DANIEL MALANN

BRAIN TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS

NEU 2020

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

By
DANIEL MALANN

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

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of Master of Science in Information Systems 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 not original to this work.

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Date: 20/01/2021

AKNOWLEDGEMENTS

With respect and a heart of gratitude I want to specially thank my supervisor, advisor and H.O.D Assoc. Prof. Dr. Boran Sekeroglu the chairman of the Information Systems Engineering Department for his guidance, direction, insight, continuous support and encouragement throughout my thesis.

I would not have come this far without my awesome parents. Thank you for everything, your labor of love will not be forgotten.

Also, to my wonderful siblings, and friends, I appreciate every single one of you for your love, care and support.

I will not particularly forget to acknowledge Sebastian Nlebedim, Gift Christopher for their complete help and support.

To my parents…

ABSTRACT

Bain tumor is one of the most predominant tumors affecting the globe in recent studies. This is an uncontrollable and abnormal growth that occurs in the cells of the brain which could be either malignant that is cancerous or destructive tumors which attacks the surrounding tissues thereby distributing it to other parts of the body through the lymph framework or the blood. This tumor could also be benign that is non-cancerous or non-destructive having structures in uniform form and does not atta other parts of the body. The classification of brain tumor is a very decisive job in tumor assessment and proffering a treatment decision in relation to their classes. For brain tumor detection, there are many imaging techniques that can be used nonetheless, MRI is most preferred widely due to its high-level image quality and does not depend on any ionizing radiation. Deep learning (DL) which is a subset under machine learning and of late has displayed exceptional performances in problems of classification and segmentation of images. In this thesis work, a deep learning model based on CNN is introduced to classify brain tumor types gotten from a repository the Cancer Imaging Achieve. From the dataset a pre-operative physical examination was conducted on one hundred and fifty-nine (159) patients with Low Grade Gliomas (WHO grade II & III). The MRI database contains a total number of seventeen thousand, three hundred and sixty (17,360) images.

The proposed CNN architecture records a reasonable performance with the Accuracy of 96.16%, Sensitivity of 99.39%, Specificity of 75.11% and ROC Accuracy of 86.88%.

Keywords: Brain Tumor; Convolution Neural Network; data augmentation; MRI

ÖZET

Beyin tümörü, son çalışmalarda dünyayı etkileyen en baskın tümörlerden biridir. Bu, beyin hücrelerinde meydana gelen kontrol edilemeyen ve anormal bir büyümedir ve kanserli veya yıkıcı tümörler çevreleyen dokulara saldırarak lenf çerçevesi veya kan yoluyla vücudun diğer bölgelerine dağıtır. Bu tümör, aynı zamanda, tek tip formda yapılara sahip olan ve vücudun diğer kısımlarına dokunmayan, kanserli olmayan veya tahrip edici olmayan iyi huylu olabilir.. Beyin tümörünün sınıflandırılması, tümör değerlendirmesinde ve sınıflarına göre bir tedavi kararı verilmesinde çok belirleyici bir iştir. Beyin tümör tespiti için, yine de kullanılabilecek birçok görüntüleme tekniği vardır, MRI, yüksek düzey görüntü kalitesi nedeniyle en çok tercih edilir ve herhangi bir iyonlaştırıcı radyasyona bağlı değildir. Makine öğrenimi altında ve geç olan bir alt küme olan derin öğrenme (DL), görüntülerin sınıflandırılması ve bölümlere ayrılması sorunlarında olağanüstü performanslar sergilemiştir. Bu tez çalışmasında, Kanser Görüntüleme Başarısı havuzundan alınan beyin tümörü tiplerini sınıflandırmak için CNN tabanlı derin bir öğrenme modeli tanıtılmıştır. Veri kümesinden Düşük Dereceli Gliomlu (WHO derece II ve III) yüz elli dokuz (159) hastaya ameliyat öncesi fizik muayene yapıldı. MRG veri tabanı toplam on yedi bin, üç yüz altmış (17.360) görüntü içermektedir. Önerilen CNN mimarisi% 96.16 Doğruluk, % 99.39 Hassasiyet, % 75.11 Özgüllük ve% 86.88 ROC Doğruluğu ile makul bir performans kaydeder.

Anahtar Kelimeler: Beyin Tümörü; Konvolüsyon Sinir Ağı; veri büyütme; MRI

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ANN: Artificial Neural Networks

CNN: Convolutional Neural Networks

CE-MRI: Contrast Enhanced Magnetic Resonance Imaging

DCNN: Deep Convolutional Neural Networks

ELM-LRF: Extreme Learning Machine Local Receptive Fields

FP: False Positive

FN: False Negative

KELM: Kernel Extreme Learning Machine

KE-CNN: Kernel Extreme Convolutional Neural Networks

MRI: Magnetic Resonance Imaging

MLP: Multi-Layer Perception

SVM: Support Vector Machine

TKFCM: Temper Based K-Means and Modified Fuzzy C-means

TP: True Positive

TN: True Negative

WHO: World Health Organization

CHAPTER 1
INTRODUCTION

1.1 Background

Brain tumor is a tumor that develops in the brain or central nervous system (Gopal et al., 2019), that occurs when an abnormal group of cells in the brain is formed by uncontrolled division of cells (Moshen et al., 2017). According to (WHO), brain cancer accounts for less than 2% of human cancer, thereby producing severe morbidity and complications (Sultan et al., 2019). The process of the treatment, success rate and follow-up of the disease depends on the experience of the physician (Pashaei et al., 2018). Categorizing brain tumor could be challenging, hence using automatic methods have been proposed to aid the radiologists and physicians for diagnosis & classification of brain tumor (Ari & Hanbay, 2018).

Gliomas are most common brain tumors, WHO classifies gliomas into four grades (grades I-IV) according to their severity. “The diffuse gliomas are divided into low-grade gliomas (LGG, WHO grade II) and high-grade gliomas (HGG, WHO grade III and IV)” (Ge et al., 2018). Gliomas include 30% and 80% of all brain tumors and malignant brain tumors respectively (Sultan et al., 2019). According to (WHO) low-grade gliomas include grade II and III diffuse gliomas (Kocak et al., 2019). LGG is also known as “diffuse low-grade and intermediate-grade gliomas (WHO grades II and III) include astrocytomas, oligostrocytomas and oligodendrogliomas”. Comparingly, the nature of LGG as a tumor are less aggressive and has better prognosis than HGG (WHO grade IV, glioblastoma) (Akkus et al., 2017).

Brain tumors and gliomas classification have been automated by developed methods in other researches. These methods are machine learning techniques, different imaging modalities (Sultan et al., 2019) and deep learning methods that require a high accuracy for solving complex problems (Alqudah et al., 2019). According to the previous research works, Ahmmed et al., 2017 firstly started with enhanced brain MRI images, TKFCM clustering algorithm was used for MRI image segmentation. Thereafter, brain tumor was detected and isolated from the normal brain MRI images by SVM. Also, ANN was used to classify the tumor into benign and four malignant stages. Accuracy of 97.37% was obtained for classifying normal and tumor brain in

the study. George et al., 2015 proposed two approaches using C4.5 and Multi-layer perception for the classification of brain tumor. About 95% accuracy was achieved using (MLP) algorithm. Alquadah et al., 2019 proposed the use of CNN to classify a dataset of "3064 T1 weighted contrast-enhanced brain MR images for grading (classifying) the brain tumor into three classes (Glioma, Meningioma and Pituitary Tumor)". The results show that cropped lesion have 98.93% of accuracy, 98.18% of sensitivity, while uncropped lesions have accuracy of 99% and sensitivity of 98.52% and the accuracy and sensitivity of the segmented lesion images represent 97.62% and 97.40% respectively. Ari & Hanbay, 2018 performed classification of cranial MR images and the detection of brain tumor with method of ELM-LRF. The performance obtained classification of 97.18%. Pashaei et al., 2018 proposed CNN and KELM (KE-CNN) to classify 3 types of brain tumor (meningioma, glioma, and pituitary tumor) in T1-weighted CE-MRI images. In the first method CNN was used to extract the features of the images which gave 81.09% of accuracy for brain tumor and the extracted features were used as input of KELM. In the second method KE-CNN was used having the accuracy of 93.68%.

1.2 Problem Statement

The prognostic test of LGGs is highly dependent on histopathological grade. Histopathological study gives diagnosis and subsequent treatment plan. Although, the diagnosis gives little or no information about other properties of tumor which has great impact on optimal therapy options Molecular and genomic biomarkers influence LGGs by improving the treatment planning, and it is strong in predicting clinical outcomes than the histopathological classification. Tumor treatment responds positively with chemotherapy and radiotherapy as offered by a molecular marker and has longer chances for survival. Therefore, $^{1}p^{19}q$ classification is important for effective treatment planning (Akkus et al., 2017; Kocak et al., 2019). To solve this problem, a model is proposed to offer analysis for classifying the LGG – $^{1}p^{19}q$ deletion using deep convolutional neural network to yield a better representation of features.

1.3 Aim of Study

The aim of this study is to evaluate the effectiveness of deep convolutional neural network as a proposed method in classifying different gliomas types (Type 1 Astrocystomas, Type 2 Oligostrocytomas, Type 3 Oligodendrogliomas) using LGG – $^{1}p^{19}q$ Deletion.

1.4 Significance of Study

Classification of brain tumor has become an essential issue in the medical field. In order to meet the demand, the model for DCNN consisting several layers is proposed in this study. By Integrating DCNN standard model that is employed for the classification of LGGs with high accuracy and by testing the method prospectively, the findings can be readily translated to the clinic. This predictive model may be adopted by clinicians for treatment planning of LGGs.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction to Human Brain Anatomy

The brain is a nervous system that is complex in nature and functions in directing the movements and the sensitivity of animals in natural environment. Generally, the sensory nerve of the brain receives input and it is processed in the brain, then the motor nerves transmit the reaction input through the motor nerves to the brain.

According to the neuroanatomy hierarchies, the brain is divided into hundreds of parts and sections consisting of the brainstem, cerebellum, diencephalon and cerebrum (Zhang, 2019).

2.1.1 Brain stem

It is situated the side of the brain that continues to the spinal cord. It comprises the midbrain, hindbrain pons and medulla oblongata. Usually, the diencephalon and the caudal portion of the brain maybe included. The primary supply of the motor & sensory nerve of the 13 pairs of cranial nerves emerge from the brainstem to the face and back. The brainstem is responsible for cardiac and respiratory control, activates the consciousness that directs the process of sleep by controlling the nervous system. It also controls the function of heart rate, breathing and feeding (Zhang, 2019).

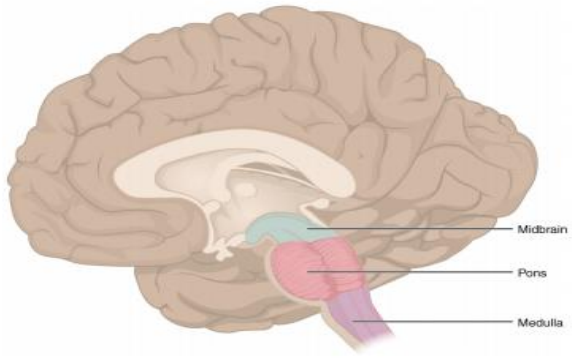


Figure 2.1: The diagram of the brainstem (Zhang, 2019)

2.1.2 Cerebellum

The cerebellum involves neuroimaging of human and animal behaviors in processing signals for ‘vision’, ‘memory’ and ‘emotion’, specifically in circumstances involving predictions and timing. It is responsible for deliberate smooth movement. The cerebellum plays a significant role in sensorimotor and vestibular control as well as memory, emotional function and autonomy. Corticol and subcortical areas of the brain mediates brain activities in higher order by interaction with cerebellum (Reeber et al., 2013). The cognitive/limbic cerebellum is located at the posterior lobe of the cerebellar. Lobe lesions can result to cerebellar cognitive affective syndrome (CCAS), characterized by function deficiencies of verbal abilities, visual spatial awareness, and subsequently affecting brain control (Schmahamann, 2019)

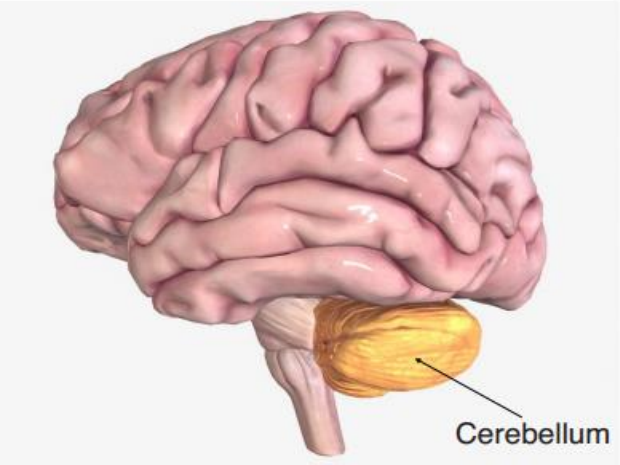


Figure 2.2: Diagram of cerebellum (Zhang, 2019)

2.1.3 Diencephalon

The diencephalon is a small structure of the central nervous system and a forebrain division, situated between the midbrain and the telencephalon. It consists of structures including the thalamus, the hypothalamus (including the posterior pituitary), the epithelium and the

subthalamus which are on the side of the third ventricle. It plays a significant role in keeping the brain healthy and active in controlling consciousness (Zhang, 2019).

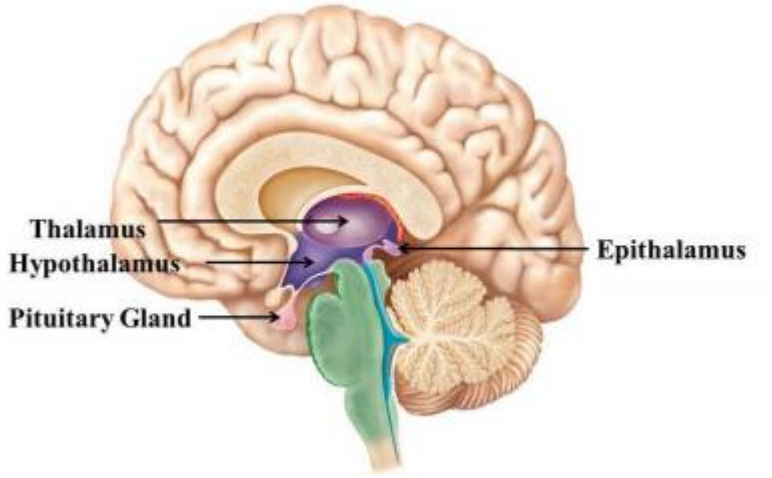


Figure 2.3: Diagram of Diencephalon (Zhang, 2019)

2.1.4 Cerebrum

This part of the brain is the main portion consisting of the cerebral cortex (Zhang, 2019). The cerebral cortex is the dominantly plays key roles in a surprisingly varied variety of behaviors, including “vision, volitional activity, reasoning, memory, and emotion. In humans, skills such as language and use of resources that make us special as both a species and as individuals are controlled in the cerebrum” (Van Essen et al., 2018).

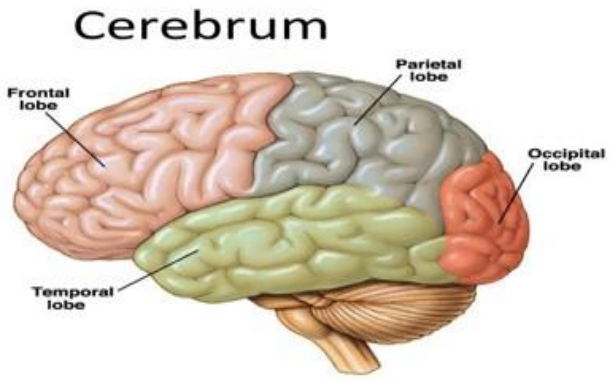


Figure 2.4: Diagram of Cerebrum ("Cerebrum - Assignment Point", 2020)

2.2 Lobes of the Brain

The cerebrum constitutes two cerebral hemispheres called ‘gray matter’ and ‘white matter’, which are the outer layer and inner layer respectively. The cortex layer of the cerebrum comprises “four lobes, the frontal lobe, the parietal lobe, the temporal lobe, and the occipital lobe” (Jawabri & Sharma, 2019).

2.2.1 Frontal lobe

Frontal lobe is situated in front of the hemispheres of the brain and as the largest lobe, it has vital functions for the body (Jawabri & Sharma, 2019). The frontal lobes, the largest brain area comprising about one-third of the entire human brain, span from the central sulcus to the frontal pole. Among primates, and particularly humans over other mammals, the evolutionary development of the frontal lobes played a key role among developing many cognitive abilities, including working memory and language. The primates 'frontal lobes, particularly humans (particularly the prefrontal cortex), grow later in an individual's life and are comparatively larger than other species' frontal cortices. The frontal lobes also have wide connections to other cortical and subcortical regions. The frontal lobe functions include (but not limited to) rational thinking, imagination, and socially responsible behavior, which are crucial to human participation in current social interactions as well as complex decisions. The anatomical and functional organization implies that the frontal lobes operate at three interdependent causal levels ranging from immediate action to conscious or unconscious feelings, to evaluative but also inhibitory

thoughts mostly conscious of the higher order. Voluntary movement and control of behavior are among the essential functions of the frontal lobes (Firat, 2019).

2.2.2 Parietal lobe

The parietal lobe is an area characterized by anatomical landmarks within the human brain. “Somatosensory information”, “spatial attention”, “visual-motor transformations”, “numerical computations”, and “language”, including reading, are processed within brain areas. “It is divided by two imaginary lines at the posterior end on the lateral surface from the occipital and temporal lobes. The first runs from the tip of the parieto-occipital sulcus that is on the brain's medial side to the troubling notch and divides the parietal lobe from the occipital lobe. In the postcentral gyrus, adjacent to the central sulcus, lies the primary somatosensory cortex of the parietal lobe. This is the main cortical area receiving proprioception (information about body and limb position) and touch information from the body” (Bisley, 2017). The parietal lobe contains much of the left hemisphere's "peri-Sylvian" cortex, which has been considered essential in nearly all accounts of language's neural foundation (Coslett & Schwartz, 2018).

2.2.3 Occipital lobe

Among the lobes, occipital lobe lies mostly at the posterior and its main function is sight coordination (Todorov & De Sousa, 2018). This lobe contains the brain's processing area of sight and visuospatial processing. It is also associated with visualizing distance and depth, determination of colors, object and face identification, and memory formation. The main visual cortex consists of dorsal and ventral and they aid in transmitting information. Furthermore, the dorsal part gathers visual information with same direction of target and transmit to the parietal lobe. The ventral collects visual information in recognition of object and sends to the temporal lobe (Rehman & Khalili, 2019).

2.2.4 Temporal lobe

The brain's temporal lobe is also called the neocortex. It forms the cerebral cortex with other lobes of the brain. It's mainly situated in the middle cranial fossa, a region near the base of the skull. It is located anteriorly and posteriorly to the side of the occipital lobe and frontal lobe

respectively. The lateral fissure is found inferior. The temporal lobe further subdivides into the "superior temporal lobe", the "temporal lobe in the middle" and the "inferior temporal lobe". It houses a variety of essential brain structures such as hippocampus and amygdala (Patel et al., 2020). The surfaces of the temporal lobes are formed by exact 17% part of the cerebral cortex, in the left hemisphere. The auditory, olfactory, vestibular, and visual senses are formed in the temporal cortex, as well as perception of spoken and written language (Kiernan, 2012). The primary functions of this lobe are “sound processing, storing and deriving sensory information into concrete memories, language, and emotions and parts of the temporal lobe aid in visual stimuli processing, mainly to enable us to recognize objects” (Patel et al., 2020).

2.3 Brain Tumor

Brain tumors are common and comprehending the diagnosis & its management by general healthcare providers essential. (McFaline-Figuero & Lee, 2018). It is primarily referred to as heterogenous group of tumors emerging within the cells of the CNS. A brain tumor is a cancerous or non-cancerous mass, or an irregular brain cell growth. Gliomas are prevalently type of brain tumor which account about 75% of major malignant brain tumor, that occurs in the glial cells. There may also be common symptoms and signs of brain tumors that are not limited to one anatomical location (Lapointe et al., 2018; Sun et al., 2019). Cranial tumor arises from meninges, neuroepithelial tissues, pituitary and associated structures, germ cells, cranial nerves, blood-forming organs or a distant main subclinical tumor are commonly known as min brain tumors (Perkin, & Liu, 2016). The frequency of primary brain tumors varies with age, sex and ethnicity. Malignant brain tumors, such as glioma, lymphoma, embryonic, and germ cell tumors, appear to occur significantly more often in men. However, brain tumors are prevalent in women especially the meningiomas and pituitary tumors which are common in women. Tumors in some of the brain's functional areas can be identified earlier on imaging and they appear apparently in focal in neurological symptoms compare to other parts. The Frontal lobe tumor is associated with the symptoms of weakness, parietal lobe is associated with numbness, spatial disorientation while visual defects due to tumors such as temporal, parietal or occipital lobes involving optical radiation. Cognitive dysfunctions are associated with “prefrontal lobe”,

“temporal lobe or corpus callus” and cranial nerve palsy, cerebellar dysfunction and long-term symptoms are associated with infratentorial tumors (Lapointe et al., 2018).

A brain tumor can be benign or malignant. Benign brain tumors are structurally uniform and are not active cells, while “malignant brain tumors” are structurally non-uniform (heterogeneous) and constituting active cells. Gliomas and meningiomas are low-grade classified under “benign tumor”, and “glioblastoma” and “astrocytomas” are high-grade classified under “malignant tumors”. According to the WHO and the American Brain Tumor Association, “the most common grading system uses grade I to grade IV scales to distinguish benign and malignant tumor types. Benign tumors fall under grade I and grade II glioma, and malignant tumors fall under grade III and grade IV gliomas. Grade I and II glioma are often referred to as low-grade tumor types and have slow growth, whereas grades III and IV are referred to as high-grade tumor types and have rapid tumor growth” (Bahadure et al., 2017).

2.3.1 Gliomas

Gliomas are main brain tumors that are emerged from neuroglial stem cells or progenitor cells (Weller et al., 2015). Traditionally, on the basis of their histological appearance, the “World Health Organization (WHO) classification of central nervous system (CNS) tumors distinguishes astrocytomas, oligodendrogliomas, and ependymomas, and assigned WHO grades I – IV, which indicate different degrees of malignancy. Grade I and II are low-grade gliomas, while grade III and IV are high-grade gliomas. Though, the updated WHO 2016 classification of CNS tumors combines biology-driven molecular marker diagnostics with classical histological cancer diagnosis” (Huang et al., 2019).

In adult, diffuse gliomas is classified as “astrocytoma (WHO Grade II and III), oliogodendroglioma (WHO Grade II and III) and glioblastoma (WHO Grade IV)”. In 2016, adult gliomas by the classification of “WHO” was revised to integrate latest findings on disseminated gliomas. The modern way of classifying the brain tumor classification in the update was extended to both the histopathological and molecular characteristics, thus incorporating “phenotypic” and “genotypic” information. The integrated pathologic diagnosis includes molecular information of the “isocitrate dehydrogenase (IDH) genes” and the “1p/19q

codeletion" mutation status. Presently, adult gliomas typically fall into three major groups: "IDH mutant with 1p/19q codeletion, IDH mutant with 1p/19q intact, and IDH wild form" (Aquilant et al., 2018). According to WHO 2016, "the combination of two separate molecular markers, such as IDH-1 and −2 mutations and 1p/19q codeletion, enables the divisions of low-grade gliomas into three specific subtypes; oligodendroglioma IDH-1 and −2 mutated with 1p/19q codeletion; diffuse astrocytoma IDH-1 and-2 mutated with 1p/19 codeletion; and diffuse astrocytoma IDH wild-type" (Pellerino et al., 2020).

Gliomas in adult is diffusedly infiltrating having a different natural history and is found to respond to treatment with positive outcome. It is classified into 3 major tumor groups which includes: "isocitrate dehydrogenase (IDH)-mutant, 1p/19q co-deleted tumors with mainly oligodendroglial morphology associated with the best prognosis; IDH-mutant, 1p/19q non-codeleted tumors with mostly astrocytic histology associated with moderate outcome; and IDH wild-type, usually higher WHO grade (III or IV) tumors associated with poor prognosis. Gliomas in children are molecularly distinct from those in adults, the majority of whom are WHO grade I pilocytic astrocytomas characterized by circumscribed development, favorable prognosis and recurrent BRAF gene fusions or mutations. Ependymal tumors can be molecularly subdivided into distinct epigenetic subgroups by position and prognosis" (Weller et al., 2015). "Isocitrate dehydrogenase 1 and 2 (IDH1 and IDH2) mutations are thought to be an early occurrence of gliomagenesis and are more frequently seen in lower grade gliomas (more than 70% grade II – III astrocytomas; 100% oligodendrogliomas) than in glioblastomas, in which only 10% are referred to as secondary glioblastoma (defined clinically when derived from lower grade astrocytoma) or glioblastoma, IDH mutant. Diffuse gliomas bearing IDH1/2 mutations are connected with a stronger prognosis than diffuse gliomas, IDH-wildtype. Imbalanced centermeric translocation t (1:19) (q10: p10) results to codeletion of chromosomes 1p and 19q. Combining IGH mutation with codeletion, is needed for diagnosis of oligodendroglioma, IDH-mutant and 1p/19q codeleted. 1p/19q codeletion provides a favorable prognosis between diffuse gliomas and predicts an enhances response to alkylating chemotherapy" (Lapointe et al., 2018).

2.3.2 Astrocytomas

Astrocytoma grade I is biologically benign and can be cured through massive surgical ablation. While grade II astrocytoma treatment cannot surgically be accomplished, it is hypercellularity and diffusely penetrate around the cerebral parenchyma. In addition, “The median survival for Grade II astrocytoma patients ranges from 5 to 8 years. Grade III or IV astrocytoma is known to be malignant. Adding to hypercellularity, Grade III astrocytomas, also known as anaplastic astrocytomas, possess nuclear atypia and increased mitotic results. The median survival for Grade III tumor patients is approximately 3 years. Grade IV astrocytomas, or glioblastomas, are distinguished by histological observations of angiogenesis and necrosis. Grade IV tumors are highly aggressive and have a median lifespan of 12 to 18 months” (Dong et al., 2015). Following histological classification of astrocytoma, it is characterized with the presence or absence of “IDH1 or IDH2 mutations” (Komori, 2017). Diffuse astrocytoma consists of two major subtypes based on the current WHO classification: “IDH-mutant and IDH-wild type (diffuse astrocytoma, anaplastic astrocytoma and glioblastoma)” (Li et al., 2019).

Diffuse astrocytoma WHO grades II (AS II) is a slow-growing invasive semi-benign astrocytoma. It is commonly diagnosed between 20 and 45 years of age with an average age of 35 years of age. “The diffuse invasive development of AS II without a clearly defined boundary between the tumor and normal tissue allows complete surgical resection nearly impossible. Tumor recurrence is seen in many cases in most patients after a few years of development to more malignant Anaplastic Astrocytoma (AS) III or Glioblastomas IV (GBM). The median survival of AS II patients is between 5 and 8 years of age” (Seifert et al., 2015). The anaplastic astrocytoma “WHO grade III (AS III) is an invasive and fast-growing malignant astrocytoma. It is characterized by increased mitotic activity and more complex tumor cell size and shape compared to AS II. The average age for patients diagnosed with AS III is 45 years. The treatment of choice is the surgical resection accompanied by radiotherapy and/or chemotherapy, if necessary. Similar to AS II, the progression of AS III to the most malignant GBM IV is also observed. The average five-year survival rate for AS III patients is 24 per cent and the mean survival is between 1 to 4 years” (Seifert et al., 2015). Glioblastomas is the most prevalent primary malignant brain tumor accounted for sixteen percent of all primary brain and

CNS neoplasms (Davis, 2016) and in adult, glioblastomas accounts for 60% of malignant gliomas (Taylor et al., 2019). W.H.O classified glioblastoma as Grade IV, it is mostly aggressive in nature, invasive and a type of tumor that cannot be differentiated (Hanif et al., 2017). Glioblastomas emerged in brain stem, cerebellum & spinal cord (Davis, 2016).

The concept of this nomenclature remains histological rather than genetic, i.e. high-grade glioma with primarily astrocytic differentiation, with nuclear atypia, cell pleomorphism as well as microvascular proliferation and/or necrosis. "Depending on the absence or existence of IDH1/2 mutations, glioblastomas are classified into glioblastoma, IDH-wildtype, corresponding to primary or de novo glioblastoma, and glioblastoma, IDH-mutant, leading to the so-called secondary glioblastoma" (Komori, 2017). "Genetic alterations typical of primary glioblastomas are epidermal growth factor receptor (EGFR) overexpression, phosphate and tensin homologue (PTEN) mutations, and chromosome 10q loss. In secondary glioblastomas, isocitrate dehydrogenase 1 (IDH1) mutations, p53 mutations, and 19q chromosome loss are commonly seen" (Davis, 2016).

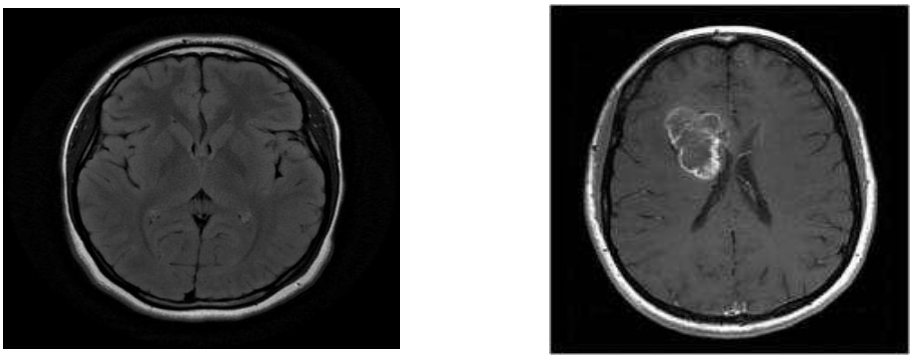
2.3.3 Oliogodendrogliomas

The histology of oligodendroglioma must be 'traditional' as this name is meant to defined "1p19q codelated glioma". More than ninety percent of classic "oligodendrogliomas exhibit IDH mutation and 1p19q codeletion, which is now known to be the genetic marker of oligodendroglioma. The final diagnosis is oligodendrolioma, when a classic oligodendroglioma is classified as IDH wildtype" (Komori, 2017).

2.3.4 Meningiomas

Meningiomas are primary brain tumor, benign and slow-growing neoplasms originating from meningothelial cells of the arachnoid mater. "The WHO classification scheme classifies meningiomas as grades I to III, based on histology. Grade I meningiomas, also called benign meningiomas, are the most prevalent and have a good prognosis. While the meningiomas grades II and III are mostly aggressive (McFaline-Figueroa & Lee, 2018). The first genetic alteration seen in meningiomas was the deletion of chromosome 22q; subsequent studies found that the key gene involved, NF2, was 22q12, encoding the merlin tumor suppressor" (Buerki et al.,

2018). Some “benign meningiomas (BMs)” follow a more violent path with frequent recurrences, while some “atypical meningiomas (AMs)” and “malignant meningiomas (MMs)” may have a more stable path with long “progression-free survival (PFS)” and “overall survival (OS)”. The classification of the (WHO) for meningiomas is simply based on “histopathological mitotic rate characterizations, atypia cellular characteristics and local invasions. Approximately 80% are WHO grade I (also referred to as Benign Meningiomas), 17% are WHO grade II (Atypical Meningiomas), and 2% are WHO grade III (anaplastic meningioma / Malignant Meningiomas)” (Shaikh et al., 2018).



(a) Normal Brain **(b) Brain with Tumor**

Figure 2.5: Brain MRI Images

CHAPTER 3
CONVOLUTIONAL NEURAL NETWORK

Convolution Neural Networks is made up of neurons alongside some weights and biases. These neurons collect some input from the preliminary layer. It is then followed with a calculation of a dot product in the middle of the input and the weights and follows it in a non-linearity voluntarily (Pathak et al., 2019). The architecture of the CNN is mathematical based which is made up of a cluster of feed forward layers (Krishnammal & Raja, 2019) which includes Convolution Layer which compromises of more than one convolution layer with activation function ReLU and Pooling layer. It is then followed by a Fully connected layer (Pathak et al., 2019).

The Convolution and pooling layers which are the first two layers carry out extraction of feature from the input image and the feature that has been extracted are mapped to final output and this is done by converting the 2D feature maps into the ID vector in classifying images through complete connected layer (Krishnammal & Raja, 2019).

There are different CNN models which includes “AlexNet, Visual Geometry Group (VGG)-16 and VGG-19”. AlexNet is more desirable and suitable model due to its pliability to modify and its capacity to train faster and the proficiency to reduce overfitting using drop outs (Krishnammal & Raja, 2019).

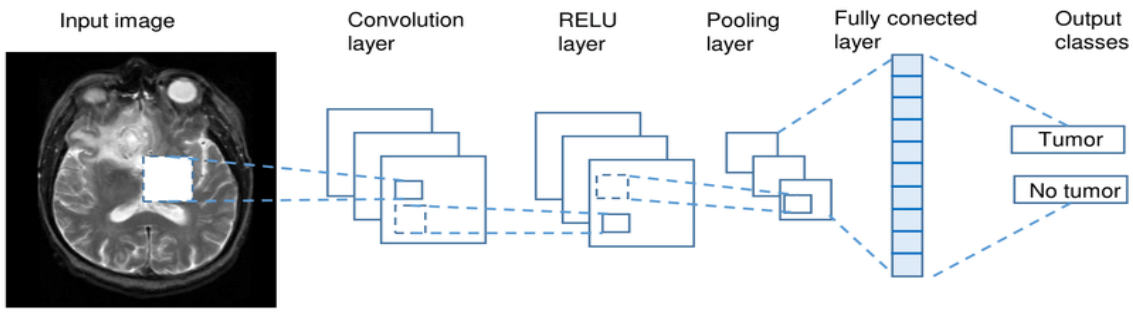


Figure 3. 1: Architecture of CNN (Ker et al., 2017)

3.1 Convolution Layer

The convolution layer is the principal building block of a CNN (Hussain et al., 2017). The constituents of the input image are specifically connected to the next convolutional layer because it will be complicated mathematically when the next layer is connected to all the pixel image input. The layer primarily functions to extract the feature of the input image (Pathak et al., 2019).

The feature from the input image of the pixels is kept in a 2D array through an optimizable extractor as convolving the kernel. The depth of the output feature map is set at the size of 3x3 or 5x5 of the kernel (Krishnammal & Raja, 2019.).

3.2 Padding

This is the merging of a zero layer outside of the size of the input so that the data concerning the borders won't be missing and we can still have the same proportion of output as input size. The output size is been calculated with this equation

$$[W_2 * H_2 * D_2] \quad (3.1)$$

Where:

$$(W_2 = (W_1 - F + 2P)/S + 1) \quad (3.2)$$

$$(H_2 = (H_1 - F + 2P)/S + 1) \quad (3.3)$$

$$(D_2 = K) \quad (3.4)$$

"$[W_1 * H_1 * D_1]$ is the size of the input image, F represents receptive field size, P for amount of padding and K is depth" (Pathak et al., 2019).

3.3 Rectifier Activation Function ReLU

The input volume has passed through the convolution layer, thereafter the application of ReLU (Non-linear activation function) was given to the feature map to obtain to the systems a non-linearity. The equation for ReLU (Pathak et al., 2019):

$$(f(X) = \max(0, X)) \quad (3.5)$$

Out of other activation functions such as sigmoid, tanh, the ReLU is often used because it is the most frequently used and doesn't have a problem by speeding up training nevertheless forcing a constant 0 which will reduce the flow of the gradient and resultant adapting of the weights.
This limitation is managed using an alternative called leaky rectifier linear unit (LReLU) which establishes a little slope on the negative side of the function. This is defined as (Pereira et al., 2016):

$$(\text{“}f(X) = \max(0, X) + \alpha \min(0, X)\text{”}) \quad (3.6)$$

3.4 Pooling Layer

This layer is placed after the convolution Layer and it reduces the feature map dimensions of the input image, minimizes computational overhead for the next layer and proficiency to control over fitting (Krishnammal & Raja, 2019.).
Max pooling, average pooling and mean pooling are the different types of pooling (Pathak et al., 2019).

3.5 Fully Connected Layers

In this layer, the conversion from the pooling layer of the feature maps into an ID vector is joined to either one or more layers that are dense, to map the final output of the networks (Krishnammal & Raja, 2019.).
This layer generates classified images due to the training dataset so the end product with either be tumor images or normal images of the brain which will be seen (Pathak et al., 2019).

3.6 Sigmoid

This is to utilize the classification of binary and logistic regression by an activated function for describing two classes (Pathak et al., 2019)

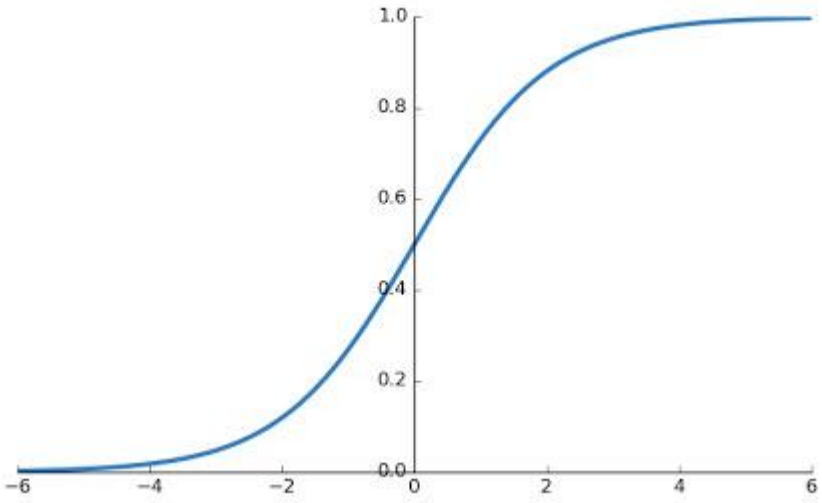


Figure 3.2: Sigmoid Function (Restrepo, 2017)

3.7 Adaptive Movement Estimation

This is applied for training deep neural network; its function is to give calculation for single learning rate of different variables. It begins the learning rate at 0.001 (Pathak et al., 2019)

3.8 Cross Entropy / Loss Function / Log Loss

During training it is a function to be reduced (Pereira et al., 2016), it also gives the calculation of performance of a model to be classified having its output value range in the region of 0 and 1 (Pathak et al., 2019)

3.9 Epochs

“This is when the entire dataset is moving forward and backwards propagation via neural network. If it moves once it is one epoch” (Pathak et al., 2019).

3.10 Batch Size

“The entire dataset for training utilized for one iteration, if the dataset is much then 25 or 32 batch size is good with an epoch of about 100” (Pathak et al., 2019).

3.11 Training Accuracy

The accuracy derived when a model is applied on a dataset to be trained. This is called training accuracy (Pathak et al., 2019).

3.12 Validation Accuracy

After training the dataset, when it is then assessed with the test dataset, it will give a validation accuracy (Pathak et al., 2019).

CHAPTER 4
EXPERIMENTAL DESIGN

4.1 MRI for Gliomas

A very common and in use image technique for detection and analysis of the brain tumor is the Magnetic Resonance Imaging (MRI). MRI is a system which is free from interference which can be made use parallel to other Imaging modalities which includes Position Emission Tomography (PET), Computed Tomography (CT) and Magnetic Resonance Spectroscopy (MRS) to give precise information about the structure of the tumors.

Nevertheless, when using MRI parallel to these other Image modalities it becomes expensive and can sometimes result to an encroachment, an example is the PET. MRI is normalized to balance contrasting tissues, making it a versatile and to visualize specific sections of the brain as a conventional imaging technique.

The combining modalities of MRI can bring about multi modal images resulting to more data about tumors that are shaped irregular, but single modality is difficult to localize. The modalities constitute of "T1-weighted MRI (T1), T1-weighted MRI with contrast improvement (T1c), T2-weighted MRI (T2) and T2-weighted MRI with fluid attenuated inversion recovery (T2-Flair)".

All these multi-modal data are utilized in segmentation with a notable advancement in performance (Hussain et al., 2017)

4.2 Tools Used

In this chapter we will look at the tools we used to achieve our results.

4.2.1 Dataset

The MRI LGG – 1p19qDeletion was acquired from a public accessed repository called The Cancer Imaging Achieve (TCIA). All the images acquired from this repository are stored up in DICOM format. These pre-operative physical examinations where conducted on one hundred and fifty-nine (159) patients with LGG which constitutes WHO grade II & III. The MRI

database contains a total number of seventeen thousand, three hundred and sixty (17,360) images.

Table 4.1: Dataset description

COLLECTION STATISTICS	
Modalities	MRI
Number of participants	159
Number of studies	160
Number of Series	319
Number of images	17,360
Image size (GB)	2.7

4.2.2 DICOM conversion

After the MRI dataset has been obtained from the repository, "YAKAMI DICOM Tools" which is a freeware, a package of applications used for handling DICOM files for research is used. This tool has many features in it but we particularly made use of DICOM converter, converting the images to either PNG/JPG which is used for both training and testing. This tool is obtained from the department of diagnostic Imaging and nuclear medicine, graduate school of medicine, Kyoto University, Japan.

4.2.3 Python programming language

The use of python programming language has been one of the most useful and effective programming languages to many researchers across the globe. Python has been applied to this work. It is used for implementing deep learning and machine learning algorithm effectively. Python programming language is widely preferred because it is enriched with various library functions making complex problems easier with few lines of codes.

A handful of libraries are:

- Pandas
- Keras

- Num_py
- Matplot Lib
- Statistics
- TensorFlow Framework

4.3 System Specification Requirement

It explains the non-functional requirement which is further categorized into hardware requirement and software requirement.

4.3.1 Non-functional requirement

Hardware requirement

- A computer System

Software requirement

- Windows 10, Ubuntu or any other operating system that supports python
- 32-bit / 64-bit Operating system
- Anaconda / Miniconda
- Gvim, Phycharm IDE or any other text editor

4.4 CNN Architecture:

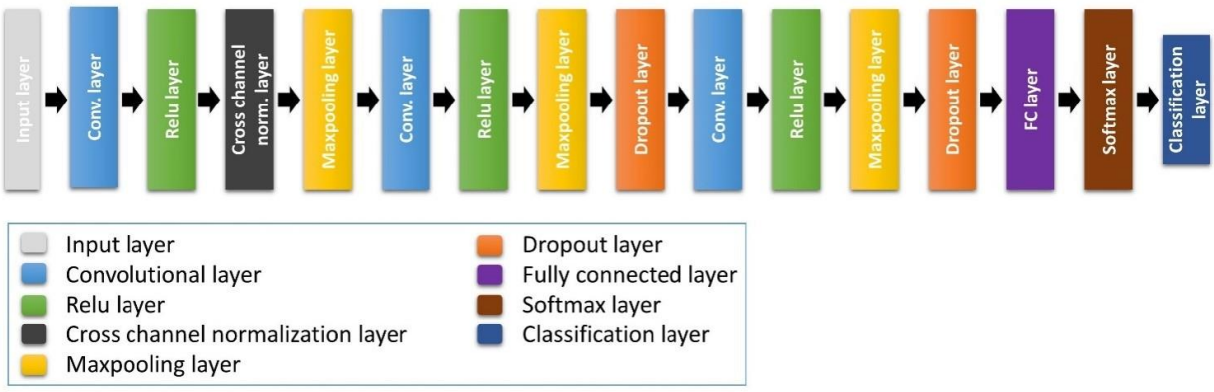


Figure 4.1: The proposed CNN architecture. (Sultan, Salem & Al-Atabany, 2019)

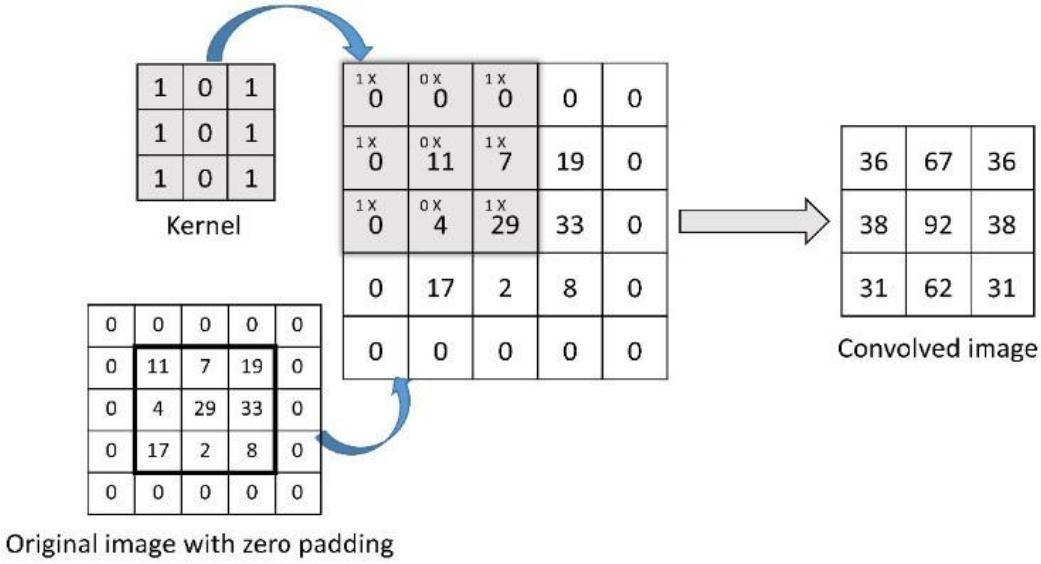


Figure 4.2: Convolution layer example (Sultan, Salem & Al-Atabany, 2019)

4.5 Filter Parameters:

- bilateral 1: 75x75
- bilateral 2: 50x50
- gaussian 1: 5x5
- gaussian 2: 3x3
- mean 1: 5x5
- mean 2: 3x3
- Laplacian: 3x3
- median: 5x5
- Histogram Equalization - no parameters.

4.6 Image Filtering

Image filtering is one of the widely used mainly to eliminate noise in the digital processing image. Amongst all the tools found in the image processing software, the image filtering tool is one of the most important tools used. (Gonzalez & Woods, 2008). Image filtering is used in

enhancing the quality of images as one of the popular techniques used. Image quality is very important for human vision and in image processing, images contain noise which cannot be easily eliminated which affects the quality of the images. That is why we utilize the use of image filtering. One of widely used method is the mean filter.

4.6.1 Mean filter

This filter is a linear filter and it is inherent and easy to apply where the density variation between the pixels is reduced. The essence of the mean filter is to alter each pixel value on images with an average value for both its neighbors and itself (Tania & Rowaida, 2016)

4.6.2 Histogram equalization

This is another fascinating and major method in image processing. It is based on the readjusting or equalization of the intensity value of images in an equal form. When this is applied the unequal distribution seemingly affecting the clarity of the image is removed to give better sights on the images. Where visual enhancement is required, the histogram equalization is applied and this aids the intensity distribution of the images.

4.6.3 Bilateral filter

The use of this filter is very predominant in image processing application. The bid to smoothen edges and still preserve edges of images is done with the bilateral filter. It can be used in a way which is non synergetic approach making parameters easy to set inasmuch its effect is not increasing over respective iterations. (Paris et at., 2007)

4.6.4 Gaussian filter

The use of this filter has been considerably been in uses in image processing for many years. This filter is familiar to be more structured for preserving details and small borders than another filter. The Gaussian filter is not suitable for elimination of spontaneous (salt and pepper) noise that needs statistical method filters. (Seddik and Braiek, 2012)

4.6.5 Laplacian filter

This filter is a substitute to existing edge-aware filters. When applied it has been proven to display high quality results in manipulating details map toning for large span of parameters. Nonetheless the running times of this filter are slow (Aubry et al., 2014).

4.6.6 Median filter

This filter is a constituent of nonlinear dynamic systems. The application of median filters on linear dynamic system which includes stability, impulse response, principle of superposition frequency analysis is not possible. This filter is evaluated on the ground of influence on the types of signals
(Micek & Jan, 2003).

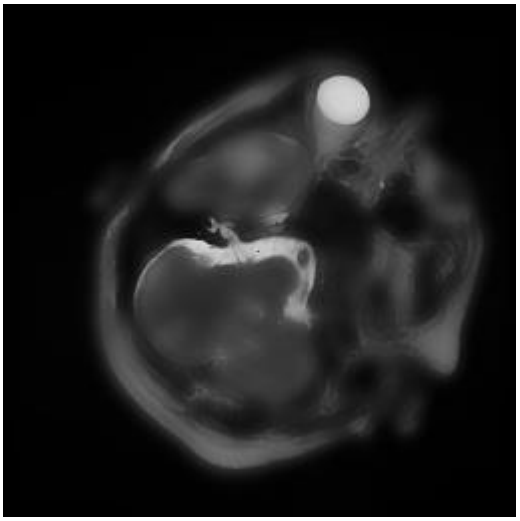
4.7 Data Augmentation

A popular approach in the subject matter of CNN is data augmentation, when the dataset is quite little. This is applied in extending the training set size and diminishing overfitting (Pereira et al., 2016).

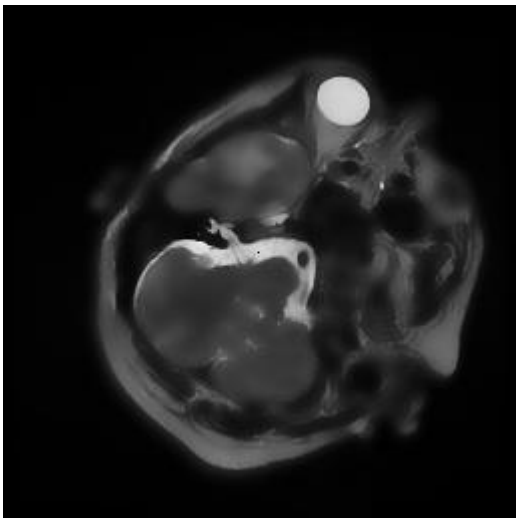
In data augmentation, many researchers now use various augmentation techniques such as introducing noise, rotation, flipping, image enhancement. Nevertheless, when some of these techniques are applied, the alter the value of the pixel intensity of the original images.

To preserve the real value of the image pixels and the associated ground truth values without altering them we apply a non-intrusive preprocessing approach. As shown below:

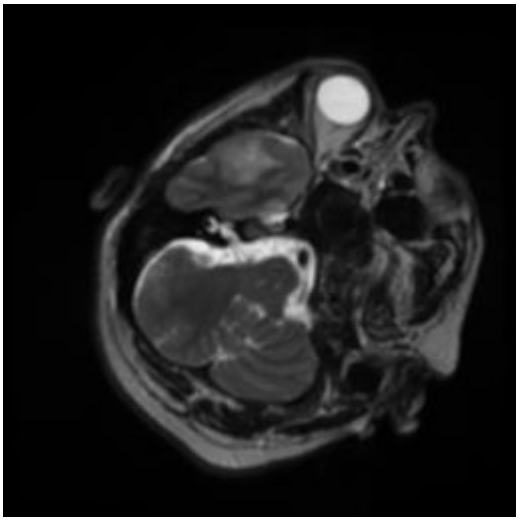
"Rotation at 90^0 (0,90,180,270) of original image; Rotation at 90^0 (0,90,180,270) of left-right flipped image" (Iqbal et al., 2017).



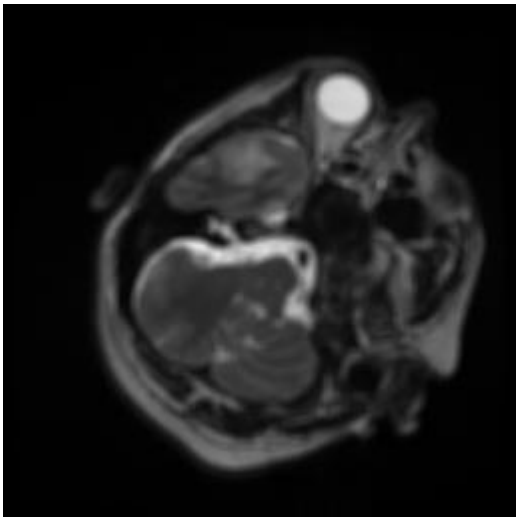
(a) Bilateral 1



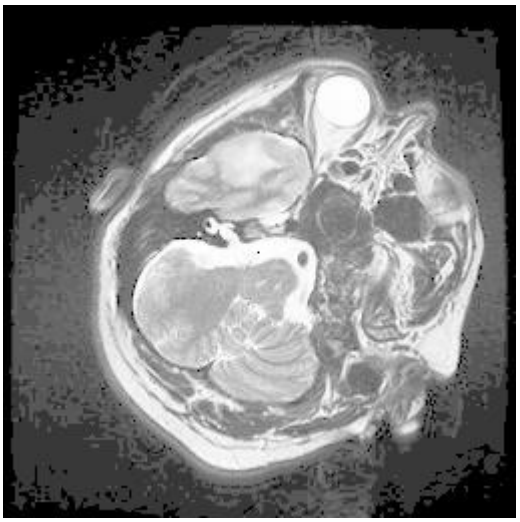
(b) Bilateral 2



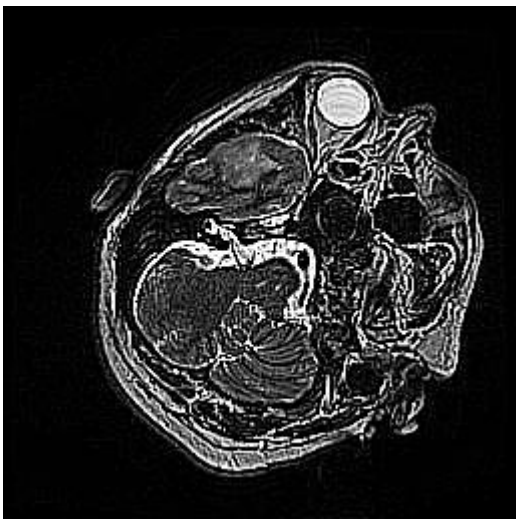
(c) Gaussian 1



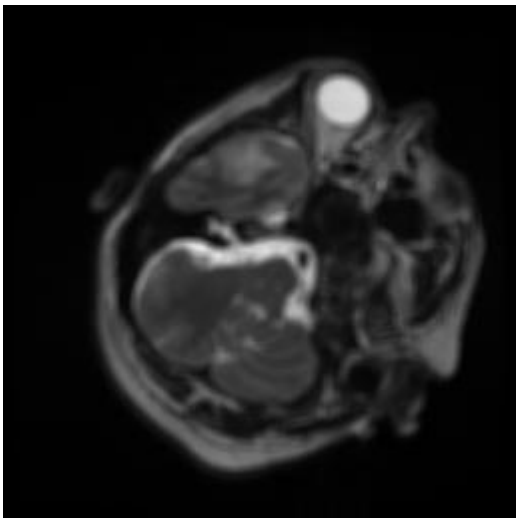
(d) Gaussian 2



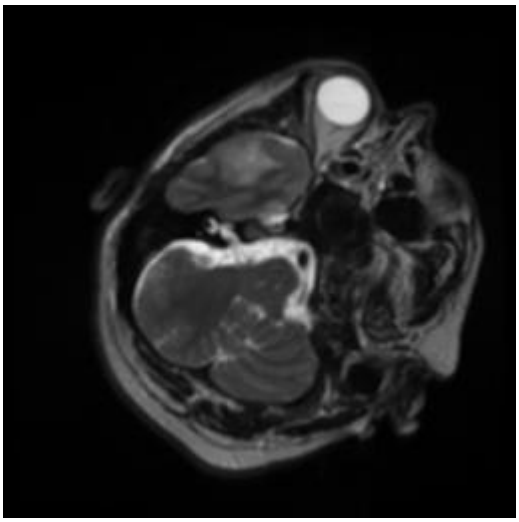
(e) Histogram Equalization



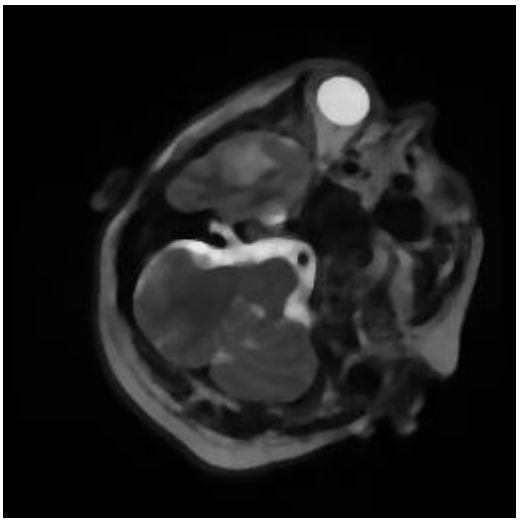
(f) Laplacian



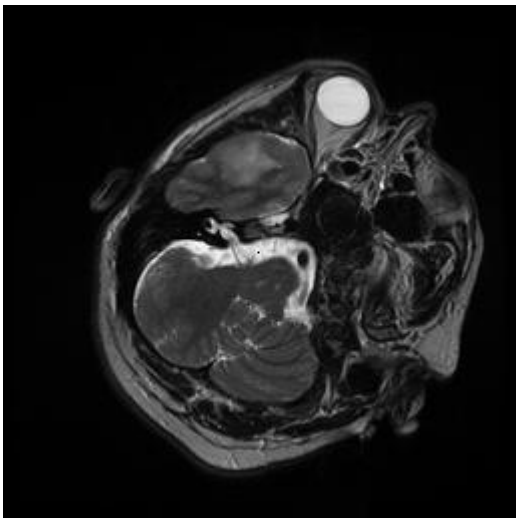
(g) Mean 1



(h) Mean 2



(i) Median



(j) Original

Figure 4.3: Filter Application on Images

4.8 Cross-validation

An 8-fold cross validation was utilized in the constructing of our model. This procedure is used to diminish “under and overfitting”, whereby the training iterations and the optimal number of hidden units of the neural networks are recognized. An iterative rotation on the sets is done so as to make single usage of each data point during training, cross-training or testing. An 8-fold model is acquired eventually (Menden et al., 2013).

CHAPTER 5
RESULT AND DISCUSSION

Result and Discussion

In this chapter, the system performance is tested. The brain MRI images are stored in the database which are under the proposed architecture and discussion.

With the basic CNN model employed we have been able to obtain some number of reasonable results, to the task of obtaining all the accuracy required.

This proposed CNN model has an approach without segmentation as we feed the brain tumor images directly to obtain correspondent class straight away.

Two convolution layers were used, 1st: 64 kernels (3x3), activation 'relu', pooling size (2x2) dropout: 0.2, 2nd: 32 kernels (3x3), activation 'relu', pooling size (1x1) dropout: 0.2

A further 2 Dense (fully connected) layers were used in the model, "1st: 128 neurons activation: relu, dropout: 0.2, 2nd: 8 neurons activation: relu, dropout: 0.2**,** output layer: 2 neurons: activation: softmax, loss: categorical cross entropy, optimizer: adam".

Used image dimensions was 80x40 (rgb) and 8 - fold cross validation.

In this designed system, the tumor is extracted from the brain MRI imaging for better analysis. Attributes such as "TP (True positive): Existing tumor and detected correctly; TN (True negative): Non-existing tumor and not detected; FP (False positive): Existing tumor and not detected; FN (False negative): Non-existing tumor detected" were used to evaluate the "accuracy, sensitivity and specificity of the system".

Accuracy is the measure of "successful classification". The accuracy is given by:

$$(\text{Accuracy} = TP + TN / TP + TN + FP + FN) \qquad (5.1)$$

Sensitivity measures a "successful determination of not having a tumor". And it is given by:

(Sensitivity = TP / TP + FN) (5.2)

Specificity measure a “successful determination of not having a tumor”. And it is given by:

(Specificity = TN / TN + FP)

(5.3)

Table 5.1: Experimental Data

Experiment	TP	TN	FP	FN	Total Patterns
Augmented	15309	1331	441	279	17360
Normal	15493	1202	570	95	17360
Augmented	15419	1259	513	169	17360
Augmented3	15318	1338	434	270	17360

Table 5.2: Experimental results

Accuracy	Sensitivity	Specificity	ROC Accuracy
0.95852535	0.98210162	0.75112867	0.86661514
0.96169355	0.99390557	0.67832957	0.83611757
0.96071429	0.98915833	0.71049661	0.84982747
0.959447	0.98267898	0.75507901	0.868879

Table 5.3: Experimental parameters

Explanation	**Filters used in Data Augmentation for Class1**
8fold	Bilateral, gaussian, mean, Histogram Equalization, median
8fold	No augmentation
8foldw/out Heq	Bilateral, gaussian, mean, median
All Augmented all	Bilateral 1, Bilateral 2, gaussian 1, gaussian 2, mean, mean 2, median

CHAPTER 6
CONCLUSION

Conclusion

Brain tumor classification has hence become one of the most difficult tasks in the process of clinical diagnosis. Machine Learning algorithms is now having a great influence in the medical imaging field. Brain tumor classification has been executed with other ML techniques over the period which cannot accurately extricate the features required in image classification but a Convolution Neural Network model was employed and proposed in this work for the MR brain image classification seeing that it has an enormous advantage over other techniques which provides a very high accuracy which is accomplished with the aid of many layers and automated feature processes in extraction. However, the CNN technique comes with its own issues since the convolution layer uses the back-propagation method which is a feedforward network algorithm leading to time consumption, convergence depending on learning rate, high cost of computational complexity and other issues. All images where obtained from the cancer Imaging Achieve (TCIA) which we used for this thesis. The proposed network was constructed with 2 convolution layers, 2 dense (fully connected) layers. an image dimension of 80x40 (rgb) was used also with an 8-fold cross validation. However, our proposed CNN algorithm is not too deep but can be further improved in the future. The utilization of data augmentation was also introduced to help obtain better results. Different filter parameters were applied to enhance the quality of the images - bilateral 1: 75x75, - bilateral 2: 50x50, - gaussian 1: 5x5, - gaussian 2: 3x3, - mean 1: 5x5, - mean 2: 3x3, - Laplacian: 3x3, - median: 5x5, - Histogram Equalization.

Our proposed CNN architecture came out with the highest Accuracy of 96.16%, Sensitivity of 99.39%, Specificity of 75.11% and ROC Accuracy of 86.88%.

REFERENCES

Ahmmed, R., Swakshar, A., Hossain, F., & Rafiq, A. (2017). Classification of Tumors and its stages in Brain MRI using Support Vector Machine and Artificial Neural Network. *In International Conference Electrical Computer and Communication Engineering.* Pp 229-234.

Akkus, Z., Ali, I., Sedlar, J., Agrawal, J., Parney, I., Giannini, C., & Erikson, Bradley. (2017). Predicting Deletion of Chromosomal Arms 1q/19q in low-Grade Gliomas from MRI Images Using Machine Intelligence. *Journal of Digit Imaging*, 30(4), 469-476.

Alqudah, A., Alquraan, H., Qasmieh, I., Alqudah, A., & Al-Sharu, W. (2019). Brain Tumor Classification Using Deep Learning Technique – A comparison between Cropped, Uncropped and Segmented Lesion Images with Different sizes. *International Journal of Advanced Trends in Computer Science and Engineering*, 8(6), 3684-3691.

Aquilanti, E., Miller, J., Santagata, S., Cahill, D., & Brastianos, P. (2018). Updates in prognostic markers for gliomas. *Neuro Oncology*, 20(S7), 17-26.

Ari, A., & Hanbay, D. (2018). Deep Learning based brain tumor classification and detection system. *Turkish Journal of Electrical Engineering & Computer Sciences*. 26, 2275-2286.

Al-Antout, A. (2017). *Brain Tumor Detection and Classification Using Neural Network* [Master's Thesis, Near East University] http://docs.neu.edu.tr/library/.

Aubry, M., Paris, S., Hasinoff, S., Kaute, J., & Durand, F. (2014). Fast Local Laplacian Filters: Theory and Applications. ACM Transaction Graphics, 35(5), 1-14

Bahadure, N., Ray, A. K., & Thethi, H. P. (2017). Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM. *International Journal of Biomedical Imaging*, 12.

Bisley, J. W. (2017). Parietal Lobe. *Encyclopedia of Animal Cognition and Behaviour,* 1-6, https://doi.org/10.1007/978-3-319-47829-6_1252-1

Buerki, R., Horbinski, C., Kruser, T., Horowitz, P., James, C., & Lukas, R. (2018). An overview of meningiomas. *Future Oncology*, 14(21), 2161-2177.

Coslett, H. B., & Schwartz, M. F. (2018). The parietal lobe and language. *Hand book of Clinical Neurology, the Parietal Lobe,* 151(3), 365–375. doi:10.1016/b978-0-444-63622-5.00018-8.

Davis, M. (2016). Glioblastoma: Overview of Disease and Treatment. *Clin J Oncol Nurs*, 20(5), S2-S8.

Dong, X., Noorbakhsh, A., Hirshman, B., Zhou, T., Tang, J., Chang, D., Carter, B., & Chen. (2015). Survival trends of grade I, II and III astrocytoma patients and associated clinical practice pattern between 1999 and 2010: A SEER-based analysis. *Neuro-Oncology Practice*, 3(1), 29-38.

Firat, R. B. (2019). Opening the "Black Box": Functions of the frontal lobes and their implications for sociology. *Frontiers in Sociology* 4(3), 1-14.

Hanif, F., Muzaffar, K., Perveen, K., Malhi, S., & Simjee, S. (2017). Glioblastoma Multiforme: A Review of its Epidemiology and Pathogenesis through Clinical Presentation and Treatment. *Asian Pacific Journal of Cancer Prevention*, 18(1), 3-9.

Hussain, S., Anwar, S., & Majid, M. (2017). Segmentation of glioma Tumors in brain using deep convolutional. *Elsevier*.

Havaei, M., Davy, A., Farley, D., Biard, A., Courville, A., & Bengio, Y. et al. (2017). Brain Tumor segmentation with Deep Neural Networks. *ELSEVIER*.

Huang, J., Yu, J., Tu, L., Huang, N., Li, H., and Luo, Y. (2019). Isocitrate Dehydrogenase Mutations in Glioma: From Basic Discovery to Therapeutics Development. Front. Oncol. 9:506. doi: 10.3389/fonc.2019.00506

Hemanth, D., Anitha, J., Naaji, A., Geman, O., Popescu, D., & Son, L. (2019). A Modified Deep Convolutional Neural Network for Abnormal Brain Image Classification. *IEEE*.

Ilhan, A. (2016). *Brain Tumor Detection Using Intensity Adjustment Based Segmentation* [Master's Thesis, Near East University]. http://docs.neu.edu.tr/library/.

Jawabri, K. H., & Sharma, S. (2019). Physiology, Cerebral Cortex Function. *Statpearls Publishing*; Treasure Island.

Kiernan, J. (2012). Anatomy of the Temporal Lobe. *Epilepsy Research and Treatment*, 1-12.

Komori, T. (2017). The 2016 WHO Classification of Tumors of the Central Nervous System: The Major Points of Revision. *Neurol Med Chir*, 57, 301-311.

Krishnammal, P., & Raja, S. (2019). Convolutional Neural network-based image Classification and Detection of Abnormalities in MRI Brain Images. *IEEE*.

Kaldera, H., Gunasekara, S., & Dissanayake, M. (2019). MRI based Glioma segmentation using Deep Learning algorithms, (SC 08).

Lapointe, S., Perry, A., & Butowski, N. (2018). Primary brain tumors in adults. *Seminar*, 1-15.

Li, Z., Guan, Y., Liu, Q., Wang, Y., Cui, R., & Wang, Y. (2019). Astrocytoma Progression Scoring System based on the WHO 2016 Criteria. *Scientific Reports*, 9: 96.

McFaline-Figueroa, J., & Lee, E. (2018). Brain Tumors. *The American Journal of Medicine*, 131, 874-882.

Moshen, H., El-Dahshan, E., Horbaty, E., & Salem, A. (2017). Classification using deep learning neural networks for brain tumors. *Future Computing and Informatics Journal*, 3; 68-71.

Olawale, O. (2020). *Individual Eye Gaze Prediction with The Effect of Image Enhancement Using Deep Neural Networks.* [Master's Thesis, Near east University] http://docs.neu.edu.tr/library/.

Patel, A., Bisco, G., Fowler, J. (2020). Neuroanatomy, Temporal Lobe. *StatPearls Publishing; Treasure Island.*

Pashaei, A., Sajedi, H., & Jazayeri, N. (2018). Brain Tumor Classification via convolutional Neural Network and Extreme Learning Machines. *IEEE*.

Pellerino, A., Bertero, L., Rudà, R., & Soffietti, R. (2020). Choosing appropriate chemotherapy for diffusely infiltrating WHO grade II gliomas in adults. *Expert Opinion on Pharmacotherapy*, 1-3

Pathak, K., Pavthawala, M., Patel, N., Malek, D., Shah, V., & Vaidya, B. (2019). Classification of Brain Tumor Using Convolutional Neural Network. *IEEE*.

Perkins, A., & Liu, G. (2016). Primary Brain Tumors in Adults: Diagnosis and Treatment. *American Academy of Family Physicians*, 93(1), 211-219.

Pereira, S., Pinto, A., Alves, V., & Silva, C. (2016). Brain Tumor Segmentation Using Convolutional Neural Network in MRI Images. *IEEE*.

Paris, S., Kornprobst, P., Tumblin, J., & Durand, F. (2007). A gentle introduction to bilateral filtering and its applications. In proceedings of the International Conference on Computer Graphics and Interactive Techniques (pp 1-45). San Diego, California.

Reeber, S., Otis, T., & Sillitoe, R. (2013). New roles for the cerebellum in health and disease. *Frontier in Systems Neuroscience*, 17(83), 1-11.

Rehman, A., & Khalili, Y. (2019). Neuroanatomy, Occipital Lobe. *StatPearls Publishing; Treasure Island*.

Schmahmann, J. (2019). The Cerebellum and Cognition. *Neuroscience Letters*, 688(1), 62-75.

Seifert, M., Garbe, M., Friedrich, B., Mittelbronn, M., & Klink, B. (2015). Comparative transcriptomics reveals similarities and differences between astrocytoma grades. *BMC Cancer*, 15:952, 1-22.

Shaikh, N., Dixit, K., & Raizer, J. (2018). Recent advances in managing/understanding meningioma (version 1; referees: 2 approved) *F1000Research*,490.

Sultan, H., Salem, N., & Al-Atabany, W. (2019). Multi-Classification of Brain Tumor Images Using Deep Neural Network. *IEEE Access*, *7*, 69215-69225 doi: 10.1109/access.2019.2919122.

Tandel, G., Biswas, M., Kakde, O., Tiwari, A., Harman, S., Turk, M., Laird, J., Asare, C., Ankrah, A., Khanna, N., Madhusudhan, B., Saba, L., & Suri, J. (2019). A Review on a Deep Learning Perspective in Brain Cancer Classification. *Cancers*, 11(111), 1-32.

Taylor, O., Brzozowski, J., & Skelding, K. (2019). Glioblastoma Multiforme: An Overview of Emerging Therapeutic Targets. *Frontiers in Oncology*, 9, 963.

Van Essen, D. C., Donahue, C. J., & Glasser, M. F. (2018). Development and Evolution of Cerebral and Cerebellar Cortex. *Brain, Behaviour and Evolution*, 9(81), 158-169.

Weller, M., Wick, W., Aldape, K., Brada, M., Berger, M., Pfister, S., Nishikawa, R., Rosenthal, M., Wen, P., Stupp, R., & Reifenberger. (2015). Glioma. *Nature Reviews Disease Priemers* 1.

Zhang, J. (2019). Secrets of the Brain: An Introduction to the Brain Anatomical Structure and Biological Function, *IFM Lab*

APPENDICES

APPENDIX 1: ETHICAL APPROVAL DOCUMENT

ETHICAL APPROVAL DOCUMENT

Date: 20/01/2021

To the Graduate School of Applied Sciences

For the thesis project entitled as “Brain Tumor classification using Convolutional Neural Network” the researchers declares that they did not collect any data from human/animal or any other subjects. Therefore, this project does not need to go through the ethics committee evaluation.

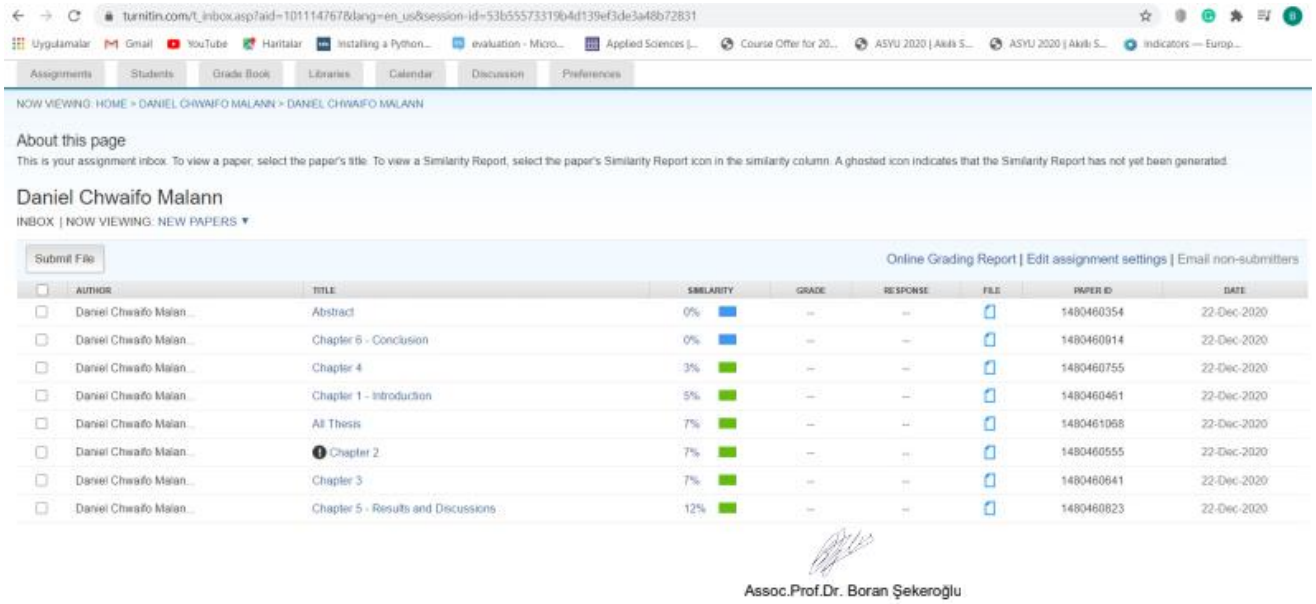
Title: Assoc. Prof. Dr.

Name Surname: Boran Şekeroğlu

Signature: 

Role in the Research Project: Supervisor

APPENDIX 2: SIMILARITY REPORT



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