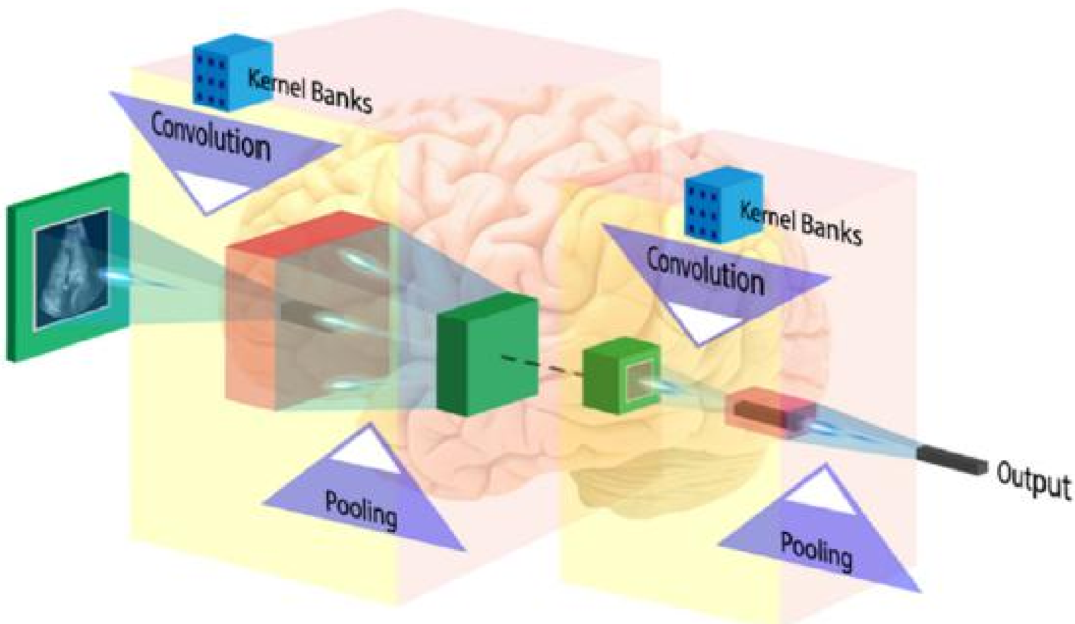

Figure 2.6: CNN construct

2.7.4 Activation Application

With ANNs, the learning is evaluated by a slope dependent methodology. The slope is regarded as a training tool. This training tool highlights the variations in the learning procedure. Due to the small scaled nature of these variations in the course of learning, it makes the training ineffective. This situation is referred to as vanishing gradient problem. This is much intense with deep learning due to the conspicuous proportions of layers. This could be prevented with the utilization of well suiting activated application which lack the feature of repressing the input expanse into a tiny section. An example of such an application is ReLu. ReLu is quite simplistic in use. Mathematically cost-effective activated application. It conducts the twisted function and supplants every negative point in the chart with zero with the use of a formula [max (0, x)]; x denotes an input data (Biswas et al., 2018).

2.7.5 Pooling Layer

To ensure cost effectiveness with regards to computation, this layer is placed among convolutional layers so as to decrease the sizes of each characteristic chart. Nonetheless, it maintains the most significant characteristic data. The two commonest pooling functions are average and maximum pooling. With average pooling, chosen characteristics are supplanted with the single mean patch value in the subsequent layer. With the max pooling, just the patch characteristics with greatest points move to the subsequent layers.

2.7.6 Fully Connected Layer

The first 3 layers (convolution, ReLu and pooling) are valuable for the isolation of significant graphic properties. For the classifying of characteristics, a totally linked layer is connected at the termination of the CNN process. This transforms the final two-dimensional layers into a 1-dimensional characteristic vector. The result of this determines by n-dimensional characteristic vector that denotes the quantity of categorical results.

2.8 The Analysis of Brain Graphics with the Use of Deep Learning

DL techniques find utilization in cerebral scans evaluation in various functional sectors like the detection of Alzheimer's disease, segmenting of injuries like growths, white matter, lacunes and microscopic wounds. DL is also utilized in the classifying of cerebral tissues (Litjens et al., 2017).

A significant proportion of current scientific investigations is restricted to the segmenting of the brain. Just a little proportion is focused on the categorizing of tumors. This thus provides much possibility of exploring the category of approximating cerebral tumors with the use of machine learning and deep learning methods. Some brain image segmenting techniques are as follows:

2.8.1 Deep Learning Based Inter-Institutional Brain Tumor Segmentation

A study conducted in 2018 by Albadawy and colleagues on CNN-dependent cerebral growth segmenting was suggested (Albadawy et al., 2018). In this investigation, they utilized 3 CNNs to train on multi-institutional information, were utilized. Every CNN comprised 4 convolution layers and then 2 completely linked layers. Statistics from sixty-eight sufferers were obtained from 2 establishments. Segmenting based on patch was utilized. Spots with same dimensions were isolated from the graphics and identified into 3 groups: tumor spots, normal spots around the abnormal cells and finally normal spots.

The abnormal graphics were again distinguished into 5 groups depending on sufferer information:

Class 0: normal

Class 1: surface reality section dependent on the collection of groups two to five

Class 2: improvement section

Class 3: diseased section

Class 4: T1 abnormality

Class 5: FLAIR abnormality

The various classes are depicted on the figure below:

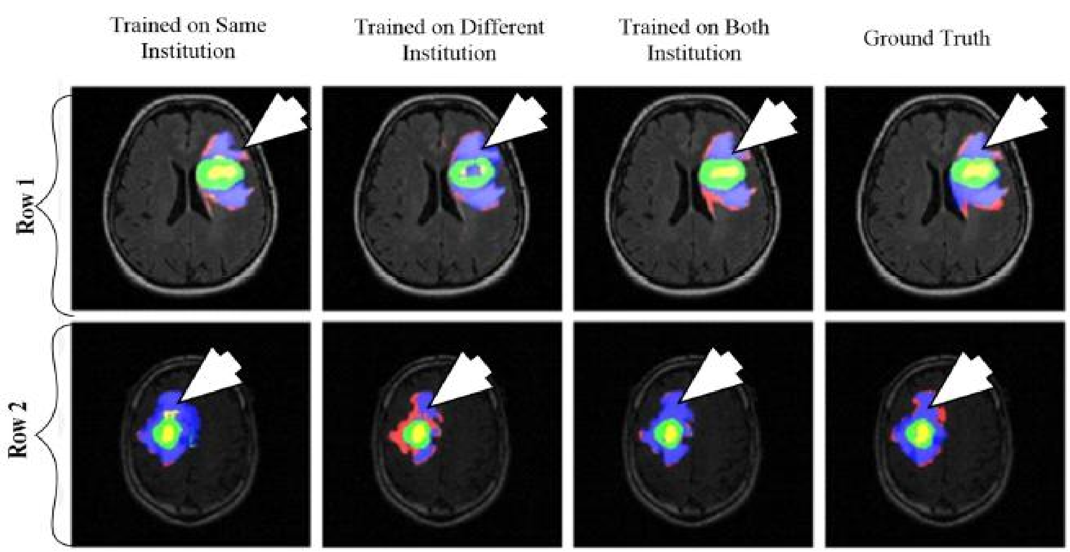

Figure 2.7: Segmenting outcomes from 2 different sufferers. Class 1: ground truth; class 2 (green), class 3 (yellow), class 4 (hypo-intensity section on T1, apart from improvement and diseased sections: red), class 5 (blue)

The primary CNN was coached for the establishment 1 information group, the second for the establishment 2 information group, the third was trained for sufferers from the two establishments. The dice likeness coefficients as well as Hausdorff displacement were utilized for the evaluation between the surface truth and automated segmenting. An authenticating strategy of 10-fold was implemented for a comparison on the operation between various techniques. From the results, it was seen that operation of the prototype reduced with the training of network and tried on various establishment information (dice coefficients: 0.68 ± 0.19) compared to similar establishment information (dice coefficient: 0.72 ± 0.17 and 0.76 ± 0.12). The deduction from this investigation was that the rationale causing this outcome needs more in depth research. The flow process is prototype is depicted below.

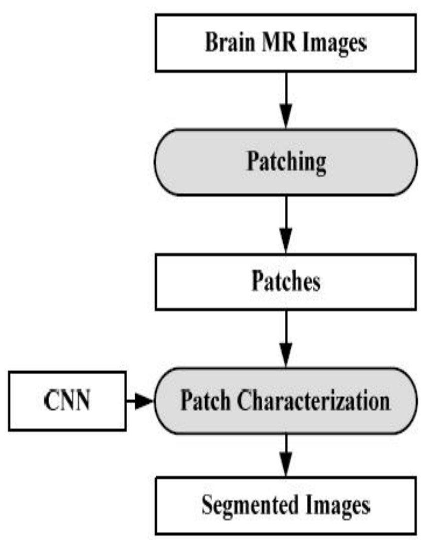

Figure 2.8: Process pattern for segmentation

2.8.2 Segmentation of Brain Tumor with the Use of Two Pathway CNN

This approach was suggested for segmenting cerebral tumors (Havaei et al., 2017). It segments glioblastomas as either low grade or high grade from MRI graphics. Both pathways are applied with the utilization of a tiny sieve for localized segmenting and large sieve for much broader or globalized segmenting. Finally, the characteristic charts from the two pathways are concatenated to generate the segmented graphic. With respect to this technique, 3 networks are utilized:

- Input cascade convolution neural network
- MF cascade convolution neural network
- Local cascade convolutional neural network

Of these cascades, the Input cascade convolutional neural network received the greatest dice likelihood of 0.89. The following figures depict the segmentation yield as well as the construct of the model utilized respectively.

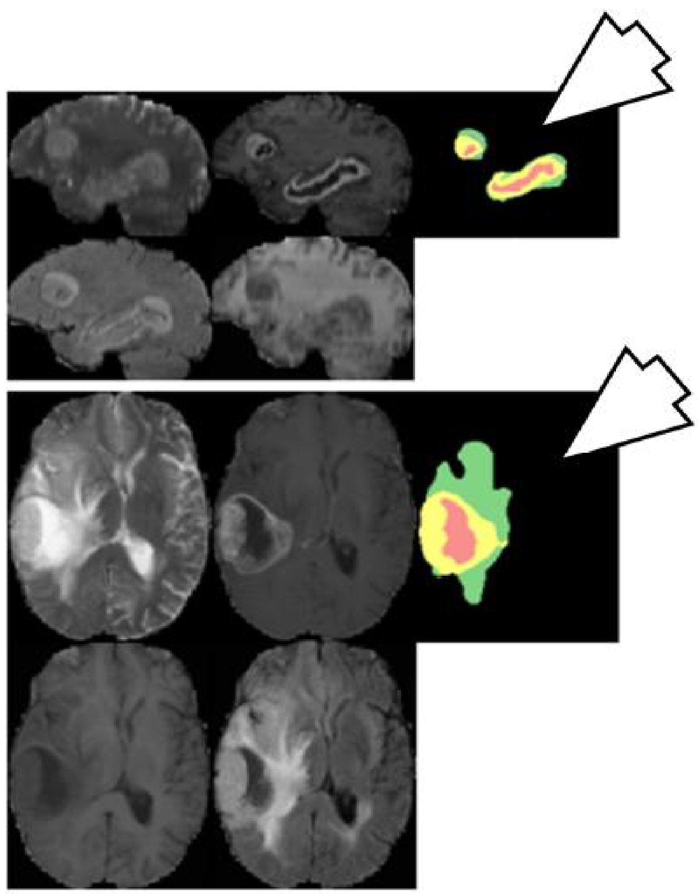

Figure 2.9: outcomes of segmentation from two different sufferers. Green (edema), yellow (advanced tumor), pink (necrosis), blue (benign tumor)

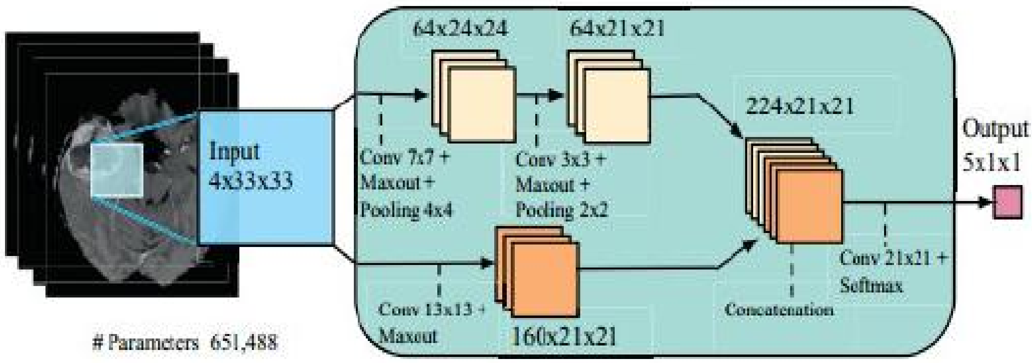

Figure 2.10: Construct of model

In conclusion, the analyses of cerebral tumors with the use of clinical imaging techniques is complex. This procedure can be classified into three steps:

- Pre-processing step
- Categorization step
- Post processing step

The numerous hurdles involved with each of these steps makes it a complex activity. At present, no particular computer assisted application which diagnoses tumor metastasis as well as its extent of aggression. In the majority of tumor situations, physicians largely rely on biopsies (Bardou et al., 2018). This relies on manual observation of cell or tissue with the microscope. Such is definitely subject to individual reader's variability. As a result, the automated detection of brain tumors with the use of Deep Learning techniques and Magnetic Resonance Imaging techniques is a growing research domain.

CHAPTER 3
METHODOLOGY

3.1 Dataset

The dataset utilized in this study was adopted from Harvard Medical School Data (http://www.med.harvard.edu/AANLIB/). The size of the images used for this study had an axial plane of 256 x 256 pixels. Normal images (27) and abnormal images (513) were used for training in this study, thus making a sum pf 613 classified images. The abnormal images from the database consisted of neoplastic (brain tumour), cerebrovascular (stroke) and inflammations. The brain MR imaging for both abnormal and normal consisted of (Chronic Subdural Hematoma, Glioma TITc-SPECT, Sarcoma and Alzheimer). The Alzheimers disease is a kind of abnormal degenerative disease as shown in Figure 3.1.

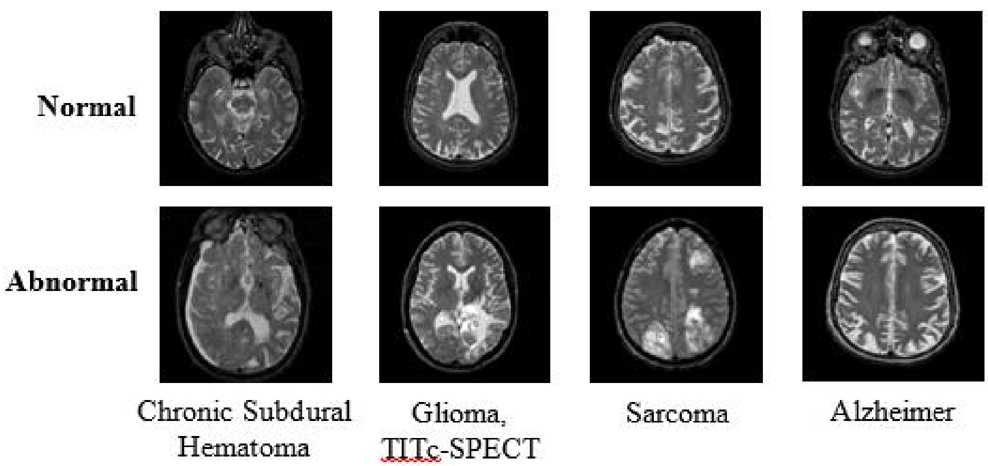

Figure 3.1: Normal and Abnormal MR images for data training

The data used for training was splinted 80% for training and 20% for testing. However, GoogLeNet and ResNet were used as a convolutional architectural method for the training of the dataset.

Table 3.1: Brain Tumor Images

Brain tumer	Number of Images
Normal	613
Abnormal	513
Total	1126

3.2 Parameters for Model Training

The Accuracy (ACC), Specificity (SP) and Sensitivity (SE) of the trained data were analysed using the formulas in the equation below. The true positive, true negative, false positive, and false negative was calculated from the confusion matrix of both ResNet and GoogLeNet architecture. This was done for accuracy, specificity and sensitivity.

$$\text{Accuracy (ACC)} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

$$\text{Specificity (SP)} = \frac{TN}{TN + FP} \tag{2}$$

$$\text{Sensitivity (SE)} = \frac{TP}{TP + TN} \tag{3}$$

Where TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

3.3 ResNet

Residual Networks (ResNets) allow training of datasets greater than 1000 layers (He et al., 2015). ResNet can connect the flow of information's using shortcuts, thereby preventing the occurrence of attenuations, hence improving the optimization of the analysed data. ResNet is a convolutional neural network, which have a unique multi-layer, that can help with several visual recognitions from the pixel images with a less amount of pre-processing. Moreover, with this technique, 152 layers of neural networks can be trained with a high rating of 3.57%, greater than human performance. The architecture of ResNet34 is very easy to use when compared with other networks.

Various enhancements in CNN have been produced using 1989 to date. These enhancements can be arranged as parameter streamlining, regularization, basic reformulation, and so on. In any case, it is seen that the primary purpose in CNN execution improvement originated from rebuilding of handling units and structuring of new squares. A large portion of the advancements in CNN have been made in connection with profundity and spatial misuse. Contingent on the kind of compositional changes, CNNs can be extensively sorted into seven unique classes in particular; spatial abuse, profundity, multi-way, width, highlight map misuse, and consideration based CNNs (Asifullah et al., 2015).

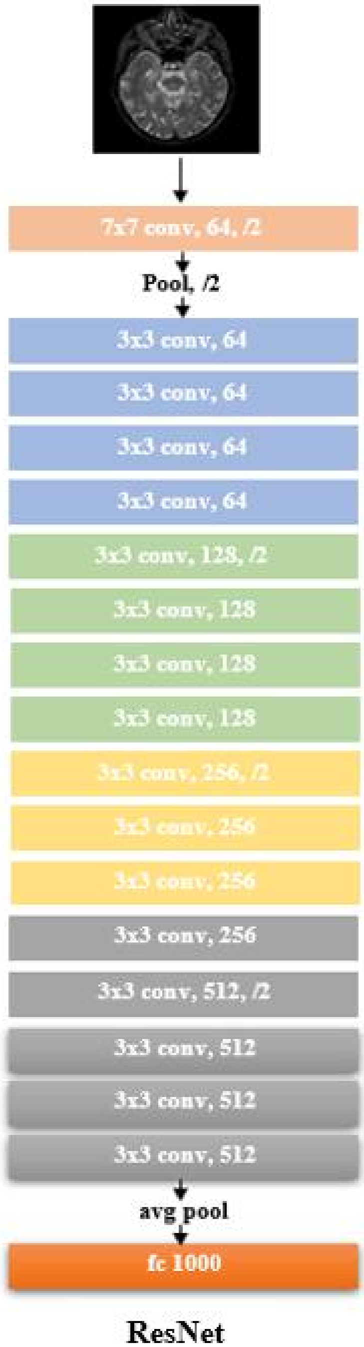

Figure 3.2: CNN architecture of ResNet

3.4 GoogLeNet

GoogLeNet, also known as the Inception V1 is a pre-trained convolutional neural network that has a dept of 22 layers. It has an error rate of 6.67%, which is slightly very close to the accuracy of human performance. This network is driven by a convolutional neural network from the inspiration of LeNet. It adopts RMSprop, batch normalization as well as image distortion for several processes.

In GoogLeNet, convolutional layers are supplanted in little squares like subbing each layer with miniaturized scale NN as proposed in Network in Network engineering. This square exemplifies channels of various sizes: 1x1, 3x3, and 5x5 to catch spatial data at various scales including both fine and coarse grain level. The abuse of split, change and converge by GoogLeNet, helped in tending to an issue identified with the learning of various kinds of varieties present in a similar classification of pictures having various goals (Asifullah et al., 2015). GoogLeNet manages the calculations by including a bottleneck layer of 1x1 convolutional channel, before utilizing enormous size parts. Notwithstanding it, it utilized meagre associations, not all the yield highlight maps are associated with all the information include maps, to beat the issue of repetitive data and diminished expense by excluding highlight maps that were not significant. Besides, association's thickness was diminished by utilizing worldwide normal pooling at the last layer, rather than utilizing a completely associated layer.

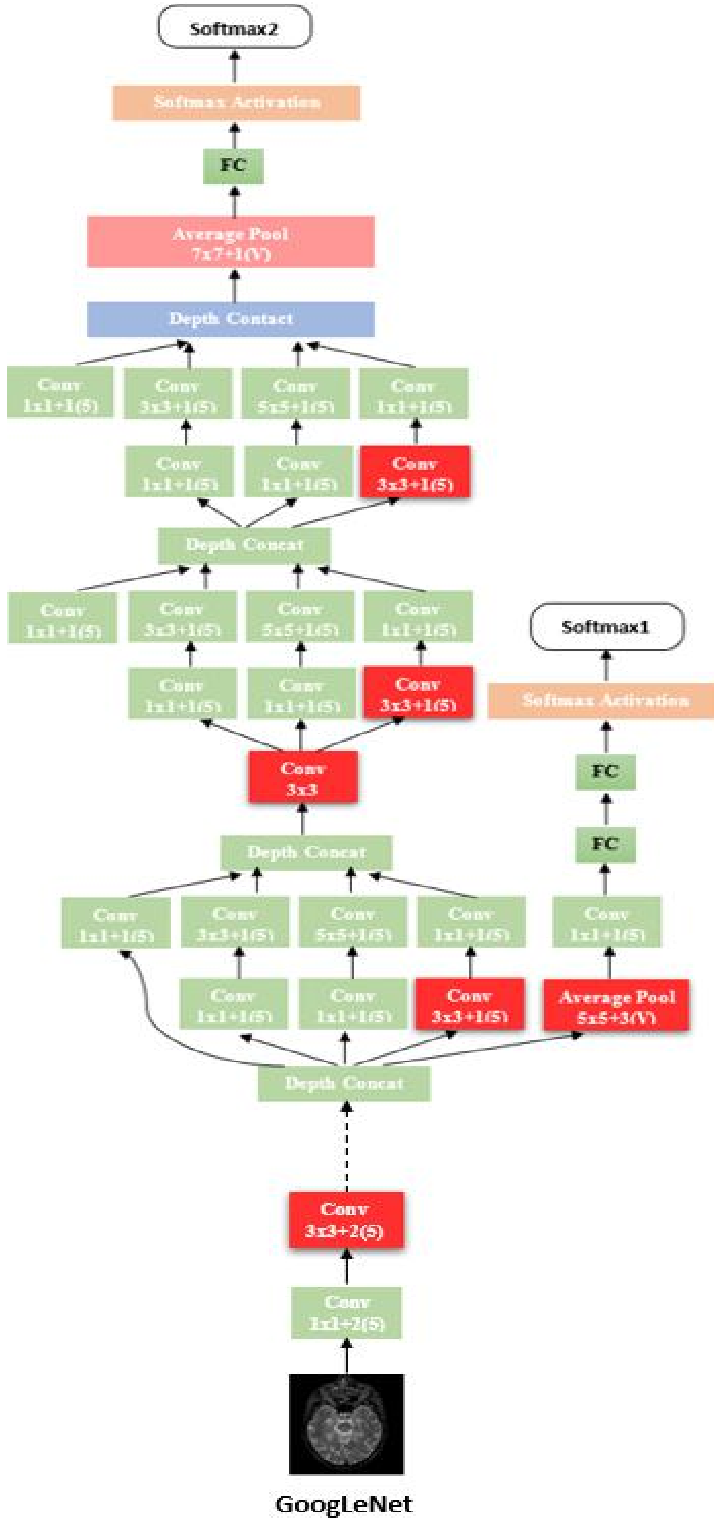

Figure 3.2: CNN architecture of GoogLeNet

CNNs starts with a progression of convolutional and pooling layers and finishes with a completely associated layer. The structure of profound learning models can regularly take after the Lego blocks. We can make a convolutional neural system by stacking some convolutional layers, pooling layers and thick layers. We have just utilized ResNet34 engineering's heap of exchanged convolutional and pooling layers.

Preparing the model with utilizing generally little information for the most part causes overfitting during preparing. The model retains the subtleties of the preparation set in any case, doesn't sum up utilizing the approval set. All together to relieve this overfitting issue, the information increase system is utilized during preparing. Information increase is a technique can create even more preparing information from the current preparing informational collection. In this way, we have utilized information growth technique to make new mind MR pictures for the preparation set. The easy method to have more information is making virtual information by information enlargement procedures, for example, zooming, flipping, turning and so forth. (Vasconcelos and Vasconcelos, 2017). We have utilized flat flipping, turning, and 10% zooming to make new pictures. For every unique picture in the preparing set, the model made four irregular counterfeit pictures.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Experimental Results

Data augmentation was very effective in determining the experimental result of this study. However, the data training involved different stages. Table 4.1 shows the learning parameters of both ResNet and GoogLeNet. The accuracy for the two networks were 99.8% and 98.7% for both ResNet and GoogLeNet respectively. The learning rate for this study was 0.01 for the two models. It should be noted that during the training of the data, the dataset was splinted into 80% for training and 20% for learning. The training rate of a data is very important during CNN studies, thus helping the machine learning language to identify the required dataset for a neural network study.

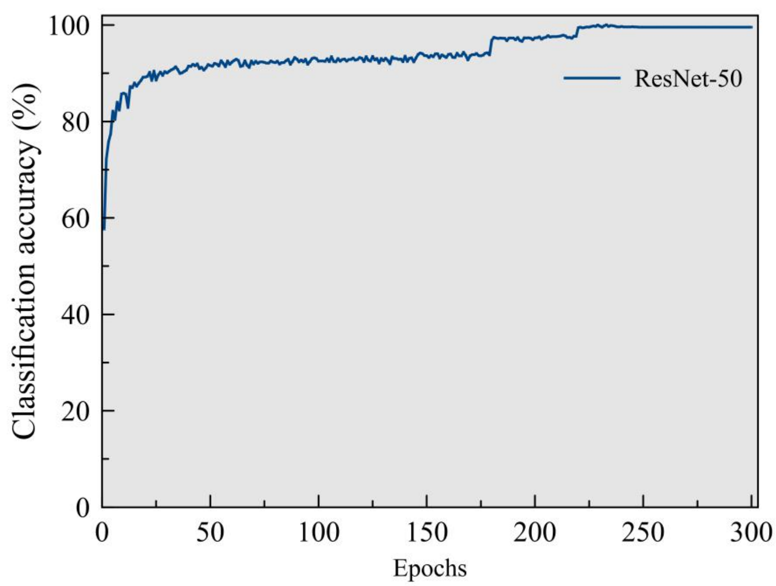

Figure 4.1: Plot of Classification accuracy against Epochs

Table 4.1 Models learning parameters

Models	ResNet	GoogLeNet
Parameters	**Values**	**Values**
Epoch	300	300
Learning Rate	0.01	0.01
Training Time	4 hours	5.5 hours
Training Accuracy	100%	100%
Testing Accuracy	99.8%	98.7%
Mean Square Error (MSE)	0.06	0.025

The learning parameters of this model was analyzed for both ResNet and GoogLeNet as indicated in Table 4.1. However, the epoch value of GoogLeNet (300) was higher with a value of 50 as compared to ResNet (300). This is as a result of a better training from ResNet. This is also evident in the training time of ResNet (4 hours), which is 1.5 hours shorter compared to GoogLeNet (5.5 hours). Moreover, the Mean Square Error (MSE) of both Resnet and GoogLeNet were 0.06 and 0.025 respectively. Several testing factors were responsible for the efficiency and accuracy of both ResNet (99.8%) and GoogLeNet (98.7%).

Table 4.2: Performance parameters of dataset

Network	Models	ACC	SP	SE	AUC
ResNet	Normal	99.75%	0.997	0.938	0.994
	Abnormal	99.85%	0.992	0.987	0.989
GoogLeNet	Normal	98.4%	0.997	0.998	0.984
	Abnormal	99.0%	0.995	0.983	0.991

Table 4.2 gives information on the different parameters of the data sets for ResNet (Normal and Abnormal and GoogLeNet (Normal and Abnormal). The AUC value of the two different networks was also analysed and compared. The confusion matrix is formulated based on the “True Positive (TP)”, “True Negative (TN)”, “False Positive (FP)” and “False Negative (FN)”. This was calculated using the appropriate formulas and values from the simulated confusion matrix.

Moreover, it could be observed that during the testing, the Abnormal group under the classifications recorded a higher accuracy compared to the normal. The difference in the depth of the two architectures (ResNet and GoogLeNet) had mad ResNet to be able to extract more features that are useful, which in turn produces a better performance.

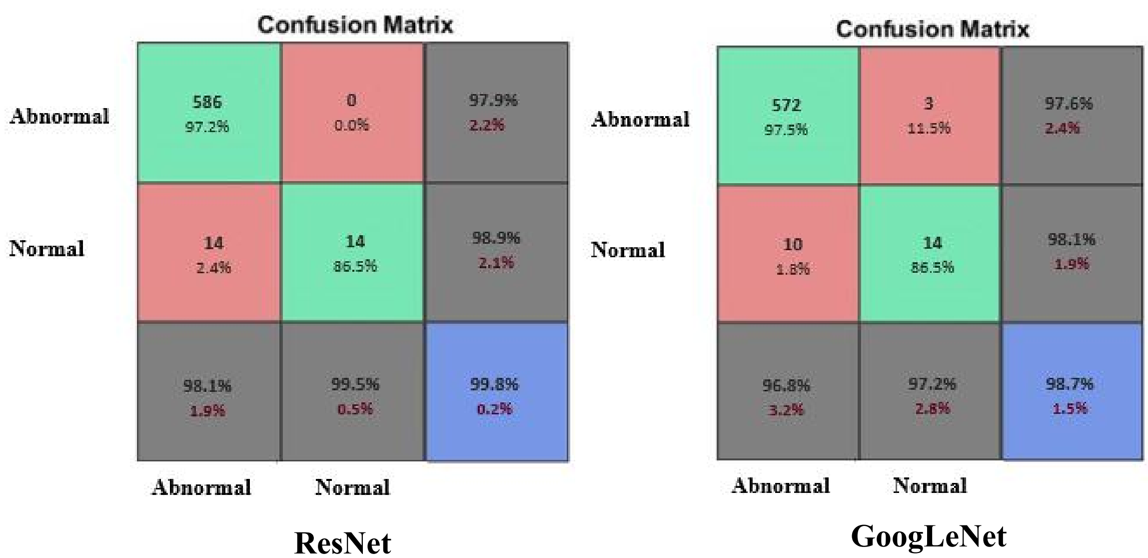

Figure 4.2: Confusion metrix of ResNet and GoogLeNet

4.2 Comparison of Model Performance

In this study, a comparison between the two-testing model (ResNet and GoogLeNet) was analyzed, to analyzed the network with a better accuracy. Informations from the accuracy result of the study indicated that ResNet (99.8%) had a better accuracy than GoogLeNet (98.7%). Moreover, the differences in accuracy was not the only observation in the network, there was also a significant boost and shortening of time in reaching smaller errors. Moreover, both networks were classified using abnormal and normal cancer datasets. The level of network performance was also observed in their AUC values. The AUC of ResNet was higher than that of GoogLeNet as a result of the performance of the modelling during testing.

Table 4.3: Result comparison of current study and previous studies

Studies	ACC	SP	SE	AUC
ResNET	99.8%	99.6%	99.1%	99.2%
GoogLeNet	98.7%	99.5%	96.3%	98.8%
Muhammed et al. (2019)	97.3%	98.2%	95.7%	-
Gudigar et al. (2019)	97.4%	-	-	-
Pugalenthi et al. (2019)	94.33%	82.5%	97.5%	-
Fatih et al. (2020)	98.3%	82.8%	95.0%	98.0%

4.3 Comparison of Current Study and Previous Studies

Table 4.3 gives a vivid information on the comparison between our study and related studies. The comparison was analyzed on different parameters, which include the accuracy, specificity, sensitivity and the area under the curve. Results have shown ResNet to be a better convolution neural network compared to GoogLeNet. This is evident in our study and related studies. Moreover, not all the previous studies have an AUC value except from a study conducted by Fatih et al. (2020), which had an AUC value of 98.0%. The AUC value of our study was higher than that of the other studies and had an AUC value of 99.2% and 98.8% for ResNet and GoogLeNet respectively, with ResNet having the highest value.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Deep learning has proven to be very effective in the area of convolutional neural network as evident in this study. Several deep learning techniques have been utilized in the training and testing of datasets that were collected from Harvard Medical School. ResNet and GoogLeNet were the networks used in the testing and training of the dataset. Brain tumor, which was staged using deep learning language, had two major classifications (Normal and Abnormal). ResNet was observed to be the most effective with a high level of accuracy in this study.

However, from the results obtained from this study, it can be concluded that the extent and dept of features obtained by ResNet has been very effective in ensuring a high level of accuracy which is extremely beneficial in cancer staging. Hence, the depth of CNN can give a better knowledge in image analysis, thus helping to design different abstracts in the network and pooling layers. Moreover, this technique has proven to be more effective in comparison to similar networks based on the level of accuracy obtained from this study.

Utilizing a pretrained system is a profoundly compelling methodology in CNN. Information from pre-prepared model that has been recently prepared with a huge scope information can be utilized in another model. It implies move learning employments portrayals learned by a past model and apply this information to another space. This is significant on the off chance that we have a little dataset like for our situation. At the point when the quantity of information is moderately little, the model beginnings overfit after a few ages. On the off chance that the past dataset is sufficiently huge and general, the educated highlights can be utilized to order various classes that don't exist in our unique dataset. Another favorable position of move learning is that, high computational power is not needed. The model uses loads of convolutional layers from pre-prepared model and as it were training the last thick layer.

Conclusively, from the results observed in this study it is evident that the use of ResNet and GoogLeNet as a deep learning neural convolutional network is a sure an effective diagnostic technique that can cause a revolutionary change in the field of oncology, if properly effected and implemented, thus yielding a high, accuracy, specificity and sensitivity.

5.2 Recommendations

As evident in this study, the effectiveness of ResNet and GoogLeNet in CNN deep leaning cannot be over emphasized. However, there is still need for constant optimization and improvement in the accuracy of a network staging. The use of Support Vector Machine (SVM), as a classifier has proven to be very effective over the years in deep learning and a combination of this nature can increase the level of accuracy. Hence, for future studies the use of SVM should be embedded with the networks used in this study, thus achieving ResNet-SVM and GoogLeNet-SVM. One important function of SVM is that regardless of whether we've made a little mistake in the area of the limit, this gives us least possibility of causing a misclassification. The objectives of SVM are isolating the information with hyper plane and stretch out this to non-straight limits utilizing piece stunt, hence improving the performance and accuracy of the convolutional neural network.

Another recommendation for future studies, involves the increase in GoogLeNet epoch and training time during classification. Thus, the higher the layer of a network, the lesser the epoch in comparison to the other networks, but with the same training time. Also, a higher number of data should be used for normal than abnormal class images. However, future studies can help amend the limitations of this study and bring about a better optimization technique in the deep learning.

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APPENDICES

APPENDIX 1
ETHICAL APPROVAL LETTER

NEAR EAST UNIVERSITY YAKIN DOĞU ÜNİVERSİTESİ

ETHICS APPROVAL LETTER

TO GRADUATE SCHOOL OF APPLİED SCİENCES

Re: SERAG MOHAMED AKILA (20176635)

I would like to inform you that the above candidate is one of our Masters of Science. students in the Biomedical Engineering department. He is taking the thesis under my supervision, and the thesis entailed: AUTOMATED DETECTION OF BRAIN TUMOR USING DEEP LEARNING AND MAGNETIC RESONANCE IMAGINING (MRI) FOR CLASSIFICATION. The data used in his thesis does not require any ethical report.

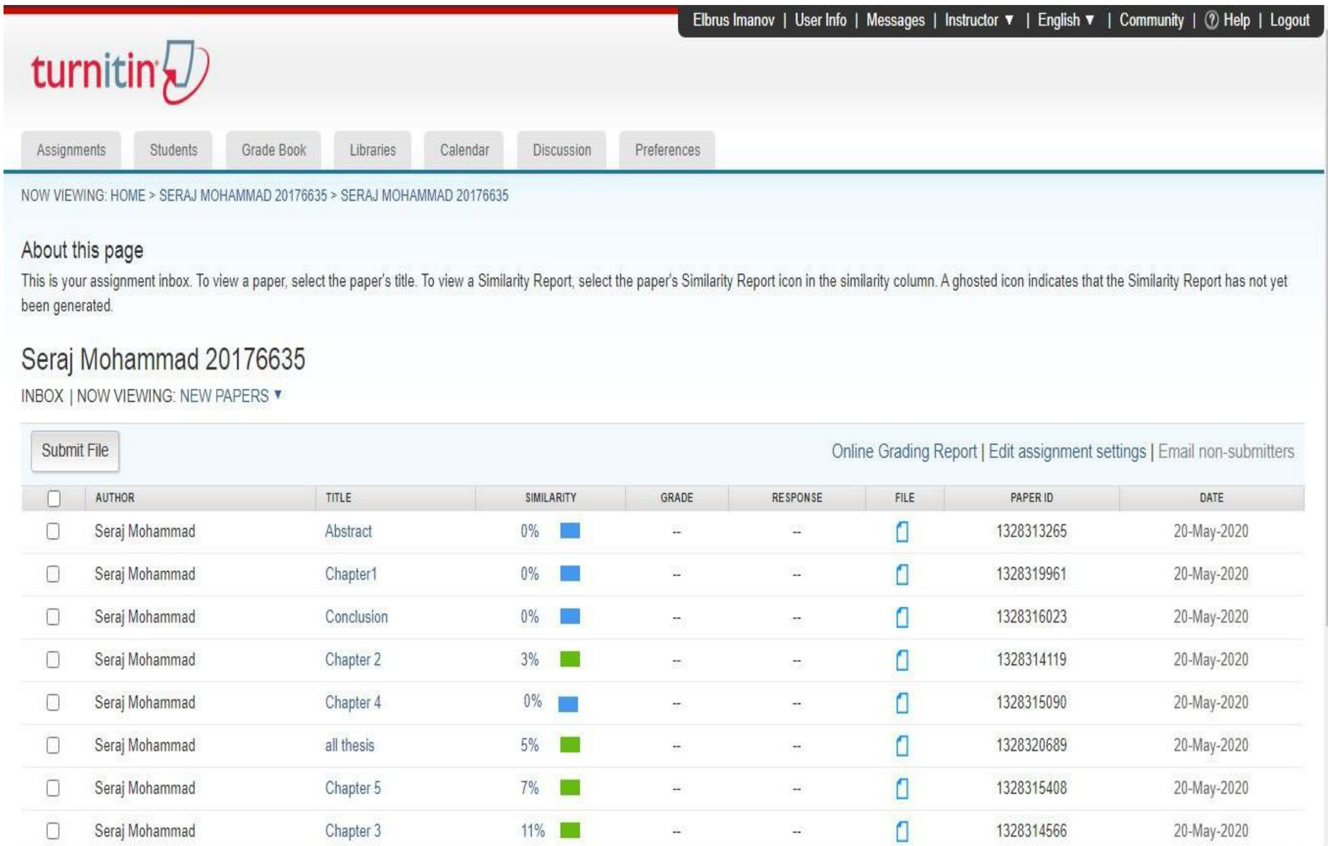
Please do not hesitate to contact me if you have any further queries or questions.

Best Regards,

Assist. Prof. Dr. Elbrus Imanov
Computer Engineering
Department, Faculty of
Engineering,
Near East Boulevard, ZIP: 99138
Nicosia / TRNC, North Cyprus,
Mersin 10 – Turkey.
Email:elbrus.imanov@neu.edu.tr

APPENDIX 2

SIMILARITY REPORT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AUTOMATED DETECTION OF BRAIN TUMOR USING DEEP LEARNING AND MAGNETIC RESONANCE IMAGINING (MRI) FOR CLASSIFICATION

Assist. Prof. Dr. Elbrus Imanov