MULTI CLASSIFICATION OF BRAIN TUMOR USING CONVOLUTIONAL NEURAL NETWORK

A PROJECT REPORT

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER

EXTERNAL EXAMINER

ABSTRACT

A key challenge for the treatment of brain tumors is the time and effort the physician has to put in studying the MRI data for diagnosing the tumor. Brain tumor classification is hence a pivotal task in detecting and classifying tumors to make a decision regarding treatment according to their classes. Among the available imaging modalities, Magnetic Resonance Imaging is preferred for having superior image quality without ionizing radiation. Convolutional Neural Network, a class of Deep Learning, is more commonly applied to analyzing and classifying visual imagery in the medical imaging field attributing to its automated feature engineering. In this work , a Deep Learning model based on CNN is proposed to differentiate between the three glioma grades (Grade II, Grade III, and Grade IV) using the publicly available REMBRANDT dataset. This dataset includes 21223 T1-weighted MR images for 73 patients. The proposed network structure achieves a significant performance with the overall accuracy of 87.8%.

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LIST OF ABBREVIATION

ML	Machine Learning
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
DNN	Deep Neural Network
CNS	Central Nervous System
MB	Medulloblastoma
PNET	Primitive neuroectodermal tumors
SIFT	Scale invariant feature transform
MIL	Multiple instance learning
GMM	Gaussian mixture models
ReLU	Rectified linear unit
CT	Computed tomography
SR	Super resolution
REMBRANDT	Repository of Molecular Brain Neoplasia Data
TCIA	The Cancer Imaging Archive
FC	Fully connected layer
ADAM	Adaptive moment estimation

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

A brain tumor is a mass or growth of abnormal cells in the brain and is one of the most dangerous causes of death among people with a survival rate of only 39%. If cancer spreads, effective treatment becomes more difficult, a person's chances of surviving are much lower. The majority of the brain tumors are contributed by gliomas and brain tumor classification is a crucial task to evaluate the tumor at the early stage and make a treatment decision according to their classes.

Manual classification of the brain tumour's glioma grades is a tedious and time consuming process and this is a major disadvantage due to its lethality and also the increasing probability of benign tumors turning into malignant tumors over time. Magnetic Resonance Imaging (MRI) is one of the most used and popular for brain tumor diagnosis. Therefore, the MR images are pre-processed and a deep learning model based on convolution neural networks is proposed to classify the different brain tumor glioma grades.

1.2 BRAIN TUMOR

The abnormal growth of brain cells is known as Brain tumor. The linked mortality and morbidity and the significant proportion of affected individuals has a major relevance on the death-adjusted life years contrasted to other malignancies although comparatively rare. The cases of brain tumor in India ranges from 5 to 10 per 100,000 populations with an increasing trend and accounts for 2% of malignancies .The degrees of malignancy ranges from benign to aggressive. Each type of tumor has its own biology, treatment, and prognosis with different risk factors. Even “benign” tumors can be lethal due to their site in the brain, their ability to infiltrate locally, and their propensity to transform to malignancy. According to world health organization, the grading system scales are used from grade I to grade IV. These grades classify benign and malignant tumor types. The grades I and II are low-level tumors whereas grade III and IV are high-level tumors. Brain tumor can affect individuals at any age. The impact on every individual may not necessarily be same. The diagnosis of tumor area in the brain is quite a challenging task because of the complex structure the brain holds.

The most malignant grades III and IV of tumor is fast growing. Affects the healthy brain cells and may spread to other parts of the brain or spinal cord and is more harmful and may remain untreated. Therefore detection of brain tumor location, identification and classification in the earlier stage is a serious issue in medical science. By enhancing the new imaging techniques, it helps the doctors to observe and track the occurrence and growth in the tumor affected regions at different stages so that they can provide suitable diagnosis with the scanned images.

This makes the classification of brain tumors a difficult science and creates problems in describing the epidemiology of these conditions . The major ratio of adult tumors are supratentorial and gliomas contribute a majority of 86% namely astrocytomas, glioblastomas, oligodendroblastomas, and unspecified gliomas. It is comparatively a very hard task to identify tumors manually.

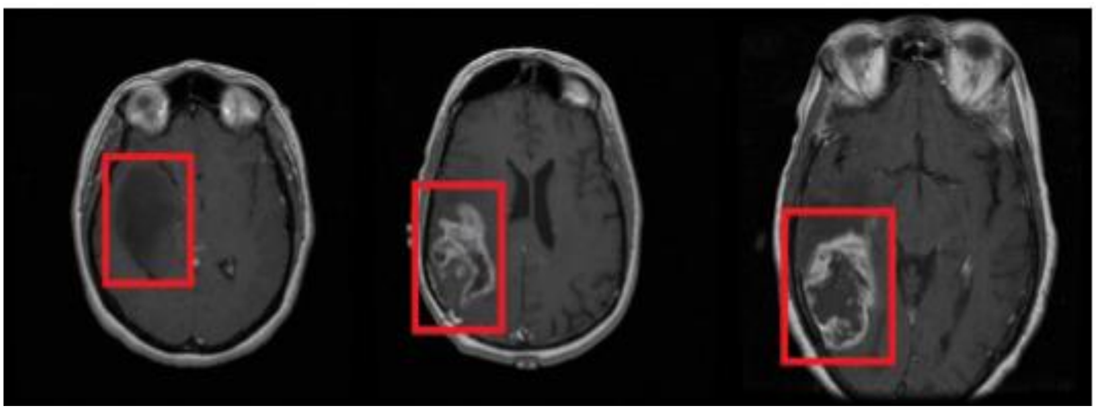

Figure 1.1 Different glioma grades included in REMBRANDT dataset (Grade II, Grade III and Grade IV from left to right respectively). Tumors are localized inside a red rectangle

1.2.1 Gliomas

Glioma is a common tumor that originates from the brain. About 33% of all brain tumors are gliomas, that originate in the glial cells that surround and support neurons in the brain, which includes astrocytes, oligodendrocytes and ependymal cells. They are called intra-axial brain tumors because they grow within the substance of the brain and often mix with normal brain tissue. A glioma can affect the functioning of your and be life threatening depending on its location and rate of growth. They are one of the most common types of primary brain tumors. The type of glioma helps determine the treatment and the prognosis. Glioma treatment generally include surgery, radiation therapy, chemotherapy, targeted therapy and experimental clinical trials.

1.2.2 Astrocytoma

Astrocytoma is a type of cancer formed in the brain or spinal cord. Astrocytoma begins in cells called astrocytes that support nerve cells.Its signs and symptoms depend on the location of your tumor. The ones that occur in the brain can cause seizures, headaches and nausea. Astrocytomas that occurs in the spinal cord causes weakness and disability in the area affected by the growing tumor. It can be a slow-growing tumor, or it can be an aggressive cancer that grows quickly. The aggressiveness of the astrocytoma determines the prognosis and treatment. The symptoms that patients present with are predicated by the location of the tumor, headache, nausea and vomiting are common, as is the occurrence of a seizure.

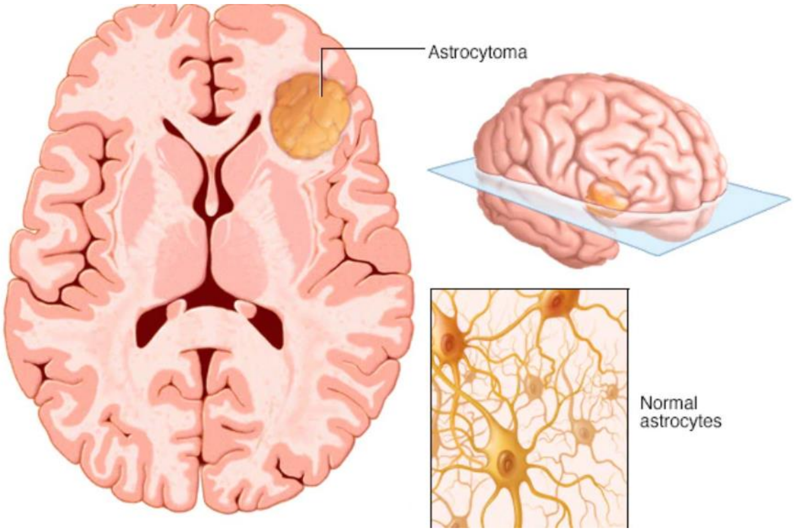

Figure 1.2 Astrocytoma (Grade II)

1.2.3 Oligodendroglioma

Oligodendroglioma is a tumor that occurs in the brain or spinal cord. Oligodendroglioma are formed from oligodendrocytes, cells in the brain and spinal cord that produce a substance that protects nerve cells. It can occur at any age, but most often affects adults. Signs and symptoms can include seizures and headaches. Weakness or disability can occur in the part of the body that's controlled by the nerve cells affected by the tumor. Symptoms related to oligodendrogliomas depend on the location of the tumor. The most common sign of oligodendroglioma is a seizure. Around 60% of people have a seizure before being diagnosed. Other symptoms people may have are headaches, thinking problems and memory, weakness, numbness, or problems with balance and movement. Oligodendroglioma treatment usually involves surgery to remove tumor. Additional treatments may be necessary if the tumor is aggressive or is more likely to recur. The cause of most oligodendrogliomas is not known. Radiation and certain gene changes which can be passed down through families have been linked to a higher chance of developing oligodendrogliomas.

1.2.4 Glioblastoma

Glioblastoma is a type of aggressive cancer that can occur in the brain or spinal cord. Glioblastoma are formed by astrocytes that support nerve cells. It occur at any age, but tends to occur more often in adults. It can cause worsening headaches, nausea, vomiting and seizures. Glioblastoma, also known as glioblastoma multiforme, can be very difficult to treat and a cure is generally not possible. Treatments may slow progression of the cancer and reduce signs and symptoms. The mainstay of treatment for glioblastoma is surgery, followed by radiation and chemotherapy. The aim of the surgery is to remove the tumor without injuring the normal brain tissue needed for normal neurological functioning of the brain. However, glioblastomas are surrounded by a zone of migrating, infiltrating tumor cells that invade surrounding tissues, making it impossible to never remove the tumor entirely. Surgery only provides the ability to reduce the amount of solid tumor tissue within the brain, remove those cells in the center of the tumor that may be resistant to radiation and/or chemotherapy and reduce intracranial pressure.

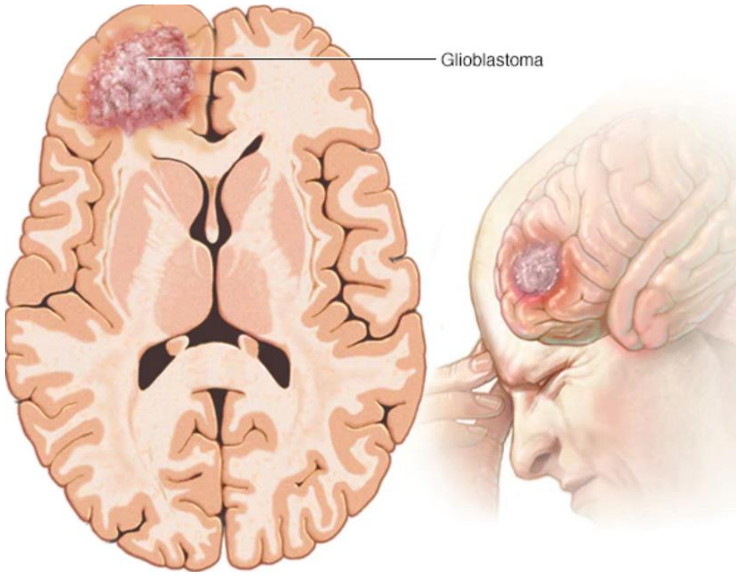

Figure 1.3 Glioblastoma (Grade IV)

1.3 DIAGNOSTIC DIFFICULTIES

Doctors use many tests to diagnose, a brain tumor and learn the type of tumor. They also do tests to find out if it has spread to another part of the body or from where it started. This is called metastasis and is a rare condition for brain tumors. For most types of tumors, taking a sample of the possible tumor is the only sure way to know if an area of the body has a tumor. This may be done in a procedure called a biopsy. For the biopsy, the doctor takes a small sample of tissue for testing. If this is not possible, the doctor may suggest other tests that will help in diagnosis. Imaging tests can help them find out if the tumor is a primary brain tumor or if it is cancerous. Imaging tests show the pictures of the inside of the body. Generally, these test diagnoses take lot of time for acquiring results, in case of a malignant brain tumor, chances of cancer cells spreading to other parts of the brain is very high. With appropriate use of accurate data mining classification techniques, early prediction of any disease can be effectively performed. In the medical field, the techniques of ML (machine learning) and Data mining holds a significant stand.

1.4 MAGNETIC RESONANCE IMAGING

Magnetic resonance imaging is used in radiology as a medical imaging technique. It forms images of the anatomy and physiological processes of the body and provides information that is different from other imaging modalities. Its major technological advantage is that it uses the physical and biochemical attributes of the tissues to identify and differentiate between them. MR image acquisition does not use ionizing radiation and hence does not have adverse health effects. It requires little patient preparation and is non- invasive, patient acceptability is high.

MRI scanners use strong magnetic fields, field gradients, and radio waves to generate images of the organs in the body. An MRI is still considered as a better choice than a CT scan. MRI is widely used in hospitals and clinics for medical diagnosis, staging and follow up of disease without exposing the body to any sort of radiation. MRI scans take longer and are comparatively very loud. Also people with medical implants or other non removable metal inside the body may be unable to undergo an MRI examination safely.

1.5 MACHINE LEARNING

Machine learning (ML) is used to perform a specific task using patterns without human interaction by the study of statistical models and algorithms. ML has been widely used in the medical field under Artificial Intelligence. Most of the algorithms used are broadly classified into supervised and unsupervised and further into classification, regression or reinforcement. The proposed model is a supervised classification model that trains to find a mapping function of given input variable to either one of three output labels to predict new subject labels.

The discipline of machine learning employs various approaches to help computers learn to accomplish tasks where no fully satisfactory algorithm is available. Machine learning approaches divided them into three broad categories based on the nature of the 'signal' or 'feedback' available to the learning system.

- Supervised learning: The system is provided with example inputs and their desired outputs. The goal is to learn a structure that maps inputs to outputs.
- Unsupervised learning: No labels are provided to the learning algorithm, leaving it on its own to find a structure with it's input. Unsupervised learning can be a goal by itself (discovering hidden patterns in data) or a means towards the end (feature learning).
- Reinforcement learning: A computer program interacts with a dynamic environment where it performs a certain goal. As it navigates its problem

space, the program is provided feedback that's analogous to rewards, which it tries to maximize.

1.6 DEEP LEARNING

The word 'Deep' in 'Deep learning' refers to the number of layers using which the data is transformed. Deep learning is a class of machine learning algorithms that uses layers to progressively extract higher level features from the given raw input. In image processing, the lower layers identify edges, while the higher layers identify human concepts such as digits or letters or faces. Each level transforms the given input data into a slightly more abstract and composite representation. In an image recognition application, the raw input may be composed of a matrix of pixels. A deep learning process learns which features to place in which level optimally all by itself. It is considered the best choice for discovering complex architecture in high dimensional data by employing back propagation algorithm. Deep learning has made significant advancements and tremendous performance in numerous applications, the widely used domains of deep learning are business, science and government which further includes adaptive testing, biological image classification, natural language processing , object detection, computer vision, cancer detection, face recognition, handwriting recognition, speech recognition, stock market analysis, smart city and many more.

1.7 CONVOLUTION NEURAL NETWORK

Deep Learning is a subset of machine learning where artificial neural networks, algorithms inspired by the human brain, One of the most popular types of deep neural networks is known as convolutional neural networks (CNN). The key factor that makes this CNN architecture well adaptive to 2D data processing such as images is that it convolves learned features with input data, and uses 2D convolutional layers. CNN learns to detect different features of an image using tens or hundreds of hidden layers which is its biggest advantage. Every hidden layer increases the complexity of the learning image features.

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, which means, each neuron in one layer is connected to all neurons in the next layer. The 'fully connectedness' of these networks makes them prone to overfitting of data. Ways of regularization include adding magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization. They take advantage of the hierarchical patterns in the data and assemble complex patterns with smaller and simpler patterns. Therefore, on the scale of connectness and complexity CNNs are on the lower extreme.

While other learning algorithms or models can also be used for image classification. CNN has emerged as the best model of choice for various reasons. These include the varied usage of the convolution operator in image processing. The benefits resulted by standard neural network training and the convolution operation to efficiently classify images is done implicitly by CNN. An emerging machine learning method that has proven its potential for different classification tasks is deep neural network. Convolutional neural network dominates giving the best results on varying image classification tasks. However, it is hard to collect medical image datasets because it needs a lot of professional expertise to label them.

CHAPTER 2

LITERATURE SURVEY

2.1 IMPROVING DEEP NEURAL NETWORKS FOR LVCSR USING RECTIFIED LINEAR UNITS AND DROPOUT

It is studied that pre-trained deep neural networks (DNNs) have exceeded the performance of traditional acoustic models based on Gaussian mixture models (GMMs) on a range of major vocabulary speech recognition benchmarks. Deep neural nets have also attained outstanding results on many computer vision assignments by making use of a random “dropout” procedure. It randomly omits a part of the hidden units in all layers and this majorly improves generalization error. It has also been deemed triumphant on a small-scale phone recognition task using larger neural nets since dropout aids in preventing overfitting. However, the disadvantage observed during training deep neural net acoustic models for major speech recognition is that it is very time consuming and dropout is likely to only increase the time for training. Neural networks using rectified linear unit (ReLU) non-linearities have been proved to be particularly successful for CV(Computer vision) tasks. Using ReLU has also been proved faster to train than standard sigmoid units, and at times also improving discriminative performance. A 50-hour English Broadcast News task that modified deep neural networks using ReLUs trained with dropout during frame level training has been shown to provide an 4.2% relative improvement over a DNN trained with sigmoid units. Additionally it has also shown a 14.4% relative improvement over a strong GMM/HMM system.

2.2 INDIAN DATA ON CENTRAL NERVOUS TUMORS: A SUMMARY OF PUBLISHED WORK

The CNS(Central Nervous System) affected tumors comprise two percentage of all the malignancies. When related to other malignancies there are two factors although comparatively rare that badly affects on the death-adjusted lifespan. First is the noteworthy ratio of affected youth and older individuals . The second factor is the related mortality and morbidity. The net encompassed by CNS tumors is quite varied in terms of age, location, histology, and clinical outcomes. Improvements in various techniques in the fields of diagnostic imaging, surgical techniques, radiotherapy personnel, and creation of newer chemotherapeutic and targeted agents over the past decade have aided in refining the outcome of the treatment. Each type of tumor has its own biology, treatment, and prognosis with different risk factors.

Even “benign” tumors can be lethal due to their site in the brain, their ability to infiltrate locally, and their propensity to transform to malignancy. This makes the classification of brain tumors a difficult science and creates problems in describing the epidemiology of these conditions. The major ratio of adult tumors are supratentorial and gliomas contribute a majority of 86% namely astrocytomas, glioblastomas, oligodendroblastomas, and unspecified gliomas

2.3 DEEP LEARNING OF FEATURE REPRESENTATION WITH MULTIPLE INSTANCE LEARNING FOR MEDICAL IMAGE ANALYSIS

The efficiency of achieving high-level tasks with a base of manual annotation and better representation for features in medical images is studied. In medical image analysis, entities like cells are distinguished by important clinical features. Previously developed features like SIFT and HARR are not able to comprehensively identify and constitute such objects. Therefore, feature representation is especially important. Hence, the study of automatic extraction of feature representation through deep learning (DNN) is done. Additionally, comprehensive notation of objects is often an ambiguous and time-consuming task. Multiple instance learning (MIL) framework in classification training is used along with deep learning features. There are a few interesting conclusions drawn from this work. The study shows that the automatic feature learning is greatly superior and also outperforms manual features.

2.4 CONVOLUTIONAL NEURAL NETWORK BASED MODELS FOR IMPROVING SUPER-RESOLUTION IMAGING

Medical imaging is an important component of pathological diagnosis, and the resolution of the medical images are an important factor for the accurate diagnosis. The high resolution medical images contain more pathological information, so that the patients can be diagnosed accurately. The typical medical imaging methods, such as magnetic resonance imaging (MRI) and computed tomography (CT), are limited to the environment, medical equipment, and intrinsic physical imaging flaws, which reduces the resolution of the images and the accuracy of the medical diagnosis. Super resolution (SR) imaging can break through these restrictions and reconstruct high-resolution images from the corresponding low-resolution images without changing the authenticity. These improved medical images can help the doctors make more accurate diagnoses.

Three-layer CNN-based models are proposed to reconstruct the super-resolution images using four optimization algorithms, i.e., stochastic gradient descent, adaptive gradient (AdaGrad), root mean square prop (RMSprop), and adaptive moment estimation (ADAM).

The ADAM algorithm combines the advantages of both the AdaGrad and RMSProp algorithms. It is improved by making full use of the first-order and second-order moments of the gradients. The purpose of this process is to adjust the learning rate of each parameter. On the basis of the improvement by

AdaGrad and RMSProp, ADAM further improves the algorithm by calculating the respective learning rates for different parameters. Therefore, it takes relatively longer to train the models with ADAM. However, their performance is the best. .In terms of performance, ADAM is superior to other methods and in terms of reconstructed images, ADAM is the best choice to optimize the models. Model with ADAM optimization converges faster and it has the lowest loss at the same number of iterations. Models with ADAM and RMSProp have the highest scores of 33.30228 and 33.10496 dB in PSNR, respectively.

2.5 ON THEORETICAL ANALYSIS OF SINGLE HIDDEN LAYER FEEDFORWARD NEURAL NETWORKS WITH RELU ACTIVATIONS

Due to its fast training speed and easy-implementation extreme learning machine has acquired a lot of popularity during the past decades. Though extreme learning machine has been proved valid when using an infinitely differentiable function like sigmoid as activation, existed extreme learning machine theory pays a little attention to consider non-differentiable function as activation. However, other non-differentiable activation function, rectifier linear unit (Relu) in particular, has been demonstrated to show better training of deep neural networks, compared to previously wide-used sigmoid activation. Today, Relu is the most popular and best choice for deep neural networks. Therefore in this note, it is considered that extreme learning machine that adopts nonsmooth function as activation, proposing that a Relu activated single hidden layer feedforward neural network (SLFN) is capable of fitting given training data points with zero error under the condition that sufficient hidden neurons are provided at the hidden layer. The proof relies on a slightly different assumption from the original one but remains easy to satisfy. Besides, it is also found that the squared fitting error function is monotonically non-increasing with respect to the number of hidden nodes, which in turn means a much wider SLFN owns much expressive capacity. Rectifier linear unit (Relu), defined as $\sigma(x) = \max(x, 0)$, was popularly employed as the activation function in deep learning community since it has been demonstrated to enable better training of the deep neural network . Relu is non-smooth unlike other differentiable functions such as sigmoid and radial basis. The main result inferred is that a SLFN equipped with Relu activation is capable of fitting with zero error when sufficient nodes are allowed in the hidden layer.

2.6 BRAIN TUMOR DETECTION USING CONVOLUTIONAL NEURAL NETWORK

Brain Tumor segmentation is one of the most difficult tasks in the terrain of medical image processing as manual classification can result in inaccurate prediction and diagnosis. Moreover, it is a time consuming task when there is a huge amount of data present to be assisted. Brain tumors have high diversity in appearance and there is a similarity between tumor and normal tissues and thus the extraction of tumor regions from images becomes cumbersome . This work has proposed a method to extract brain tumor from 2D Magnetic Resonance brain Images (MRI) by Fuzzy C-Means clustering algorithm which was followed by traditional classifiers and convolutional neural network. In traditional classifier part, six traditional classifiers namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and Random Forest was applied which was implemented in scikit-learn. Afterward, Convolutional Neural Network (CNN) was implemented using Keras and Tensorflow because it yields to a better performance than the traditional ones. CNN gained an accuracy of 97.87%, which is very compelling. The main aim of this work was to distinguish between normal and abnormal pixels, based on texture based and statistical based. Image segmentation plays a significant role in medical image processing as medical images have different diversities. For brain tumor segmentation, MRI and CT scan images were used. MRI is most vastly used for brain tumor segmentation and classification. In this work, Fuzzy C-Means clustering for tumor segmentation which can predict tumor cells accurately is used. In the traditional classifier part, comparison between the results of different traditional classifiers such as K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine was performed. Among these traditional ones, SVM gave the highest accuracy of 92.42%. Further, for better results, CNN was implemented which brought in the accuracy 97.87% with a split ratio of 80:20 of 217 images, i.e. 80% of training images and 20% of testing images.

2.7 CONVOLUTIONAL NEURAL NETWORK(CNN) FOR IMAGE DETECTION AND RECOGNITION

Algorithms such as Deep Learning are designed in a way to imitate the functionalities of the human cerebral cortex. The representation of deep neural networks is the essence of such algorithms, that is, neural networks with many hidden layers. And hence convolutional neural networks are the deep learning algorithms to train huge datasets with thousands of parameters. This is done by taking the input in the form of 2D images and the desired output is produced by convolving it with filters. The study is to present CNN models which are built to evaluate its performance on image recognition and detection datasets. The algorithm is then implemented on MNIST and CIFAR-10 dataset. Lastly the performance is evaluated on various parameters. The accuracy of models on MNIST is 99.6 %. For the CIFAR-10 using real-time data augmentation and dropout on CPU unit is proved better. While the accuracy of MNIST is satisfactory the accuracy of CIFAR-10 can be further improved. This is done by training with larger epochs and on a GPU unit. Hence, the accuracy computed on MNIST is 99.6% and on CIFAR-10 is 80.17%. The 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC) 281 training accuracy on CIFAR-10 is 76.57 percentage after 50 epochs. It is further discussed that the accuracy on training set may also be improved further by adding more hidden layers. And this system can be improved by implementing as an assistance system for machine vision for detecting nature language symbols.

2.8 DEEP CONVOLUTIONAL NEURAL NETWORKS FOR COMPUTER-AIDED DETECTION: CNN ARCHITECTURES, DATASET CHARACTERISTICS AND TRANSFER LEARNING

Noteworthy improvements have been made in image recognition. This is mainly attributing to the accessibility of large-scale annotated datasets like the Image Net and the progress of deep convolutional neural networks (CNN). CNNs permits this by learning data-driven, exceedingly representative, layered hierarchical image features from lesser available training data. But finding datasets as thoroughly annotated as available in the Image Net is a major challenge and this is especially true in the medical imaging domain. There are currently three important techniques that have successfully employed CNNs to medical image classification. The first is by training the CNN from scratch. Second technique uses available pre-trained CNN features, and the third technique conducts unsupervised CNN pre-training with supervised fine-tuning. An additional efficient method is transfer learning, i.e., adjusting supervised CNN models pre-trained from other image datasets to medical image tasks or transferring the domains between medical datasets. The three important, but less explored factors of using deep CNN to computer-aided detection problems are exploited in the study. The different CNN architectures are explored and evaluated. The studied models contain 5 thousand to 160 million parameters, and vary in numbers of layers. Then the influence of dataset scale and spatial image context on performance is evaluated. Finally, the usefulness of transfer learning from pre-trained

ImageNet (via fine-tuning) is explained. Two specific computer aided detection (CADe) problems, namely thoraco-abdominal lymph node (LN) detection and interstitial lung disease (ILD) classification is studied for the above mentioned purpose achieving state-of-the-art performance on the mediastinal LN detection, with 85% sensitivity at 3 false positive per patient, and report the first five-fold cross-validation classification results on predicting axial CT slices with ILD categories. The extensive empirical evaluation, CNN model analysis and valuable insights can be extended to the design of high performance CAD systems for other medical imaging tasks.

CHAPTER 3

EXISTING WORK

Though correct manual diagnosis for certain subtypes of brain tumors has its own hardships, they have still received substantial attention in neuropathology community. The challenge in classifying gliomas lies in fitting brain tumors, into distinct categories. A majority of about 86% of adult glioma are constitutes by astrocytomas and other unspecified gliomas. Classifying tumors manually may have errors that have characteristics of two or more histologies, making particular tumor subtypes problematic to replicate.

Brain tumor classification has been done using many machine learning techniques and imaging modalities over the years. Rahul Chauhan et al. implemented Convolutional Neural networks to the MNIST and CIFAR-10 datasets with a 99.6% and 80.17% accuracy respectively to prove that deep learning algorithms are best suited for image detection and recognition. The problem of obtaining comprehensively annotated datasets in the medical imaging field is solved by Hoo-Chang Shin et al. by successfully exploring and employing three techniques using CNN. This is done on two specific computer aided detection (CADe) problems, namely thoraco-abdominal lymph node (LN) detection and interstitial lung disease (ILD) classification and a state-of-the-art performance has been achieved. The usefulness of CNN in the medical imaging field is further proved by the work proposed by Yan Xu et al. that studied previously existing features like SIFT and HARR failed to comprehensively represent the objects like cells characterized by significant clinical feature and hence the automatic feature learning provided by deep learning outperforms manual features. Tonmoy Hossain et al. compared the performance of brain tumor classification for traditional classifiers and CNN. In traditional classifier part, six traditional classifiers namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and Random Forest were used. Afterward, Convolutional Neural Network (CNN) was implemented using Keras and Tensorflow and gained an accuracy of 97.87% proving a better performance compared to the traditional classifiers. Guorui Shen and Ye Yuan prove that non-differentiable activation functions like rectifier linear unit (Relu) in particular demonstrate better training of deep neural networks, compared to previously wide-used sigmoid activation. The improvement of performance by the using a combination of ReLU and dropout layers in CNN has been shown by George E. Dahl et al. on a 50-hour English Broadcast News task that modified deep neural networks using ReLUs trained with dropout during frame level training by providing an 4.2% relative improvement over a DNN trained with sigmoid units, and a 14.4% relative improvement over a strong GMM/HMM system. Yingyi Sun et al. proposed a three-layer, CNN-based models are to reconstruct the super-resolution images using four optimization algorithms, i.e., stochastic gradient descent, adaptive gradient (AdaGrad), root mean square prop (RMSprop), and adaptive moment estimation (ADAM) and showed that among these four optimizations, ADAM is considered to have the best performance.

CHAPTER 4

PROPOSED WORK

4.1 RECOMMENDED METHOD

The block diagram of the proposed method is shown at Figure 4.1 in which the system initiates by extracting and loading the dicom images along with its labels from the raw files of the REMBRANDT dataset. After preprocessing and shuffling technique the dataset is split into training and validation sets followed by which the proposed method is introduced along with setting the hyper parameters and an optimization algorithm. Lastly, the performance computations are shown.

4.2 PROPOSED ARCHITECTURE DIAGRAM

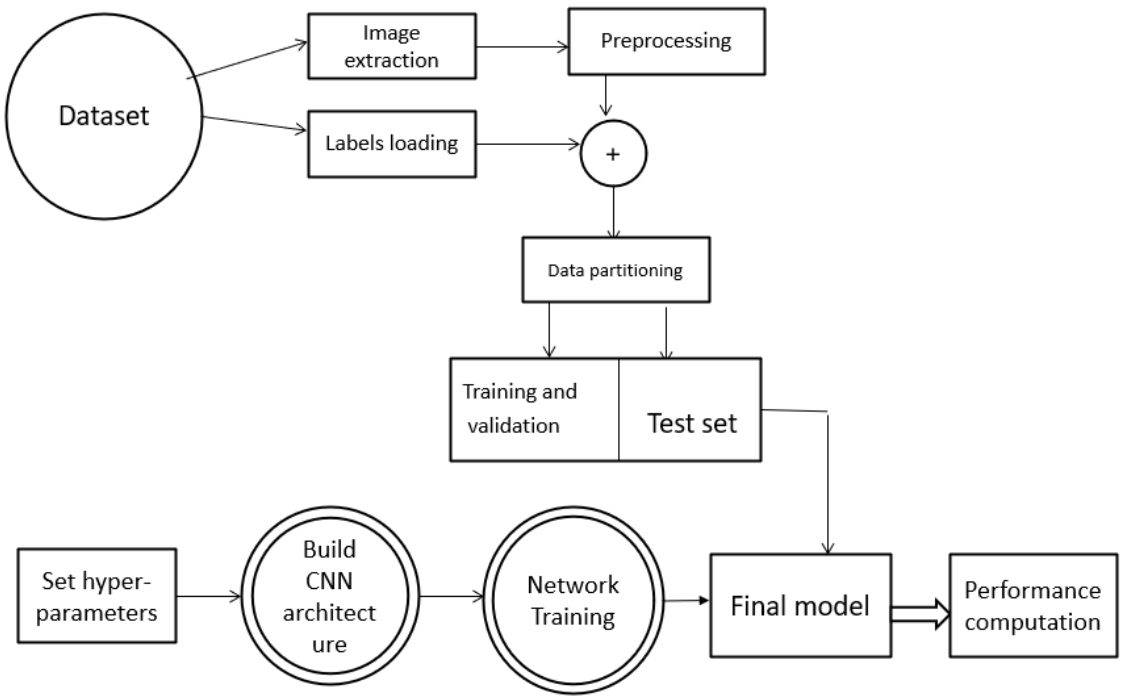

Figure 4.1 Architecture Diagram

4.3 DESCRIPTION OF THE ARCHITECTURE DIAGRAM

4.3.1 Dataset

The dataset used in this method is obtained from The Cancer Imaging Archive (TCIA) public access repository. MRI multi-sequence images from 130 patients with varied ages, grades, cases and races is contained in The Repository of Molecular Brain Neoplasia Data (REMBRANDT). These T1-

weighted contrast-enhanced images contain different grades of glioma - Astrocytoma, Oligodendroglioma, Glioblastoma (Grade II,III,IV). Supplementary details about the description of the REMBRANDT dataset are shown in Table 1. The data is extracted from the raw dataset consisting of dicom files and the images and labels are loaded for pre-processing along with the metadata.

Table 1.1 Dataset description

Tumor Category	Number of Patients	Number of tumor slices
Grade II	33	205
Grade III	19	129
Grade IV	21	182

4.3.2 Preprocessing

A preprocessing step is required before feeding the images into the proposed structure. The raw dataset contains varied images of pixel sizes – N*N*1 where N= 256, 288, 432, 512. These images were downscaled to a uniform size of 256*256*1 using bi-cubic interpolation for direct down sampling as it produces least noise relatively. This down sampling is done to decrease dimensionality and hence computations resulting in direct calculations and helping the network to lower the time to show a better performance. To prevent focusing on tapered band of the whole dataset and to maintain the training on unsorted data the data is shuffled before splitting. Finally the data of 21223 images is divided into two sections: training and validation.

4.3.3 Model Training and Validation

The CNN architecture consisting of 11 layers is constructed as the model with base hyper parameters. The training data is fed into the model for it to learn to classify the images to denote the label as one of the three glioma grades. The accuracy metrics are measured as per the testing data and the model parameters are fine-tuned accordingly and the process is repeated again. The final model is then presented with its performance metrics displayed and evaluated through a confusion matrix.

CHAPTER 5

PROPOSED CNN ARCHITECTURE

5.1 CNN ARCHITECTURE

The proposed CNN architecture consists of 11 layers as shown in figure 5.1 . It starts with the input layer that holds the images obtained from the pre-processing step passing through the convolution layers and their activation functions that are used in feature selection and down-sampling. A dropout layer is used to prevent overfitting followed by a fully connected layer and a softmax layer to predict the output. A classification layer is the final layer that gives the predicted class.

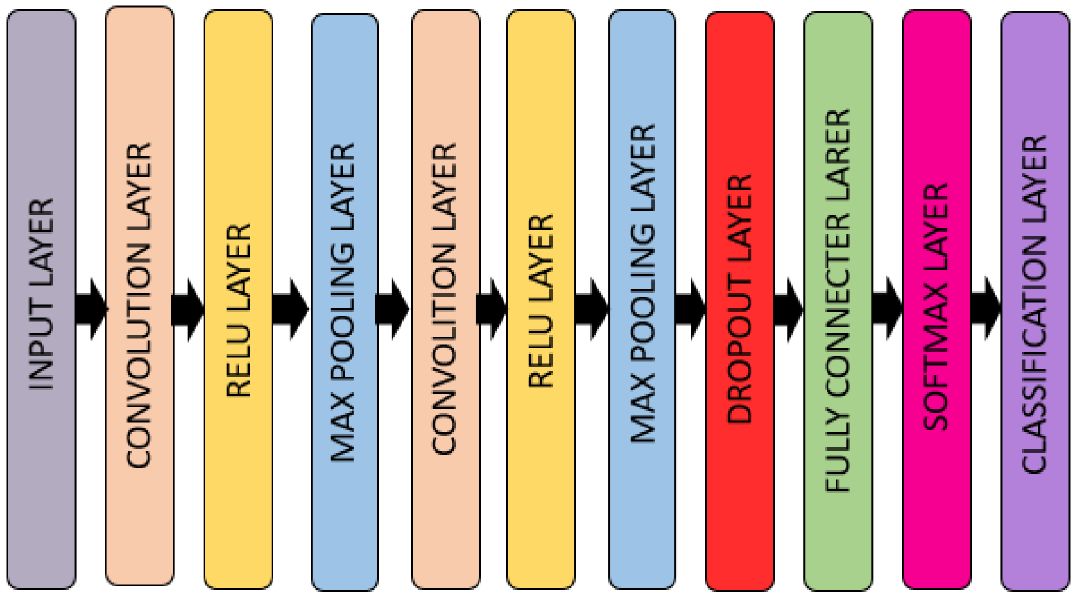

Figure 5.1 The proposed CNN architecture

5.2 CNN ARCHITECTURE LAYER DESCRIPTION

First, Input layer should confirm the image data and its proposed size. It starts with the input layer which hold the augmented images from the previous pre-processing step passing through the convolution layers and their activation functions that used in features selection and down-sampling (convolution, Rectified Linear Unit (ReLU), normalization and pooling layers).In the proposed model, two convolutional layers are used. Each convolutional layer makes use of a set of K learnable filters or kernels. These filters are used to detect the presence of specific features or patterns present in the original image which is the input. These kernels are usually expressed as a matrix of MxN. This filter is convolved at steps (S) across the width and height of the input file along with padding to retain edge information, and a dot product is computed to give an activation map. Varied filters to detect different features are convolved on the input file .A set of activation maps is given as output and is passed as input to the next layer in the CNN. FIGURE 5.2 shows an example of applying a kernel of size 2 × 2 (appears in blue) over a 3 × 3 image producing the same input dimensions of 3×3 after kernel sliding and dot product. The involved parameters we have used are; K=5,5, M×N=8×8, 16×16 and 2×2, S=[1, 1], P = 2,2 for the convolutional layers 1 and 2 respectively.

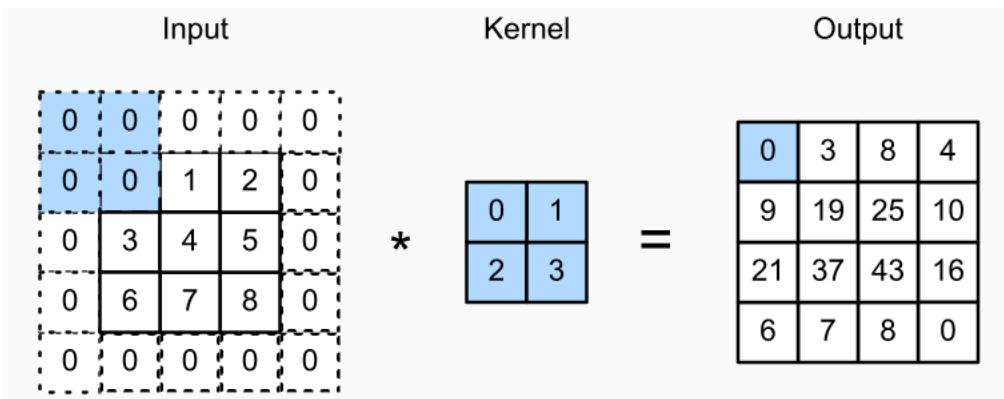

Figure 5.2 Example of convolutional layer

5.2.1 ReLU Activation layer

A non-saturated activation function called ReLU follows every convolutional layer due to its better performance compared to other activation functions. Using the ReLU function as the activation function just after the convolutional layer reduces the likelihood of the vanishing gradient and avoids sparsity. This way we dont loose the important data and even get rid of redundant data like a lot of 0‟s in the pixels.

This rectified linear activation function will output either zero if negative or the input itself if negative. This piecewise-linear is easier to train and often achieves better performance. ReLU function is represented as

$$F(x) = \max(0, x) \tag{1}$$

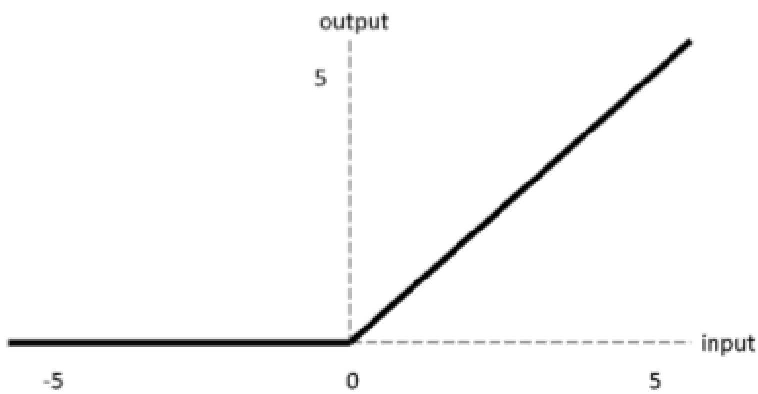

Figure 5.3 ReLU Activation function

5.2.2 Max Pooling layer

The max pooling layer is that which calculates the maximum, or largest, value in each patch of each feature map. The output is either down sampled or is presented as pooled feature maps that emphasizes the most present feature in the patch, unlike the average presence of the feature in average pooling. Discretization process is Max pooling is sample based max pooling. Reducing its dimensionality and allowing the assumptions to be made about features contained in the sub regions binned is the main objective of down sampling the input representation. This is done to help over fitting by providing an abstract form of the representation. The computational cost is reduced by reducing the number of parameters to learn and provides basic translation invariance to the internal representation. Max pooling is done by applying a max filter to sub regions of the initial representation that are non overlapping.

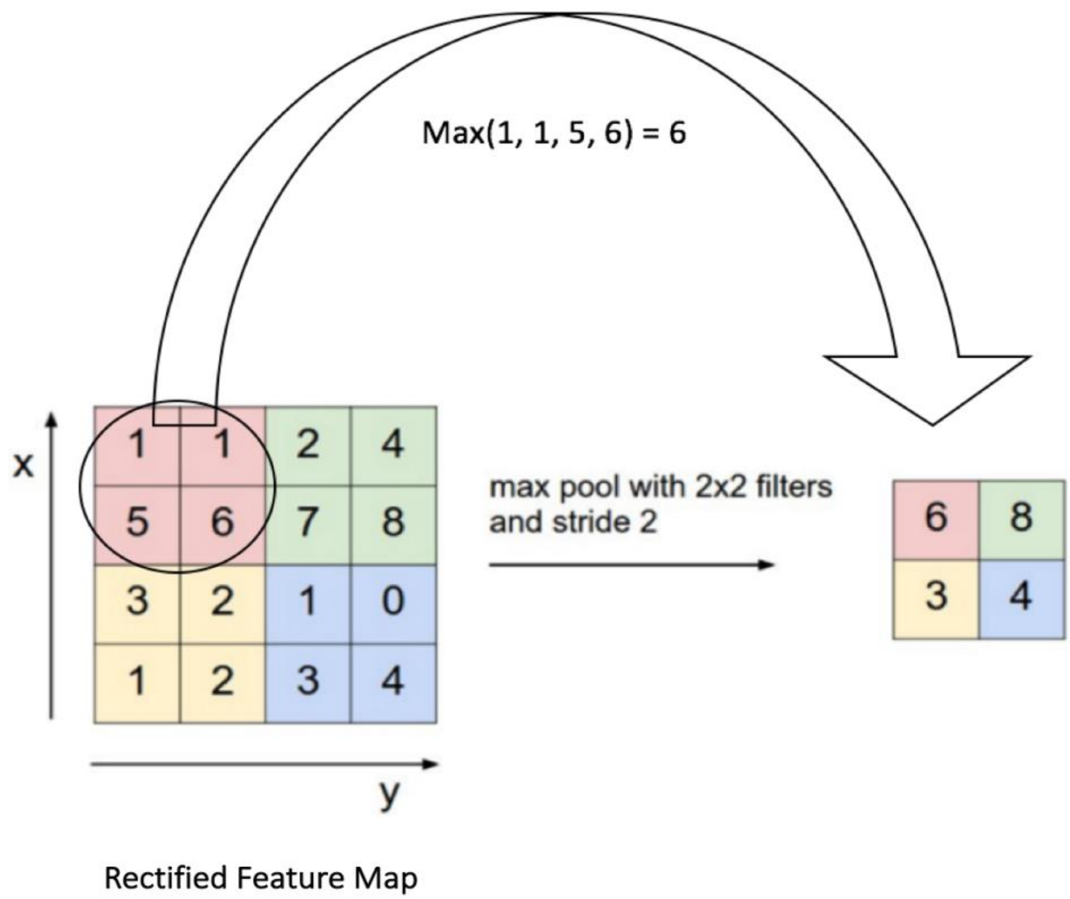

Figure 5.4 Example of a max-pooling layer (the maximum value out of a specific window is only considered)

5.2.3 Dropout layer

The dropout layer is used for preventing overfitting in a neural network and is done by dropping out units both hidden and visible. Dropout refers to ignoring units or neurons during the training phase of which is chosen at random. Some number of layer outputs are randomly ignored or 'dropped out' during training . This has the effect of making the layer look like and be treated like a layer with a different number of nodes and connectivity in comparison to the prior layer. In the proposed structure, we have found that 10% probability was most suited.

Finally, the advanced layers used are: Fully connected layer (FC), softmax layer and classification layer. The layers where all the inputs from one layer are connected to every activation unit of the next layer is called as a fully connected layer and is followed by the softmax layer also known as normalized exponential function.

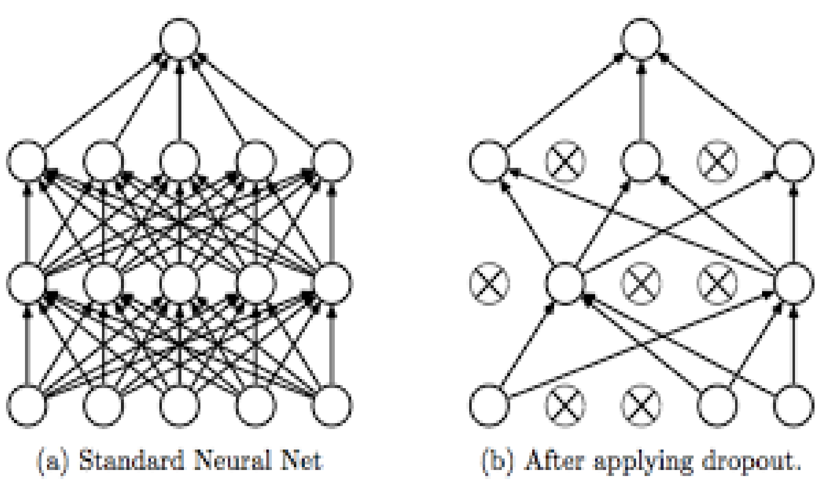

Figure 5.5 Example of a dropout layer

5.2.4 Fully Connected layer

Fully Connected layers in neural networks are the layers where all the inputs from one layer are connected to every activation unit of the next layer which is followed by the softmax layer which is also called the normalized exponential function. The fully connected layer is used to connect each of the previous layers to the next layers. Finally, we apply a Softmax Classifier that returns a list of probabilities for each of the class labels. The final classification from the network is chosen as the class label with the largest probability and shown in the output. The confusion matrix for the model is made using the output received. In this we can add more number of layers but adding more layers might affect the accuracy of the system. since, it uses multiple layers, so its called a Deep Learning.

5.2.5 Softmax layer

The main aim of using a softmax layer is for the output probabilities range. The range is process to range from 0 to 1, where the sum of all the probabilities equals to one. A Softmax function is a type of squashing function Squashing functions limit the output of the function into the range 0 to 1. This allows the output to be interpreted directly as a probability. Likewise, softmax functions are multi-class sigmoids, meaning they are used to determine the probability of multiple classes at once. Since the outputs of a softmax function can be interpreted as a probability (i.e.they must sum to 1), a softmax layer is typically the final layer used in neural network functions. It is important to note that a softmax layer must have the same number of nodes as the output later. In the proposed model, the softmax function is used for a multi-classification model that returns the probabilities of each class and the target class will have the high probability. The output of this layer can be calculated as:

$$fj\ (z)\ =\ \frac{e^{z_j}}{\sum_k\ e^{z_k}} \qquad (2)$$

Finally, we use a classification layer that computes the cross entropy loss for multi-class classification problems with mutually exclusive classes and provides the final predicted class for each input image. Cross-entropy loss, or log loss, measures the performance of a classification model whose output is a probability value between 0 and 1. Cross-entropy loss increases as the predicted probability diverges from the actual label. Loss can be estimated from given equation, where p is the target labels vector, and q (x) is the output vector from the softmax layer.

$$H(p,q) = \ -\sum_x(p(x) * \log\big(q(x)\big)) \qquad (3)$$

5.3 REGULARIZATION AND OPTIMISATION

Regularization is a method that tweaks the learning algorithm to make the model generalize better. This technique prevents learning a overly complex or flexible model to refrain from the risk of Overfitting**.**

Among the many techniques available for avoiding overfitting, data augmentation, dropout layers are used. To remove hidden units weights stochastically, dropout layers have been used. The L2 regularization is the most common type of all regularization techniques and is also commonly known as weight decay or Ride Regression. In L2 regularization, the values of weight matrices decrease because it assumes that a neural network with smaller weight matrices leads to simpler models and hence resulting in reduction of overfitting to an extent.

In L2 we have,

$$\text{Cost function} = \text{Loss} + \frac{\lambda}{2m} * \sum \|w\|^2 \qquad (4)$$

Here, lambda is the regularization parameter. It is the hyper parameter whose value is optimized for better results. Since it forces the weights to gradually decay towards zero, it is otherwise known as weight decay.

Optimization algorithms are also defined as error functions as it minimizes or maximizes an objective function. E(x) is a mathematical function that is dependent on the model's internal learnable parameters involved in computing the output values from the model's range of predictors. Adaptive Moment Estimation (Adam) finds the respective adaptive learning rates for every parameter. We have used this technique as it works favorably in practice and fares better in relation to other adaptive learning-method algorithms due to its fast convergence speed. It rectifies all problems faced by other optimization techniques such as vanishing Learning rate, slow convergence or High variance in the parameter updates leading to fluctuating Loss function and the learning speed of the model is efficient and swift .

5.4 CONFUSION MATRIX

A confusion matrix is the synopsis of prediction results on a classification problem. The number of correct and incorrect predictions are broken down by each class after summarizing with the count values. It acts as the key to the confusion matrix. The confusion matrix shows the ways in which the classification model is confused when its predictions are made. It gives us insight not only into the errors made by a classifier but mainly the types of errors that are being made.

CHAPTER 6

SYSTEM REQUIREMENT SPECIFICATIONS

6.1 HARDWARE REQUIREMENTS

PROCESSOR	: Intel i7-8550U CPU (1.8GHz)
GPU	: NVIDIA GeForce MX150 (4GB GDDR5)
HARD DISK DRIVE	: 50GB+
RAM	: 8GB RAM

6.2 SOFTWARE REQUIREMENTS

OPERATING SYSTEM	: Windows 10
LANGUAGE	: Python 3.7.4
PACKAGES USED	: Pytorch, os, numpy, h5py, torchvision, matplotlib, pydicom, pandas, csv, re

CHAPTER 7

SNAPSHOT OF MODULES

7.1 CNN TRAINING

```
Epoch [8/10], Step [200/625], Loss: 0.5852, Accuracy: 78.12%
Epoch [8/10], Step [300/625], Loss: 0.3129, Accuracy: 81.25%
Epoch [8/10], Step [400/625], Loss: 0.4847, Accuracy: 78.12%
Epoch [8/10], Step [500/625], Loss: 0.3917, Accuracy: 84.38%
Epoch [8/10], Step [600/625], Loss: 0.4651, Accuracy: 78.12%
Epoch [9/10], Step [100/625], Loss: 0.3087, Accuracy: 84.38%
Epoch [9/10], Step [200/625], Loss: 0.2286, Accuracy: 87.50%
Epoch [9/10], Step [300/625], Loss: 0.2303, Accuracy: 90.62%
Epoch [9/10], Step [400/625], Loss: 0.5892, Accuracy: 84.38%
Epoch [9/10], Step [500/625], Loss: 0.2615, Accuracy: 90.62%
Epoch [9/10], Step [600/625], Loss: 0.1843, Accuracy: 93.75%
Epoch [10/10], Step [100/625], Loss: 0.2482, Accuracy: 87.50%
Epoch [10/10], Step [200/625], Loss: 0.2971, Accuracy: 84.38%
Epoch [10/10], Step [300/625], Loss: 0.2862, Accuracy: 84.38%
Epoch [10/10], Step [400/625], Loss: 0.2157, Accuracy: 93.75%
Epoch [10/10], Step [500/625], Loss: 0.2348, Accuracy: 96.88%
Epoch [10/10], Step [600/625], Loss: 0.4237, Accuracy: 81.25%
Training Done...
Validation Accuracy:
 Loss: 0.5396, Accuracy: 84.38%
 Loss: 0.4592, Accuracy: 84.38%
 Loss: 0.6209, Accuracy: 75.00%
```

Figure 7.1 CNN TRAINING

One epoch is when an entire dataset is passed both forward and backward through the neural network only once. One epoch is too big to feed to the computer at once. So, we have divided it in several smaller batches. The number of epochs should be set as high as possible and terminate training based on the error rates. The model is to set to 10 epochs. The training time was 150 minutes for 21223 images. The average test execution time was 25.44 milliseconds per image.

7.2 CONFUSION MATRIX

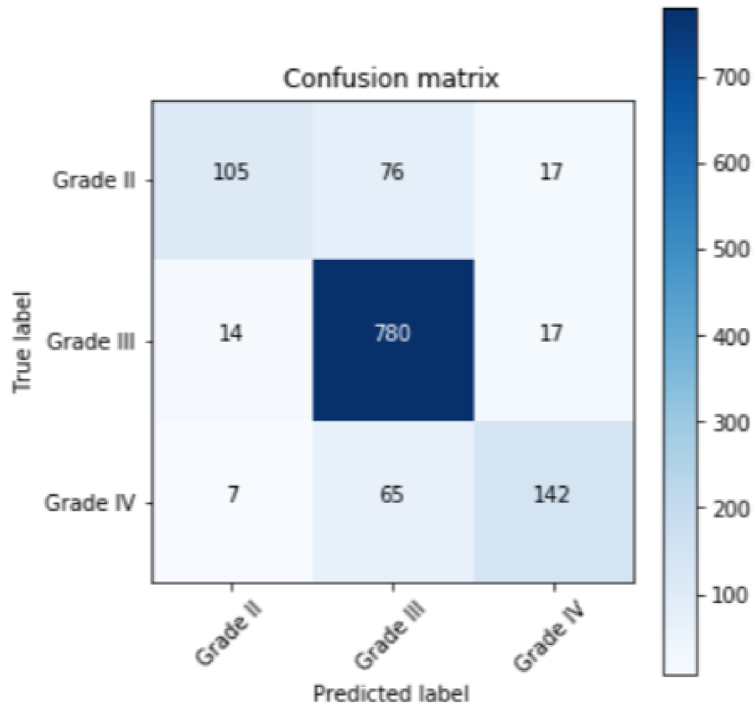

Figure 7.2 CONFUSION MATRIX

Expected down the side: Each row of the matrix corresponds to a predicted class.

Predicted across the top: Each column of the matrix corresponds to an actual class.

The total number of correct predictions for a class go into the expected row for that class value and the predicted column for that class value. Figure 7.2 shows the confusion matrix that summarizes the model's performance where the x-axis and y-axis are the true labels and predicted labels respectively.

7.3 ACCURACY

Tumour Type	TP	TN	FP	FN	Precision	Sensitivity	Specificity	Accuracy
GRADE II	105	1004	21	93	0.834	0.530	0.915	90%
GRADE III	780	300	141	31	0.846	0.961	0.906	88%
GRADE IV	142	890	34	72	0.806	0.663	0.925	84%

Figure 7.3 ACCURACY

Figure 7.3 shows the accuracy metrics as Precision, Sensitivity, Specificity and Accuracy extracted from the confusion matrix. Accuracy is calculated as:

$$\text{Accuracy} = TP+TN / (P+N) \tag{5}$$

We have achieved accuracy of 90.6% in classifying Grade II, 88.3% for Grade III and 84.3% for Grade IV.

CHAPTER 8

CONCLUSION AND FUTURE WORK

In this work, we have proposed a system for the classification of brain tumor MR images into different grades (Grade II, Grade III and Grade IV) using a custom deep neural network structure as it is best suited for medical image processing due to its automated feature learning. The proposed network is constructed from 11 layers starting from the input layer having the pre-processed images passing through the convolution layers and their activation functions (2 convolution, 2 ReLU and 2 Maxpooling layers). Also, to prevent overfitting a dropout layer is used followed by a fully connected layer and a softmax layer to predict the output. Lastly, a classification layer produces the predicted class. The proposed architecture has achieved the accuracy of 87.8% concerning the REMBRANDT dataset used in this paper. In the future, we plan to work with larger datasets to accelerate the scope of the work. The accuracy on the training set can be further improved by increasing the number of kernels and adding more hidden layers by working with multiple GPUs.

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